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The impact of COVID-19 on online music listening behaviors in light of listeners' social interactions

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Abstract

This study investigated the global changes in online music listening behaviors in response to COVID-19 and its restrictions (such as quarantine, school and workplace closures, and travel restrictions). In addition, the research included an examination of how friendship networks and online communication motives have moderated the effect of COVID-19 on music listening behaviors. The causal inference methods: difference in differences (DiD) and two-way fixed effects (TWFE), were conducted to analyze the online music listening behaviors and social interactions of 37,328 Last.fm users in 45 countries before and after the first wave of confinement. It was found that in response to COVID-19, the quantity, variety, and novelty of music consumption decreased, shifting toward mainstream artists, whereas individuals with more online social connections and communications showed the reverse behavior. Our research shows that online social interactions and community development significantly impact listeners' behaviors and can be used as a guide to developing new design strategies for digital media, such as music, movies, and games.

Keywords COVID-19 pandemic · mental health · music listening · online platform · social dynamics

1 Introduction

The COVID-19 pandemic has affected many people across the globe since its debut, with accompanying high mortality and infection rates. In an effort to cope with COVID-19 health consequences, many countries have enacted social distancing regulations, lockdown restrictions, or canceled large gatherings and events at different times, measures that have varied in scope, duration, and rigidity [120]. Although these measures have reduced public health risks,

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the social and economic consequences may have long-term effects on people's minds and emotions [35]. It has been known for a long time that music benefits mental health. During the COVID-19 pandemic, researchers have studied its role in reducing loneliness, raising mood, helping people cope with difficult situations, and creating a sense of community e.g., [18, 71, 120]. Therefore, in the wake of the COVID-19 impact on people's lives, a new stream of research is being developed to better understand how music listening behaviors have changed.

Results of studies using self-reported data show that people have increasingly used music as a coping strategy during the challenging times of the COVID-19 pandemic [18, 35, 62]. As a result, there has been an expectation that the pandemic could boost the popularity of streaming services. However, the findings from streaming platform statistics indicate a decrease in music listening during lockdowns, which contradicts the results of direct questionnaires [54]. Nevertheless, we found the current literature does not examine changes in other aspects of music listening behaviors at the individual level, such as novelty, variety, and mainstreaminess in music consumption.

At the same time, people who lacked face-to-face interaction during the initial lockdowns resorted to online social communication and building online friendships to alleviate feelings of social isolation [35]. Ultimately, this motivated us to examine the social dynamics of music streaming services (in this case, Last.fm), which are also considered social network sites, to understand better how social networking and communication motives intersect with music streaming. As far as ascertained, no study has reconsidered the social dynamics of music streaming platforms during the COVID-19 crisis. We drew upon the current controversy regarding the demand for online music listening and the lack of research on fundamental musical listening behaviors – variety, novelty, and mainstreaminess – during the COVID-19 pandemic to discuss how individuals' choices of songs have changed. We aimed to determine the degree to which COVID-19 related variables influence online music listening behaviors based on theories about social contexts and functional goals that determine music selection behaviors [41, 93]. In addition, based on the social dynamics theory of online platforms [46, 92], we questioned the moderating roles of social networks and the communication motives of listeners.

As a result, we proposed the following research questions with reference to the independent variables (IV) and dependent variables (DV) of our study:

RQ1. What is the effect of the COVID-19 pandemic (IV) on the quantity, novelty, variety, and mainstreaminess of music consumption (DVs)?
RQ2. What is the effect of the number of new COVID-19 cases (IV) on the quantity, novelty, variety, and mainstreaminess of music consumption (DVs)?
RQ3: What is the effect of COVID-19 restrictions (IV) on the quantity, novelty, variety, and mainstreaminess of music consumption (DVs)?
RQ4: Do online social connection and communication (moderators) have a different effect on the impact of COVID-19 restrictions (IV) in terms of the quantity, novelty, and variety of music consumption (DVs)?

This study sought to address the research gap by using demographically representative samples of Last.fm users (N = 37,328; age: M = 26 years, SD = 10; gender: 27,125 men, 10,203 women) from 45 countries. Our study examined the unanticipated outbreak of COVID-19 as a real-world event to investigate outcome variables using the difference in differences (DiD) method, a widely used causal inference approach. In the second part of the study, which examined the effects of new COVID-19 cases and restriction policies on the behaviors under investigation, the fixed effects (FEs) method was used to analyze the results. We furthered our investigation through the lens of the online community provided by Last.fm that enables social connections and communication with other people.

Our results showed a decrease of 15% in online music listening due to the COVID-19 pandemic. In addition to this decline in online music consumption, the novelty and variety of tastes decreased and shifted toward mainstream artists. We additionally found that with the increase of weekly COVID-19 cases and strengthening lockdown policies, music listeners' choices became more mainstream with less variety and novelty. In contrast, due to COVID-19 restrictions, listeners who had more social ties and more communication with friends demonstrated distinct changes in behavior: they consumed more music, discovered more music, and had a wider variety of tastes. Our study of Last.fm users, based on their individual characteristics, revealed that it was not the virus infection (as measured by new cases of COVID-19) but instead major changes caused by the initial lockdowns (measured by the stringency index) that changed the demand for online music listening.

The findings of our study make several significant contributions. First, shifts in mood caused by an event can drive changes in music listening behaviors. Thus, we addressed whether users changed their music listening habits due to the COVID-19 pandemic and the initial lockdowns. The results of this study work for a wide range of music recommendation systems, such as Last.fm and Spotify, by identifying the causality of context and its impact on novelty and variety, thus highlighting the need to have a real-time musical response in a similar context. The results of our study show that online social interaction can be essential to the analysis of music listening behavior, which aids the development of further consumer behavior research and marketing strategies for other digital media, such as movies and software. Our findings suggest that the meaning of user connections within a platform may change if the context changes (in this case, the COVID-19 pandemic). Online music communities that foster communication and social ties can improve music consumption on online music platforms through this awareness. Therefore, we contribute to improving the design of digital platforms such as music, movies, and games by infusing design-oriented research into our research goals.

The rest of the paper is organized as follows. The following section examines the literature on online music listening and the social dynamics of streaming platforms to present a conceptual model. In Section 3, we discuss the research method. The analysis and findings are presented in Section 4. We discuss the academic and practical implications and future research directions in Section 5. We conclude our research in Section 6.

2 Research background

Our research background is centered on (1) listening to music within the context of the COVID-19 pandemic and (2) the social dynamics of streaming platforms.

2.1 Listening to music within the context of COVID-19

Since the start of the COVID-19 pandemic, people worldwide have faced several challenges. Many countries have implemented different lockdowns and social distancing strategies to keep the disease under control, but this has adversely affected all citizens' mental, social, and spiritual well-being [84, 90, 110, 119]. Researchers have increasingly examined the possible benefits of musical activities for people who have experienced different mental health issues and a sense of uncertainty due to COVID-19 [111]. In particular, music has been found to alleviate social health concerns, such as loneliness and social isolation [120], and create positive and regulating emotions [39]. Therefore, having identified the COVID-19 pandemic as a significant threat, research across many disciplines has focused on music listening habits during the COVID-19 crisis.

A rich literature has emerged about music's role in providing social connection, comfort, and humor to cope with negative emotions e.g., [18, 35, 88, 120]. During the initial stages of the COVID-19 pandemic, one of the initiatives people chose to alleviate stress was participating in music-related activities, whether on balconies, streets, or online, to strengthen their relationships, empower themselves, and build connections with others [36, 57]. Singing on balconies, clapping for healthcare workers, whistling, and using kitchen utensils as musical instruments appeared on social media videos, showing how music serves as a social tool [48]. These music-related activities further confirm that the current COVID-19 pandemic has increased musical contact among people [88]. Music has kept people connected even when physically separated.

Studies using self-reported data suggest that over half of the surveyed population used music as a coping strategy during challenging times of the COVID-19 pandemic [18, 35, 62]. Additionally, studies focused on how music affects people based on age, familiarity with music, and the significance of music in their everyday lives [35, 40]. Mas-Herrero et al. found that music was preferred over reading or watching TV for coping with COVID-19 psychological distress [73]. Researchers have also studied the role of music-related activities in mental health; for example, Cabedo et al. studied the impact of musical activities on individuals' perceived well-being [18], and following a broad literature review, Ramesh linked music-making and music-playing to therapeutic interventions during the COVID-19 pandemic [88]. However, the design of this type of research has generally relied on the role music has played in the past or self-reported data at the single-country level from a limited sample size e.g., [51, 72, 83, 120]. Further, a gap remains in exploring online music listening behaviors where the behavioral traits are not limited to a dichotomous variable (e.g., listening or not listening).

On the other hand, the findings from streaming platform statistics contradict the results of direct questionnaires, which indicate a decrease in music listening during lockdowns [54]. Among a few researchers, Sim et al. found that the consumption of visual entertainment (e.g., live video on demand) increased while audio consumption decreased during COVID-19 lockdowns [101]. However, further studies on changes in music listening behaviors are missing from the current literature, such as studies on novelty, variety, and mainstreaminess at the individual level. These are the leading variables in studying online music listening [12, 28, 95], as different kinds of music can reflect users' musical preferences and desires for variety [28]. However, it has also been found that individuals often choose only one or two styles of music from their favorite playlist in a specific context [64].

Users' music listening behaviors are increasingly being tracked in music recommendation systems considering additional taxonomies, such as mood and activity [34]. For example, during the COVID-19 pandemic, researchers have formulated a better way to recommend music based on users' emotions by reading users' facial expressions or obtaining direct input from them [109]. Studies have also shown that emotion-aware algorithms can utilize the information provided by COVID-19 cases and outperform baseline algorithms [112]. Typically, context-aware music recommendation systems are concerned with studying users' musical listening behaviors in the context of the real-world and utilizing that information as input for the system. It is not a new topic in music recommendation systems to relate users' music listening to the context of events or situations [31] and the consequent emotions [118]. Music recommendation systems incorporate user emotion into the operation to enrich the user experience of music streaming services [116]. Therefore, researchers emphasize the importance of considering situational or contextual aspects and their association with user emotions that shape users' musical tastes and affect their consumption behaviors [98]. For example, Spotify reported that listeners' musical habits have significantly altered since the start of the COVID-19 pandemic: people listen to music more often during the weekend, and music taste is becoming increasingly focused on being relaxed and calm [65].

Therefore, our study aimed to examine the impact of the COVID-19 pandemic and the accompanying restrictions on individuals' music listening behaviors by using empirical data from Last.fm and studying individual-level music listening behaviors.

2.2 Social dynamics of streaming platforms

During the most restrictive periods of the COVID-19 pandemic, businesses that could stream content directly to their customers saw the most success [44]. However, during these periods of isolation and social separation, listening to music through streaming services declined [101]. We looked for reasons in the literature from the perspective of the social dynamics of streaming platforms. In recent years, streaming has become the most popular method of listening to music [2], and online music services have made the music experience more personal [103]. Digital platforms have changed how people listen to music, turning music listening into a more individual activity [58]. However, during the initial COVID-19 isolation periods, people turned toward activities with a stronger sense of community, belonging, and social elements [42]. Music streaming lacks this feature. During the time of this pandemic, researchers have observed a change in music consumption patterns, with an increasing number of users transitioning from audio-based streaming services to video-based platforms like YouTube. This shift can be attributed to the enhanced interactive features and active engagement opportunities provided by YouTube, distinguishing it from platforms such as Spotify and Pandora [54].

Following the first wave of the COVID-19 pandemic, many countries implemented restrictions and limited social interaction at different levels; however, people still found creative ways to participate in activities and keep in touch with each other [108, 120]. Because of the loss of in-person connection, people actively socialized online and built online friendships to alleviate feelings of social isolation [35]. For this reason, social network sites' usage has encountered an upward trend worldwide compared to before the pandemic [9], and people use this platform for content (e.g., news, videos, music, etc.) consumption as well. However, despite the variety of ways people communicate online in social network sites, streaming services do not appear to prominently facilitate social interaction in their technological design or substitute the social network sites [103].

The desire to communicate and interact with others also moves individuals toward streaming platforms. The user communities provided by content providers show that consumer communities have become one of the most active online communities [111]. An important characteristic of social network sites is that the nodes in the community have a greater number of internal connections than external ones [37], which can help bring people together in times of social isolation. In this sense, the role of social networking tools in music streaming platforms is akin to Ray Oldenburg's concept of a "third place" in creating a sense of community since they support communication and interaction between members [74]. Social and community motivations have a stronger hold on users when they join live music streaming channels than similar channels in mass media [52]. Likewise, the decision to subscribe to online music platforms can also be significantly influenced by participation in the community rather than by the amount of content consumed [79].

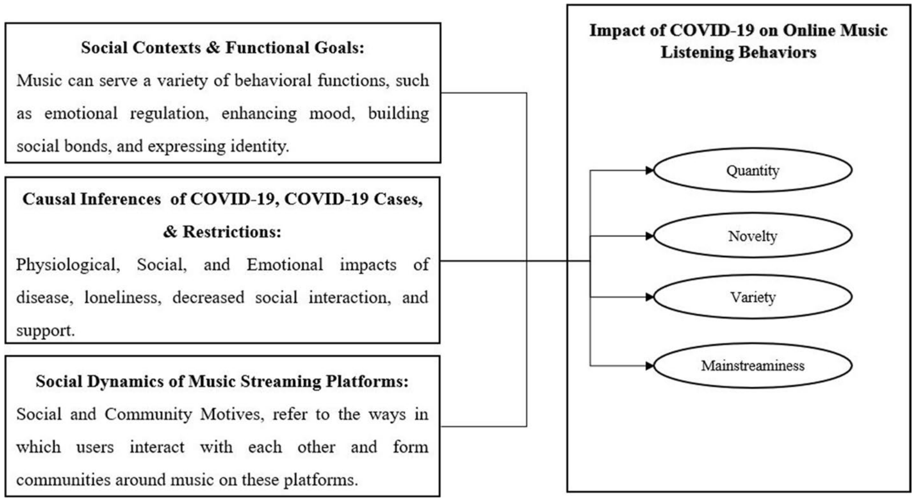

Fig. 1 Research conceptual model

Last.fm enables members to create a social network and socially interact using a personal profile, where they can follow and be followed by other users and communicate through private chat and shouts.[1] Considering the above discussion, we aimed to measure whether increased online social interaction during the COVID-19 pandemic has moderated the effect of COVID-19 on online music listening. As far as can be ascertained, the social dynamics linked to online music platforms is missing from researchers' analysis of the impact of COVID-19 on online music behavior.

2.3 Conceptual model

Figure 1 represents our conceptual model that offers a multifaceted framework for understanding the influence of three theoretical pillars on individuals' online music listening behaviors during the initial COVID-19 lockdown period. These pillars are social contexts and functional goals, the causal inference of COVID-19, and the social dynamics of music streaming platforms, which play an essential role in influencing online music listening behaviors and consumption patterns but have not been studied in an integrated manner to the best of our knowledge. Our model provides researchers and practitioners with a comprehensive understanding of analyzing these factors and making more accurate predictions about their impacts on music listening behaviors during a pandemic or other contexts.

Social contexts and functional goals: the first pillar refer to the social norms, reasons, and motivations behind an individual's music listening behaviors. While people generally enjoy variety in the music they listen to, they tend to select specific genres based on their listening context. For instance, an individual may listen to music to relax after a long workday or choose to listen to a particular genre or artist to feel a sense of connection with others who share similar musical preferences. Thus, the proposed model suggests that social contexts and functional goals play a significant role in shaping individuals' music listening behaviors, particularly in the specific context of the COVID-19 pandemic, which is the focus of our study.

[1] Shouts in Last.fm work in a similar manner to posts and replies in social network sites such as Twitter and Facebook.

The causal inference of COVID-19: the second pillar is the causal inference of COVID-19 as a natural event, highlighting the potential impact of the pandemic on online music listening behaviors. The closure of music venues, cancellation of live music events, and the implementation of lockdowns and social distancing may have resulted in changes to online music listening. Specifically, the model proposes that during times of heightened uncertainty and instability caused by the COVID-19 pandemic, individuals might gravitate toward familiar music and avoid seeking novelty and variety in music. These behaviors might happen, for example, due to individuals might stick to music that relieves the stress and loneliness caused by the uncertainty and hardships during the pandemic. At the same time, preserving a sense of belonging and emotional connection to happier times before the pandemic.

The social dynamics of music streaming platforms: a third pillar of the model represents the possibility that people have increasingly turned to online platforms for social interaction; as a result, music streaming platforms such as Last.fm have become more than just a means of accessing music but also a context for socializing and connecting with others. This social aspect of music streaming platforms can provide a sense of belonging and emotional support, particularly for those experiencing loneliness or isolation due to lockdowns and social distancing. In addition to accessing music, users can also engage in social interactions such as sharing playlists, commenting on music preferences, and following other users. So social interaction, measuring the social network size and communication through an online platform such as Last.fm could moderate the impact of COVID-19 on online music listening behaviors.

The present study focuses on the actual music listening behaviors rather than the quantity of music listening or self-reported data, which can only provide information on whether individuals listen to music more or less. To achieve this goal, the proposed conceptual model includes ovals representing various dimensions of music listening behaviors at the individual level. These include the amount of music listened to (Quantity), the extent to which individuals sought out new music (Novelty), the range of different artists that they listened to (Variety), and the extent to which they listened to popular or mainstream music (Mainstreaminess).

3 Research methodology

In this section, we first describe the variables and data we used for the analysis and then explain the methods by which we conducted the analysis.

3.1 Definition of variables

In this study, we chose to employ DiD and FEs analysis to gauge the causal impact of the: (1) COVID-19 intervention as a natural event, alongside two independent variables, namely the (2) new COVID-19 cases and (3) stringency index [101], on the dependent variables. In addition, to encompass the entirety of research on users' music listening behaviors, in addition to the dependent variable of (1) quantity of music listening, we included (2) novelty, (3) variety, and (4) mainstreaminess. These variables are established measures of music listening behaviors and are widely utilized in the literature [28, 29, 95, 97]. Our choice to incorporate these variables in our study was to provide a comprehensive understanding of how COVID-19 impacted music listening behaviors. As a result, we conducted three separate data analysis for each independent variable and each time on one of the dependent variables.

The first dependent variable is "quantity", which measured the number of songs that user i listened to in a specific week t [28]. Furthermore, we estimated the results by measuring novelty and variety within two different formulas to test the robustness of our analysis. Considering two indexes for variety and novelty analysis, we built two models to test the robustness of our results as suggested and used in the literature e.g., [28, 95]. The dependent variable of "variety" in consumption consists of two indexes. The variable variety1 determines the number of unique artists that user i listened to in a specific week t [28, 95]. Variety2 is the average amount of listening to each artist by user i in a specific week t [95].

Similarly, the dependent variable of "novelty" in consumption includes two indexes. We collected a history of music listening one month before our official data analysis time period for each user as the baseline time to operationalize the novelty measurement (i.e., from 1st-31st October 2019). Therefore, we measured novelty for each user based on their music history. For week t, if an artist that user i listened to was new within the baseline period or the weeks before each week, it was considered new. The variable novelty1 is defined as the number of unique new artists that user i listened to for the first time divided by the total number of unique artists in a specific week t [28]. The variable novelty2 is the value of the discoveries measured by the number of consumptions of new artists divided by the total number of consumptions for user i in a specific week t [28].

We then defined listening preferences toward mainstream artists by the dependent variable of the "mainstreaminess" [12, 70, 95]. The popularity of songs, albums, or artists on music streaming services is commonly determined by the number of times they have been played [12]. Another way to assess the popularity of artists is to count their total number of listeners [96]. Similar to novelty and variety explained according to the song artists, we measured users' mainstreaminess regarding the artists they listened to. Accordingly, we first determined the number of listening in total from all listeners and the number of listeners to particular artists to select the top 20 public artists during the baseline period and the weeks before each week. Considering the method introduced by Bauer and Schedl's (2019) and based on these two artist popularity measures, user mainstreaminess is defined as the number of consumptions matching the top 20 public artists divided by the total consumptions for user i in a specific week t.

We also found it worthwhile to explore the role of social interactions as moderators and the importance of individual characteristics as control variables in our study. Last.fm also allows members to build social networks and conduct social communications using their personal profiles. Based on the social dynamics of Last.fm, (1) social network connections and (2) social communication constituted the moderator variables analyzed for their ability to affect the variables of interest. In addition, for causal inferences to be drawn from the study context, it was essential to control for variables relevant to music listening behaviors [98]. We used several control variables in our study, which are characteristics commonly found in individual-level studies on music listening. Thus, we analyzed the differences in music listening among individuals as determined by their 1) age, 2) gender [14, 86], 3) age of the account, and 4) subscriber status [5, 28].

"Social network size" was calculated by the total number of followings and followers of user i. However, we were interested in obtaining the panel data on building social networks through the platform during the study period, data relating to the following and follower dates were not available to us. Thus, as in previous research, we used the total number of social networks to measure this variable in our study e.g., [29]. To assess the "social communication" effect in our study, the number of comments and replies posted on the user i profile showed the amount of communication for that user over a specific week t [24, 60]. Social communication did not include private messages through inboxes, as these were unavailable data and did not fall under the scope of this study.

Table 1 Definition of research variables

Variable	Description
Independent Variables	
COVID-19	A binary variable in which unaffected countries in a specific week are represented by 0 and affected countries are defined by 1 following the COVID-19 outbreak [67].
New COVID-19 Cases	The sum of confirmed new COVID-19 cases for a specific week [67].
COVID-19 Stringency Index	Enforced social distancing by governments drawn from OxCGRT for a specific week [47].
Dependent Variables	
Quantity	The total number of songs a user listened to in a specific week [28].
Novelty1	The number of unique new artists a user listened to for the first time is divided by the number of unique artists in a specific week [28].
Novelty2	The amount of listening to new artists is divided by the total consumption for a user in a specific week [28].
Variety1	The number of unique artists a user listened to in a specific week [28, 95].
Variety2	The average number of a user's listening to artists in a specific week [95]
User Mainstreaminess	The number of listenings that match up to the top 20 public artists is divided by the total number of listenings for a user in a specific week [12].
Moderator Variables	
Social Communication	The total number of comments and replies on a user's profile in a specific week [24].
Social Network Size	The total number of a user's followings and followers [29].
Control Variables	
Age	A user's age at the time of the investigation [14, 86].
Gender	Gender of a user [14, 86].
Age of the account	The number of weeks passed since a user's registration on Last.fm [5, 28].
Subscriber	The subscription status was 1 for a paid member and 0 otherwise [28].

Table 1 summarizes the study variables and their definitions. We present our research model in Fig. 2.

3.2 Data and measurement

Our dataset was constructed using Last.fm, including a panel on individuals' music consumption and social interactions. The advantage of research using a music-focused social network site, such as Last.fm is that real observational data can be collected from users concerning their social connections while their music listening behaviors are also evident [29]. We collected the music listening data of 37,328 users from 1st November 2019 to 27th March 2020 (dividing our research into 21 weeks). This timeline represents the first COVID-19 cases confirmed in countries based on international studies [67, 101]. Although the outbreak has continued in many places since this period, we can refer to this period as the first wave of the COVID-19 pandemic. The following steps were involved in data collection:

Step 1). The sample consisted of randomly selected single users from different geographical areas (45 countries), excluded individuals with missing data on key variables, those

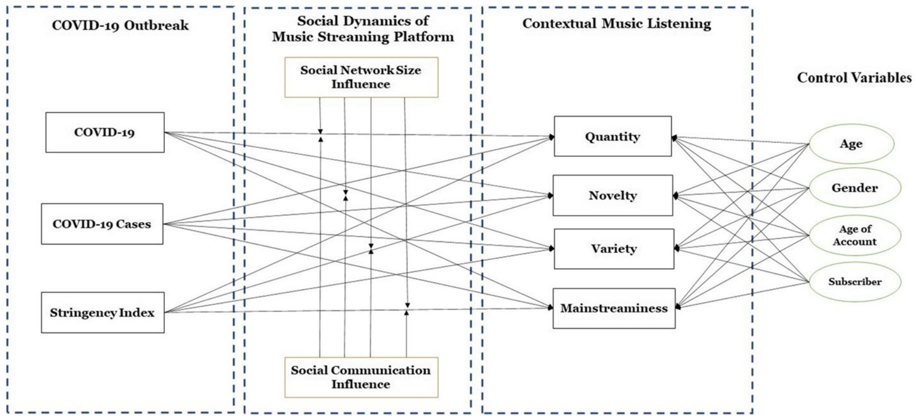

Fig. 2 Research model

who registered on Last.fm after the investigation started, and those with a listening exceeding the 99th percentile. As a result, the total sample size was 37,328 individuals.

Step 2). Using the dataset introduced by [75], we recorded the individuals' age, gender, and country. Then, users were divided into four age groups: adolescence (12-19): n =1387 young adulthood (20-39): n =32,664, middle adulthood (40-65): n =2,999, and above 65: n=278 according to the primary life stages [32]. Individuals' resident country was used to collect data in step 5.

Step 3). We obtained the songs users listened to using the service's application protocol interface (API), "user.getRecentTracks" built on Python (with BeautifulSoup library). We were able to identify unique artists based on the name of the artists associated with each song using an algorithm to gain a unique artist list [for more details, see 27]

Step 4). We then broadened the sample by identifying friends' networks (a directed network of the followings and followers) using API "user.getFriends", with a result of 2,647,578 following and follower relationships. Additionally, we accessed a separate data set containing a time-stamped log of users' comments and replies and used this to determine users' social communication.

Step 5). The COVID-19 variables for every country, including the COVID-19 start week and weekly new cases, were derived from the "Our World in Data website"[2] along with the stringency index derived from the OxCGRT dataset [47]. The descriptive statistics of the dataset are presented in Table 2.

3.3 DiD and fixed effects analysis

DiD analysis is a quasi-experimental method well-suited for analyzing natural experiments [7], such as the COVID-19 pandemic as an exogenous event. Using DiD analysis to compare online music listening behaviors between treatment groups exposed to COVID-19 and control groups not exposed can estimate the causal effect of COVID-19 on online music

[2] https://ourworldindata.org/covid-cases

Table 2 Summary statistics of variables

Variable	Mean	SD	Min	Max
Independent variables (weekly)				
COVID-19 (start week from 1 to 21)	14.89	2.33	10	20
New COVID-19 cases	1,402	7,883	0	73,030
Stringency index (%)	11.06	19	0	100
Dependent variables (weekly)				
Quantity	48.52	158.17	0	6,979
Variety1	1.57	12.24	0	2,852
Variety2	14.38	44.59	0	3,962
Novelty1 [0-1]	0.14	0.28	0	1
Novelty2 [0-1]	0.18	0.34	0	1
User mainstreaminess [0-1]	0.94	0.14	0	1
Moderators				
Follower	37.37	116.46	0	7,433
Following	34.79	119.92	0	7,534
Social communication (weekly)	0.02	0.14	0	44
Controls				
Gender (female=1)	0.27	0.44	0	1
Age	25.42	9.33	12	115
Hofstede cultural value [0-1]	0.56	0.05	0.38	0.71
Age of the ccount (weeks)	543	109	24	883
Subscriber (paid =1)	0.007	0.08	0	1

listening while controlling for other potential influencing factors. In addition, quasi-experimental designs are often favored when the randomized assignment of participants is challenging or unfeasible, as such conditions commonly occur in real-world research settings [85]. In situations where random assignment is not feasible or ethically justifiable, such as in our study where we have no control over the spread of COVID-19 in different countries, FEs analysis can also be employed as a viable alternative [104].

Moreover, DiD and FEs analysis can both control for time-invariant confounders that may affect the treatment (COVID-19) and the outcome variables (online music listening behaviors), such as individual-level characteristics or unobserved heterogeneity [7, 56]. This is crucial in studying online music listening behaviors [1], where individual-level factors could influence both COVID-19 exposure and online music listening behaviors. Controlling for these time-invariant confounders can minimize omitted variable bias, and the actual causal effect of COVID-19 on online music listening behaviors can be estimated accurately. Furthermore, FEs analysis can also be used to explore the moderation effect of social interactions on the relationship between COVID-19 and online music listening behaviors by incorporating an interaction term between the treatment (COVID-19) and social interaction variables, as well as the within-person changes in social interaction variables over time [4].

Our study relies on using archival data obtained from Last.fm music platform. It employs a competing outcome framework within a quasi-experiment setting to measure the causal impact of COVID-19 on music listening behaviors. However, as with any analysis of archival data, there may be validity and exploratory concerns that require more than one method to address them (as discussed on page 69, paragraph 2 in [115]). We chose these methods as they are commonly utilized in the literature and have a reputation for their reliability in measuring intervention effects e.g., [15, 21, 28, 29, 41, 55, 67, 100, 115]. In addition, using multiple equations allows us to account for a wide range of variables that may impact music listening behaviors during the COVID-19 pandemic. As a result, we have employed multiple methods and included multiple equations to mitigate the risks of omitted variable bias, confounding effects, time-varying covariates, fixed effects, unobserved heterogeneity, and reverse causality.

3.3.1 DiD analysis for the causal effect of COVID-19

Researchers increasingly employ the DiD method to estimate treatment effects on treated groups (i.e., the causal effect of policy interventions) [21]. In online music listening research, the DiD method with two periods and groups is used to examine the impact of events or new design options on music listening behaviors e.g., [28, 29, 67]. We applied the DiD method to analyze the causal effect of COVID-19 on music listening behaviors during our research period. The most common regression approach researchers utilize to identify the DiD effect is two-way fixed effects (TWFE) regressions [19] as in the following:

$$Y_{it} = \alpha_i + \upsilon_t + \theta D_{it} + \epsilon_{it} \tag{1}$$

According to Eq. 1, D_{it} is a binary variable that shows participation in the treatment for unit i at time t. The unit FEs (α_i), and the time FEs (υ_t) are included as well as idiosyncratic, time-varying unobservables (ϵ_{it}). Assuming the homogeneity of the treatment effect and that the parallel trends assumption is valid, θ in the TWFE regression represents the effect of taking part in the treatment [19]. However, in our study, it was necessary to apply a multi-time period DiD approach to investigate the effect of COVID-19 on music listening behaviors since the intervention period varied across individuals from different countries.

Compared to single-treatment design, there are several theoretical advantages to applying multi-time DiD design, also known as staggered DiD. First, when only one treatment period is used, there is a possibility that confounding variables undermine the exposure of interest (i.e., treatment), which violates the parallel trends assumption [11]. Also, recent econometric theory studies challenge the validity and robustness of TWFE estimates when more than two treatment groups or periods are included or when treatment timing varies [11]. Additionally, the observational data may also be subject to interactive fixed effects that contradict the parallel trends assumption compared to the experimental data. Therefore, in this study, we used a novel approach built to handle staggered treatment adoption designs i.e., [21]. This method of estimating the average treatment effects on treated (ATT) is based on the variation in the timing of the treatments, with the parallel trends assumption conditional on observed covariates.

In this DiD analysis, the control group included users in countries before the confirmation of the first COVID-19 case who became part of the treatment group after the start of the COVID-19 outbreak in those countries. In particular, we identified the date of the first confirmed COVID-19 case in each country and defined it as when the COVID-19 pandemic started. In addition, as the "never-treated" group of units was not available in our dataset, we favored the "not yet treated" group of units as a control group, making it possible to employ more comparison units to enhance inference procedures potentially [21]. As far as we know, this is the first study to analyze the impact of COVID-19 on music listening behaviors using the staggered DiD method, which is well suited to real-world situations.

The COVID-19 effect might differ between treatment groups g at time t, with group g including the time users were first treated (e.g., individuals in countries where the COVID-19 pandemic began in week 12 have a separate group from individuals in countries where it started in week 13). In terms of treatment groups, there were different causal parameters of interest, ATT(g, t), called the "group-time average treatment effect". The ATT(g, t) was used in the estimation procedure that incorporated the clustered bootstrapped standard error of the data, thereby accounting for autocorrelation and clustering [21]. A generalized propensity score was estimated as part of this doubly robust estimation procedure, thereby allowing a logit model to be constructed that considers each individual characteristic [21]. As explained above, the conditional parallel trends assumption was that the observed covariates were considered.

While the interpretation of ATT(g, t) can be difficult when there are many groups and periods, Callaway and Sant'Anna [21] present a family of causal effect parameters in staggered DiD setups to estimate the overall effects of participation in the treatments: simple aggregation (a weighted average according to the group size of all ATT(g, t)), event studies (average effects of treatment at different exposure durations), group-specific effects (average effects within each group), and calendar time effects (aggregations across different time periods). A group-specific effect is the analysis of treatment effects across all groups where the ATT will be interpreted the same way as there are exactly two time periods and two groups of individuals [21]. We used a tool in the R programming language, the "did package" introduced by Callaway and Sant'Anna [22], to implement the method.

3.3.2 Fixed effects analysis

FEs regression was used to analyze the impact of other characteristics of the COVID-19 outbreak (i.e., new COVID-19 cases and the stringency index) on music listening behavior. Using FEs analysis in our panel data allowed us to control unobserved heterogeneity and eliminate potential biases [17]. We also reviewed different research areas to examine the FEs method's ability to estimate time-variant variables in the study of music listening behaviors [e.g., 7, 27, 59, 71-73]. Equation 2 illustrates the FEs model used in this study.

$$Y_{it} = \alpha_i + \upsilon_t + \beta_1 X_{it} + \beta_2 Gender_i + \beta_3 Age_i + \beta_4 Subscriber_i + \beta_5 Age\ of\ account_i + \epsilon_{it} \tag{2}$$

In Eq. 2, Y_{it} are the dependent variables, and X_{it} are the independent variables for individual i at week t. Furthermore, FEs variables and control variables are also included in the equation. α_i is a country-level FEs, υ_t is a week-level FEs, and ϵ_{it} is the error term. In the case of too many entities, the individual FEs may only explain minimal variations in our dependent variables. Individual-level EFs are recommended to be placed in several meaningful categories to prevent type II errors – for example, citizenships or ethnicities [81]. Thus, we used country-level FEs to deal with the large number of individuals we included in our analysis. Country-level FEs are reliable indicators of time-invariant characteristics and circumstances that differ among countries (e.g., population, population density, GDP per capita, life_expectancy, and the human development index in different countries). Week-level FEs accounted for common time patterns throughout the weekly variation. Finally, we controlled for individuals' age, gender, age of the account, and subscriber. As a result, the coefficient of the independent variable represented the average impact of the independent variables on music listening quantity, variety, novelty, and user mainstreaminess in this study.

4 Analysis and findings

In this section, we present our findings using a staggered DiD method to examine COVID-19's impact on the dependent variables of our study. Then, the results of the TWFE are depicted relating to the effects of new COVID-19 cases and the stringency index on dependent variables. Finally, we present the results of the interaction between independent variables and the model's moderators, including social connection size and social communication.

4.1 The causal effect of COVID-19 on music listening behaviors

We chose to analyze data from 1st November 2019 to 27th March 2020 (21 weeks), the time of the first wave of the COVID-19 pandemic and two months prior to that. We defined treatment groups based on the period when a country first became infected by COVID-19, while those living in countries not yet affected by COVID-19 represented the untreated group. With multiple groups and time periods, the overall ATT based on a family of causal effect parameters became easier to interpret, as discussed in Section 3.3. Summary statistics for staggered DiD under the assumption of unconditional parallel trends are provided in Table 3 with the overall ATT in column ATT, followed by bootstrapped standard errors in column SE, and a 95% confidence interval in the next column.

The first set of results based on the unconditional parallel trends assumption shows that the COVID-19 pandemic significantly decreased all six dependent variables compared to a no-pandemic scenario (Table 3). The quantity of online music listening was associated with a 21% reduction caused by the COVID-19 pandemic when using a simple average effect, and close to 19%, 17%, and 15% less quantity when using group-specific, event studies, and calendar-time aggregation methods, respectively (see Panel (a) of Table 3). The results showed that the novelty in consumption – that is, the number of unique new artists divided by the total number of unique artists (Novelty1) – decreased compared to a no-pandemic scenario by around 3%, measuring simple average, group-specific, event studies, and calendar time effect (see Panel (b) of Table 3). Also, the COVID-19 pandemic significantly decreased the value of the discoveries (Novelty2), by about 3% to 4%, measuring a simple average, group-specific, event studies, and calendar time effect (see Panel (b) of Table 3).

In terms of the variety indexes, COVID-19 caused a decrease in the number of unique artists (Variety1) users listened to by about 7% to 8%, measuring a simple average, group specific, event studies, and calendar time effect (see Panel (c) of Table 3). Further, the COVID-19 pandemic significantly decreased the average listening of users to each artist (Variety2) compared to a no-pandemic scenario, with 15%, 14%, 12%, and 11%, measuring a simple average, group-specific, event studies, and calendar-time effect, respectively (see Panel (c) of Table 3). There was a small increase in the user mainstreaminess percentage for listening to the top 20 artists using all four aggregation methods (see Panel (d) of Table 3). Therefore, music consumption did not decline based on a shift to niche music since novelty and variety declined while mainstream music listening increased slightly.

The first extension in our DiD method is that the parallel trends assumption could only be confirmed by considering covariates. We furthered the conditional parallel trend assumption to prove the negative effect of the COVID-19 pandemic on music listening behaviors. Therefore, the second set of results was based on the assumption that individuals with the same characteristics would similarly listen to music if no treatment had been initiated (Table 4). The individual characteristics that we used are age and gender.

Table 3 Estimates of aggregated COVID-19 effect (Unconditional Parallel Trends)

Panel (a) Quantity				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
log Quantity	Simple weighted average	-0.2067	0.0295	[-0.2896 -0.1237] **
	Group-specific effects	-0.1907	0.0245	[-0.2593 -0.1220] **
	Event study	-0.1696	0.0371	[-0.2737 -0.0654] **
	Calendar time effects	-0.1546	0.0205	[-0.2121 -0.0971] **
Panel (b) Novelty				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
Novelty1	Simple weighted average	-0.0319	0.0040	[-0.0398 -0.0240] **
	Group-specific effects	-0.0278	0.0036	[-0.0348 -0.0207] **
	Event study	-0.0274	0.0060	[-0.0392 -0.0157] **
	Calendar time effects	-0.0242	0.0029	[-0.0298 -0.0186] **
Novelty2	Simple weighted average	-0.0376	0.0050	[-0.0474 -0.0279] **
	Group-specific effects	-0.0337	0.0043	[-0.0421 -0.0253] **
	Event study	-0.0317	0.0063	[-0.0440 -0.0194] **
	Calendar time effects	-0.0283	0.0037	[-0.0356 -0.0210] **
Panel (c) Variety				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
log Variety1	Simple weighted average	-0.0863	0.0119	[-0.1096 -0.0631] **
	Group-specific effects	-0.076	0.0098	[-0.0952 -0.0568] **
	Event study	-0.074	0.0178	[-0.1089 -0.0391] **
	Calendar time effects	-0.0663	0.0083	[-0.0825 -0.0501] **
log Variety2	Simple weighted average	-0.1515	0.0213	[-0.1932 -0.1098] **
	Group-specific effects	-0.1397	0.0189	[-0.1767 -0.1026] **
	Event study	-0.1235	0.0236	[-0.1698 -0.0772] **
	Calendar time effects	-0.1129	0.0153	[-0.1430 -0.0829] **
Panel (d) Mainstreaminess				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
Mainstreaminess	Simple weighted average	0.01	0.0029	[0.0032 0.0144] **
	Group-specific effects	0.01	0.0023	[0.0021 0.0111] **
	Event study	0.01	0.0038	[0.0003 0.0128] *
	Calendar time effects	0.01	0.002	[0.0036 0.0115] **

The unconditional parallel trends assumption is used in the DiD method. Variables of interest include novelty, mainstreaminess, and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05

The analysis showed small changes between unconditional and conditional parallel trend assumptions when considering quantity (Panel (a) of Table 4). However, the results were almost the same following novelty, variety, and mainstreaminess analysis (Panels (b), (c), and (d) of Table 4). Overall, we can conclude a decreasing trend in online music listening behaviors during the initial stages of the COVID-19 pandemic, as shown in Table 4. As the results of our research reveal, it is not surprising that the COVID-19 pandemic reduced online music listening quantity (see the literature review in section 2.1); however, as far as we know, no previous studies have looked at novelty, variety, and mainstreaminess concerning COVID-19, meaning this research was exploratory in nature.

Table 4 Estimates of aggregated COVID-19 effect (Conditional Parallel Trends)

Panel (a) Quantity				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
log Quantity	Simple weighted average	-0.2181	0.0327	[-0.2821 -0.1541] **
	Group-specific effects	-0.2008	0.0311	[-0.2617 -0.1399] **
	Event study	-0.1824	0.0352	[-0.2515 -0.1134] **
	Calendar time effects	-0.1606	0.0235	[-0.2067 -0.1145] **
Panel (b) Novelty				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
Novelty1	Simple weighted average	-0.0334	0.0046	[-0.0423 -0.0244] **
	Group-specific effects	-0.0292	0.004	[-0.0370 -0.0214] **
	Event study	-0.0285	0.0057	[-0.0397 -0.0173] **
	Calendar time effects	-0.0252	0.0035	[-0.0321 -0.0183] **
Novelty2	Simple weighted average	-0.0396	0.0055	[-0.0503 -0.0288] **
	Group-specific effects	-0.0354	0.0049	[-0.0450 -0.0259] **
	Event study	-0.0335	0.0067	[-0.0466 -0.0203] **
	Calendar time effects	-0.0295	0.004	[-0.0374 -0.0216] **
Panel (c) Variety				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
log Variety1	Simple weighted average	-0.0874	0.0122	[-0.1113 -0.0634] **
	Group-specific effects	-0.0771	0.0114	[-0.0995 -0.0547] **
	Event study	-0.0748	0.0169	[-0.1079 -0.0417] **
	Calendar time effects	-0.0666	0.0087	[-0.0837 -0.0494] **
log Variety2	Simple weighted average	-0.1623	0.0241	[-0.2094 -0.1152] **
	Group-specific effects	-0.1491	0.0219	[-0.1920 -0.1062] **
	Event study	-0.1355	0.0264	[-0.1872 -0.0838] **
	Calendar time effects	-0.1191	0.018	[-0.1544 -0.0838] **
Panel (d) Mainstreaminess				
Outcome	Estimand	ATT	SE	[95% Conf. Int.]
Mainstreaminess	Simple weighted average	0.01	0.0017	[0.0022 0.0088] **
	Group-specific effects	0.01	0.0014	[0.0014 0.0069] **
	Event study	0.01	0.0023	[0.0004 0.0086]*
	Calendar time effects	0.01	0.0013	[0.0022 0.0072] **

The conditional parallel trend assumption based on age and gender is used in the DiD method. Variables of interest include novelty, mainstreaminess, and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05

The second extension in our DiD method is that the parallel trends assumption was violated despite including covariates. We supplemented our DiD approach with an additive time-invariant covariate whose effect on untreated outcomes might vary over time [20]. To use this method, we had to obtain a never-treated group. Researchers suggest that when at some point, all units have been treated, the available periods should be reduced so that at least one never-treated group remains throughout the investigation. Notably, the resulting data loss is not an issue for time periods with no comparison groups since DiD cannot be utilized to determine treatment effect parameters [19]. In our data set, we eliminated weeks 19, 20, and 21 and continued with 18 weeks. Using

Table 5 Aggregated COVID-19 effect estimates (Linear Trends Model)

Panel (a) Quantity				
Outcome	Estimand	ATT	SE	[90% Conf. Int.]
log Quantity	Linear trend	-0.15	0.0235	[-0.2760 -0.0284] *
Panel (b) Novelty				
Outcome	Estimand	ATT	SE	[90% Conf. Int.]
Novelty1	Linear trend	-0.02	0.0177	[-0.0399 0.0183]
Novelty2	Linear trend	-0.02	0.0171	[-0.0443 0.0120]
Panel (c) Variety				
Outcome	Estimand	ATT	SE	[90% Conf. Int.]
log Variety1	Linear trend	-0.07	0.0436	[-0.1443 -0.0008]*
log Variety2	Linear trend	-0.11	0.0665	[-0.2172 -0.0001]*
Panel (d) Mainstreaminess				
Outcome	Estimand	ATT	SE	[90% Conf. Int.]
Mainstreaminess	Linear trend	0.02	0.0112	[0.0059 0.0429] *

The confidence interval is at the 90%* level. The covariates included in the model are age, gender, and cultural values. Variables of interest include novelty, mainstreaminess, and the natural logarithm of quantity and variety. The results of the novelty are not significant at the 90% confidence interval.

this method, an interactive FEs structure, also referred to as a factor structure, was used to model untreated potential outcomes. A time-invariant unobservable can have different effects over time if such a structure is used. The interactive FEs model for untreated potential outcomes is as follows:

$$Y_{it}(0) = \upsilon_t + \alpha_i + \lambda_i F_t + \epsilon_{it} \tag{3}$$

As shown in Eq. 3, $Y_{it}(0)$ represents the potential outcome for an untreated individual in time period t, along with unit FEs (α_i), time FEs (υ_t), the unobserved, and time-invariant covariates (λi), whereas F_t represents the time-varying effect of these individual characteristics. For a special case of the model where $F_t = t$, a linear trend model can be used to solve the model [50, 76, 114]. Equation 4 presents a linear trends model.

$$Y_{it}(0) = \upsilon_t + \alpha_i + \lambda_i t + \epsilon_{it} \tag{4}$$

Therefore, our study sought results based on age, gender, and cultural values of time-invariant covariates. We added Hofstede cultural dimensions [53], computed based on a user's country of origin, as additional covariates for determining cultural preferences [33, 94, 102]. The ATT results are represented in Table 5. The results of the linear trends model were similar to those obtained through the previous method.

4.2 The impact of new COVID-19 cases and restrictions on music listening behaviors

This section presents our findings on whether new COVID-19 cases and the stringency index led to changes in online music listening behaviors considering quantity, novelty, variety, and user mainstreaminess. We report our first set of results examining the impact of the logarithm of new COVID-19 cases on quantity, novelty, and variety (see Table 6). Overall, we found a causal relationship between the prevalence of new

Table 6 COVID-19 cases effect estimates

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log COVID-19 cases	-0.007***	-0.001	-0.001**	-0.002*	-0.006***
	(0.003)	(0.0004)	(0.0004)	(0.001)	(0.002)
20<age≤39	-0.212***	-0.024***	-0.034***	-0.061***	-0.169***
39<age≤65	(0.013)	(0.002)	(0.002)	(0.005)	(0.010)
65<age	-0.362***	-0.046***	-0.062***	-0.117***	-0.275***
	(0.015)	(0.003)	(0.003)	(0.006)	(0.012)
	-0.492***	-0.062***	-0.082***	-0.155***	-0.355***
	(0.030)	(0.005)	(0.005)	(0.011)	(0.023)
Gender (m)	0.420***	0.058***	0.070***	0.151***	0.294***
	(0.005)	(0.001)	(0.001)	(0.002)	(0.004)
Age of the account	0.003***	0.001***	0.001***	0.001***	0.003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Subscriber (1)	3.091***	0.356***	0.456***	1.006***	2.271***
	(0.026)	(0.004)	(0.004)	(0.010)	(0.020)
R^2	0.12	0.12	0.12	0.10	0.11
Users	37,304	37,304	37,304	37,304	37,304
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs; control variables are reported in the table. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

COVID-19 cases and decreases in all outcome variables. According to the coefficient for the dependent variable, the logarithm of quantity (Table 6, column 1), a 1% increase in new cases of COVID-19 in a week would cause users' total listening to decrease by approximately 1% (exp (-0.007)-1) at p<0.01. The average weekly music listening of individuals following the start of the COVID-19 pandemic was 46 songs, so a 10% increase in COVID-19 cases reduced the weekly listening by almost five songs. As a result, COVID-19 cases had an economic impact in addition to their statistical significance.

The negative impact of new COVID-19 cases was evident in novelty: a 1% increase in weekly new COVID-19 cases caused the novelty of listening to music to decrease by 0.001 (Table 6, columns 2 and 3). However, the effect of new COVID-19 cases on novelty was not economically and statistically significant for novelty1. Then, we found a significant and economic decrease in two variety measures of listening to music (Table 6, columns 4 and 5). Based on variety1 and variety2, a 1% increase in new COVID-19 cases in a week resulted in a reduction of 0.2% in the number of artists in a user's listening history in a week and a reduction of 0.6% in the average listening to each artist (Table 6, columns 4 and 5).

The second set of results examined the stringency index of lockdown levels. The data were collected during the early stages of the COVID-19 outbreak, when governments worldwide responded differently to the pandemic, as determined by the University of Oxford on a scale of 0 to 100. This presented an opportunity to look at the impact of the stringency index on our studied variables. For example, the average stringency index in all 45 countries reached 76% during week 21 of the study (week beginning on 20th March 2020), while some countries experienced no stringency until week 18.

Table 7 Stringency index effect estimates

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log Stringency index	-0.04*** (0.005)	-0.003*** (0.001)	-0.005*** (0.001)	-0.011*** (0.0001)	-0.034*** (0.0003)
20<age≤39	-0.212*** (0.013)	-0.019*** (0.001)	-0.024*** (0.002)	-0.061*** (0.005)	-0.169*** (0.010)
39<age≤65	-0.362*** (0.015)	-0.035*** (0.002)	-0.044*** (0.002)	-0.117*** (0.006)	-0.275*** (0.012)
65<age	-0.492*** (0.030)	-0.047*** (0.003)	-0.059*** (0.004)	-0.155*** (0.011)	-0.355*** (0.023)
Gender (m)	0.420*** (0.005)	0.043*** (0.001)	0.050*** (0.001)	0.151*** (0.002)	0.294*** (0.004)
Age of the account	0.003*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.003*** (0.000)
Subscriber (1)	3.091*** (0.026)	0.356*** (0.004)	0.456*** (0.004)	1.006*** (0.010)	2.271*** (0.020)
R^2	0.12	0.12	0.12	0.10	0.11
Users	37,304	37,304	37,304	37,304	37,304
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs; control variables are reported in the table. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty, and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

Overall, with the increase in the stringency index of lockdown levels, we observed the presence of negative and decreasing coefficients (Table 7).

Column 1 of Table 7 shows that with a 1% increase in the stringency index in a week, the music listening dropped by 0.1% (exp (-0.001)-1) at $p<0.01$. We ran the same model for the impact of the stringency index on novelty and variety (Table 7, columns 2 to 5). Results strongly pointed to a decrease in novelty and variety due to the increased stringency index. In Table 7, columns 2 and 3, the coefficient for the effect of the stringency index on novelty1 and novelty2 was significant at $p<0.01$, and the impact of the stringency index on the novelties showed a decreasing result. Similar to the impact of new COVID-19 cases, the stringency index had a greater effect on the variety variables compared to the novelty variables. With a 1% increase in the stringency index in a week, the number of unique artists (variety1) and average listening to each artist (variety2) decreased by 1% and 3%, respectively, at $p<0.01$ (Table 7, columns 4 and 5). Thus, the stringency index clearly impacted users' music listening behaviors compared with no government restrictions.

Given that the quantity and variety of music consumption declined with the increase of both new COVID-19 cases and the stringency index, we looked at mainstream consumption to measure the share of unique varieties [28]. The trend of users' play counts for the top 20 mainstream artists (superstars) showed the user mainstreaminess value based on two definitions of popular artists, as discussed in detail in Section 3.1. Table 8 shows the impact of new COVID-19 cases and the stringency index on user mainstreaminess. A doubling increase in the COVID-19 cases in a week caused users to listen to 10% more mainstream music at $p<0.05$ (Table 8, column 1). There was a consistent impact of COVID-19 on users' mainstreaminess when considering the stringency index,

Table 8 The effect of the stringency index and COVID-19 cases on user mainstreaminess

Model	log Mainstreaminess	log Mainstreaminess
log COVID-19 cases	0.001** (0.001)	
log Stringency index		0.002*** (0.000)
20<age≤39	0.007*** (0.001)	0.012*** (0.001)
39<age≤65	0.014*** (0.001)	0.025*** (0.001)
65<age	0.015*** (0.001)	0.028*** (0.002)
factor(gender) m	-0.011*** (0.001)	-0.019*** (0.001)
Age of the account	-0.0002*** (0.000)	-0.0002*** (0.000)
Subscriber (1)	-0.125*** (0.002)	-0.125*** (0.002)
R^2	0.07	0.07
Users	37,304	37,304
Observations	723,467	723,467

All models include country FEs and week FEs; control variables are reported in the table. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include user mainstreaminess.

*p < 0.10; **p < 0.05; ***p < 0.01.

indicating that it had a considerable effect. In column 2 of Table 8, the stringency index is shown as having increased mainstream listening among individuals by 0.2% at $p< 0.01$, indicating that, for example, when there were governmental restrictions of 50%, users listened to 10% more mainstream music (mainstreaminess of 0.653) than when there were no governmental restrictions (mainstreaminess of 0.594).

We performed this last step to ensure our analysis was reliable and valid. In the first step, we conducted diagnostic tests appropriate for the fixed effects model [87], including the following three tests in R. For *heteroscedasticity*, the Breusch-Pagan test was conducted using the bptest() function. Afterward, we tested *autocorrelation* using the function pbgtest(). We ran the third test for *cross-sectional independence* using the Breusch-Pagan LM test of independence using the pcdtest() function. According to the results of the tests, heteroscedasticity, autocorrelation, and cross-sectional dependency were present, which may invalidate the standard error in the original model.

Consequently, we used the panel-corrected standard error (PCSE) estimator as an advantage in panel data analysis because it addresses the problems of heteroscedasticity, autocorrelation, and cross-sectional dependency [10, 87]. The PCSE estimator proposed by Beck and Katz [13] can be computed using the function vcovBK() when applied to panel models estimated by the plm package in R [10]. As shown in Table 9, the results of the PCSE model are consistent with the estimations from the original model. Using the PCSE estimator and the original estimator, we were able to ensure the robustness of our analysis and that the results could be interpreted with confidence.

Table 9 Panel corrected standard error (PCSE) model results

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2	Log Mainstreaminess
Original Model						
log COVID-19 cases	-0.007*** (0.003)	-0.001 (0.0004)	-0.001** (0.0004)	-0.002* (0.001)	-0.006*** (0.002)	0.001** (0.001)
log Stringency index	-0.040*** (0.005)	-0.003*** (0.001)	-0.005*** (0.001)	-0.011*** (0.0001)	-0.034*** (0.0003)	0.002*** (0.000)
PCSE Model						
log COVID-19 cases	-0.007*** (0.003)	-0.001 (0.0004)	-0.001*** (0.0004)	-0.002** (0.001)	-0.006*** (0.002)	0.001*** (0.0002)
log Stringency index	-0.040*** (0.005)	-0.004*** (0.001)	-0.006*** (0.001)	-0.011*** (0.002)	-0.034*** (0.004)	0.002*** (0.000)

All models include country FEs and week FEs; control variables are age, gender, age of the account, and subscriber. The panel-corrected standard errors of the PCSE model and the robust standard errors clustered at the individual level of the original model are reported in parentheses.

*p < 0.10; **p < 0.05; ***p < 0.01.

4.3 Social network size and social communication

As part of our research, we also explored how socializing features offered by streaming platforms such as Last.fm can be leveraged to counteract the negative effects of the COVID-19 pandemic on the music streaming industry. Among the standard features associated with streaming platforms and social network sites, we placed special emphasis on individuals' social communication and social network size since they are significant features of the built-in interactive capabilities of social network sites [24, 60, 74]. Among the listed features in Last.fm, social communication was the only variable available in the Last.fm service that could be exploited through time series. Due to this limitation, we could only access data about daily communications (including time and date), based on users' profiles to provide a perspective of users' social communications. We then used the total number of users' social networks as a second variable that measures social network size.

We hypothesized that utilizing social communication through Last.fm coupled with the social network size, led to a greater music play count, the discovery of new music, and a variety in music consumption, even though COVID-19 negatively impacted these variables (based on our findings presented in Sections 4.1 and 4.2). Therefore, we empirically evaluated the following regression equation:

$$\begin{aligned} \mathrm{Y_{it}} &= \alpha_{\mathrm{i}} + \upsilon_{\mathrm{t}} + \beta_1 \mathrm{X_{it}} + \beta_2\left(\mathrm{Xit} \times \mathrm{Communication_{it}}\right) + \beta_3\left(\mathrm{X_{it}} \times \mathrm{Social\ network\ size_{it}}\right) \\ &\quad + \beta_4 \mathrm{Gender_i} + \beta_5 \mathrm{Age_i} + \beta_6 \mathrm{Subscriber_i} + \beta_7 \mathrm{Age\ of\ account_i} + \varepsilon_{\mathrm{it}} \end{aligned} \tag{5}$$

In Eq. 5, $\mathrm{Y_{it}}$ are the dependent variables and $\mathrm{X_{it}}$ are the independent variables for individual i at week t. Furthermore, FEs variables are also included in the equation: α_{i} is a country FE, υ_{t} is a week FE, and ϵ_{it} is the error term. The moderator variable for individual i at week t is social communication and the social network size within Last.fm. Similar to previous equations, we controlled for age, gender, subscriber, and age of account when conducting our analysis. Considering the COVID-19 lockdown conditions associated with increased online social interaction, among the independent variables in this study, the stringency index accurately reflected the lockdown conditions [47]. Therefore, we measured the moderating effect of social communication and social network size at various levels of the stringency index (0, 25%, 50%, 75%, and 100%).

The results are reported in Table 10. As in Section 4.2 (Table 7), we determined the negative effects of the stringency index on quantity, novelty, and variety, and we will not repeat them in this section. The main impact of social communication was 0.38 at $p<0.01$, indicating that an increase in social communication by one unit resulted in a rise of 46% (exp (0.38)-1) in music play counts when the stringency index equaled zero. Similarly, we observed the positive main effect of social communication on novelty1 (0.05), novelty2 (0.06), variety1 (0.21), and variety2 (0.18) at $p<0.01$. Therefore, in cases where the stringency index was zero, social communication through the platform substantially impacted how music was consumed in terms of quantity, novelty, and variety.

The key variable of interest was the interaction term stringency index × social communication, representing the average effect of the stringency index on music listening quantity, novelty, and variety when considering the social communication of listeners. This interaction term was estimated to be positive, with varying degrees of coefficient in the five columns (Table 10). According to the interaction measures, the effect of the stringency index on quantity, novelty, and variety was positive for users who took part in social communication. The relationship between this increment and the stringency index was intriguing.

Table 10 Stringency index interaction with social communication

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
Social communication	0.377***	0.053***	0.059***	0.207***	0.183***
	(0.020)	(0.003)	(0.003)	(0.007)	(0.015)
0< stringency≤25 × communication	0.057 (0.039)	0.006 (0.005)	0.010 (0.007)	0.037*** (0.014)	0.020 (0.030)
25< stringency≤50× communication	0.188* (0.080)	0.036*** (0.011)	0.037*** (0.013)	0.084*** (0.029)	0.129** (0.061)
50< stringency≤75× communication	0.518*** (0.126)	0.068*** (0.017)	0.082*** (0.021)	0.130*** (0.046)	0.417*** (0.097)
75< stringency≤100× communication	0.970*** (0.213)	0.164*** (0.029)	0.182*** (0.036)	0.317*** (0.078)	0.683*** (0.164)
R^2	0.12	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs, and control variables are age, gender, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty, and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

When there was an interaction of the stringency index of 25% in social communication, there was an increase of 6% in quantity. There was also 19% more music listening when the stringency index was between 25% to 50%, and 52% more music listening when the stringency index was between 50% and 75%. Finally, there was 97% more music listening when the stringency index went above 75% (Table 10, column 1). Similarly, interactions of the stringency index with novelty and variety were also significantly positive, supporting the moderating effect of social communication (Table 10, columns 2 to 5).

Using the moderating effect of social communication, we found that the negative impact of the COVID-19 stringency index on music listening behaviors tended to be more pronounced among those who did not use Last.fm as a social network site to interact with the community. In contrast, the stringency index that governments utilized during the COVID-19 pandemic had less impact on socially active listeners. To fully understand the interaction effects, we used the interact plot as the most suitable method of interpretation [3]. We note in Fig. 3 that socially active users listened to more music and that there was also a positive relationship between the

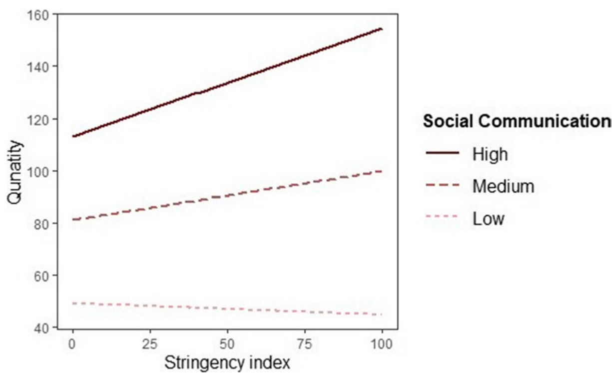

Fig. 3 Interaction plot of the stringency index and social communication (related to the quantity)

Table 11 Stringency index interaction with social network size

Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log network size	0.354*** (0.002)	0.046*** (0.001)	0.059*** (0.001)	0.121*** (0.001)	0.261*** (0.001)
0< stringency≤25 × log network size	-0.003 (0.003)	-0.001*** (0.001)	-0.001* (0.001)	-0.001 (0.001)	-0.003 (0.002)
25< stringency≤50 × log network size	-0.015** (0.006)	-0.002*** (0.001)	-0.002** (0.001)	-0.004 (0.002)	-0.012** (0.005)
50< stringency≤75 × log network size	-0.022*** (0.005)	-0.003*** (0.001)	-0.003*** (0.001)	-0.006*** (0.002)	-0.016*** (0.004)
75< stringency≤100 × log network size	0.031*** (0.008)	0.003*** (0.001)	0.005*** (0.001)	0.011*** (0.003)	0.024*** (0.007)
R^2	0.18	0.18	0.18	0.16	0.16
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs; control variables are age, gender, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

stringency index and the amount of music they listened to. As a result, we conclude that social communication moderated the negative impact of the stringency index on music listening quantity, which may have been due to the effects of social distancing or the shock to music streaming services caused by the COVID-19 crisis. The interaction plots of novelty and variety values are presented in Appendix A Figs. 5 and 6, which exhibited a similar trend.

Next, we examined the users' total social network size as a moderator, which significantly explained the relationship between the stringency index and studied variables, including quantity, novelty, and variety (Table 11). The main impact of social network size was 0.35 at p<0.01, indicating that a 1% increase in social network size resulted in a rise of 42% (exp (0.35)-1) in music listening when the stringency index equaled zero (Table 11, column 1). Similarly, we observed the positive and significant main effect of social network size on novelty1 (0.05), novelty2 (0.06), variety1 (0.12), and variety2 (0.26) at p<0.01 (Table 11, columns 2 to 5). Therefore, in cases where the stringency index was zero, the social network size of the users within the platform substantially impacted how music was consumed in terms of quantity, novelty, and variety.

The key variable of interest was the interaction term of stringency index × social network size, representing the average effect of the stringency index on quantity, novelty, and variety of music consumption when considering the listeners' social network size. The magnitude of the interaction term showed that when considering the size of the social networks, the negative impact of the stringency index on all studied variables was smaller for users with more friends. Further, when the stringency index exceeded 75%, the interaction term of the stringency index and social network size demonstrated a positive coefficient. Comparing Tables 10 and 11 indicates that the effect of network size was not as prominent as social communication. However, the results of this study are not necessarily conclusive that social communication is more effective than a social network size since our analysis was not based on panel data on weekly social network size.

Table 12 COVID-19 case interaction with gender

	Panel (a) Female				
Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log COVID-19 cases	-0.005 (0.004)	-0.0002 (0.001)	-0.0003 (0.001)	-0.0004 (0.002)	-0.005 (0.003)
R^2	0.10	0.10	0.10	0.09	0.10
Users	10,198	10,198	10,198	10,198	10,198
Observations	195,902	195,902	195,902	195,902	195,902
	Panel (b) Male				
log COVID-19 cases	-0.008** (0.003)	-0.001 (0.0004)	-0.001** (0.001)	-0.002* (0.001)	-0.007*** (0.002)
R^2	0.11	0.10	0.11	0.10	0.10
Users	27,106	27,106	27,106	27,106	27,106
Observations	527,565	527,565	527,565	527,565	527,565

All models include country FEs and week FEs; control variables are age, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

4.4 Individual characteristics of music listeners

Finally, the analysis of individual characteristics related to the outcome variables indicates that the negative impact of new COVID-19 cases was not significant in females' music listening behaviors; however, the effect of the stringency index on music listening was significant for males and females (Tables 12 and 13). Although males listened to significantly more music than females, with more novelty and variety, the negative impact of COVID-19 on males' music listening behaviors was more than on females. During the investigation,

Table 13 Stringency index interaction with gender

	Panel (a) Female				
Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log Stringency index	-0.035*** (0.009)	-0.004*** (0.001)	-0.005*** (0.002)	-0.010*** (0.003)	-0.029*** (0.007)
R^2	0.10	0.10	0.10	0.09	0.10
Users	10,198	10,198	10,198	10,198	10,198
Observations	195,902	195,902	195,902	195,902	195,902
	Panel (b) Male				
log Stringency index	-0.042*** (0.007)	-0.004*** (0.001)	-0.006*** (0.001)	-0.011*** (0.002)	-0.035*** (0.005)
R^2	0.11	0.10	0.11	0.10	0.10
Users	27,106	27,106	27,106	27,106	27,106
Observations	527,565	527,565	527,565	527,565	527,565

All models include country FEs and week FEs; control variables are age, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

Table 14 COVID-19 cases and stringency index interaction with age

		Panel (a)			
Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log COVID-19 cases ×	0.008*	0.001	0.001	0.002	0.005
20≤age≤39	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)
39<age≤65	0.003	0.0004	0.0003	0.0005	0.002
65<age	(0.005)	(0.001)	(0.001)	(0.002)	(0.004)
	-0.001	-0.001	-0.001	-0.005	-0.0001
	(0.010)	(0.001)	(0.002)	(0.004)	(0.007)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
		Panel (b)			
Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log Stringency index ×	0.014*	0.002	0.002	0.004	0.011*
20≤age≤39	(0.008)	(0.001)	(0.001)	(0.003)	(0.006)
39<age≤65	0.005	0.001	0.001	0.001	0.004
65<age	(0.010)	(0.001)	(0.002)	(0.003)	(0.007)
	-0.034*	-0.005**	-0.007**	-0.018**	-0.016
	(0.019)	(0.003)	(0.003)	(0.007)	(0.015)
R^2	0.12	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs; control variables are gender, age of the account, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

increasing restrictions and social distancing policies resulted in a greater reduction in music listening among males than females (Table 13). The variety and novelty analysis also showed that restriction policies affected males more than females (Table 13, columns 2 to 5).

Furthermore, the results showed that when new COVID-19 cases and the stringency index increased, young adults (20-39) listened to more music than adolescents (under 20); however, older adults over 65 listened to significantly less music than adolescents (Table 14). In addition, the impact of the COVID-19 pandemic on novelty and variety in music consumption among all age groups did not significantly differ, except for those over 65, for whom the effect of COVID-19 was more negative than it was for adolescents.

The impact of the new COVID-19 cases and stringency index on subscribers was positive (Table 15, panels (a) and (b)). With the increase in the stringency index, subscribers listened to more music with more novelty and variety than non-subscribers. The impact of the stringency index was significantly and economically greater than the new COVID-19 cases' imapct. However, considering the age of the account, the coefficient of the impact of new COVID-19 cases and the stringency index of all dependent variables were close to zero (Table 16). Our analysis pointed to how platform providers can target their marketing efforts to those who contribute to the system. For example, the impact of the first wave of the COVID-19 pandemic had a more negative impact on the amount of music listened to by males. In addition, subscribers remain the most significant contributor to the Last.fm platform's value, even after the big shock of the COVID-19 pandemic. Since Last.fm's

Table 15 COVID-19 cases and stringency index interaction with subscribers

		Panel (a)			
Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log COVID-19 cases × Subscriber	0.015* (0.009)	0.001 (0.001)	0.003* (0.001)	0.005* (0.003)	0.007 (0.007)
R^2	0.12	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
		Panel (b)			
log Stringency index × Subscriber	0.070*** (0.017)	0.008*** (0.002)	0.012*** (0.003)	0.029*** (0.006)	0.038*** (0.013)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs; control variables are gender, age, and age of the account. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

most loyal customers are its subscribers, when it suffers a crisis like the COVID-19 pandemic, it could benefit from developing special plans or policies to increase subscribers or target this specific group. The policy of Spotify to offer a three-month free subscription relates directly to our results, aside from the subscription fee.

Furthermore, as we examine the user characteristics reported in this section, we also observe variations in the effects of new COVID-19 cases and the stringency index on online music listening behaviors, including quantity, novelty, variety, and mainstreaminess. Our study revealed that it was not the virus infection (as measured by new cases

Table 16 COVID-19 cases and stringency index interactions with age of account

		Panel (a)			
Model	log Quantity	Novelty1	Novelty2	log Variety1	log Variety2
log COVID-19 cases × Age of account	0.000 (0.0000)	0.000 (0.0000)	0.000 (0.0000)	0.000 (0.0000)	0.000 (0.0000)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467
		Panel (b)			
log Stringency Index × Age of account	0.000** (0.0000)	0.000*** (0.0000)	0.000*** (0.0000)	0.000*** (0.0000)	0.000 (0.0000)
R^2	0.11	0.11	0.12	0.10	0.11
Users	37,428	37,428	37,428	37,428	37,428
Observations	723,467	723,467	723,467	723,467	723,467

All models include country FEs and week FEs; control variables are gender, age, and subscriber. Standard errors in parentheses are robust and clustered at the individual level. Variables of interest include novelty and the natural logarithm of quantity and variety.

*p < 0.10; **p < 0.05; ***p < 0.01.

of COVID-19) but instead major changes caused by the initial lockdowns (measured by the stringency index) that changed the demand for online music listening. Therefore, new COVID-19 cases might not be a robust estimator of changes in COVID-19 level in a study of online music listening, in contrast to the stringency index, a measure of the extent of COVID-related lockdowns, school closures, and social distancing.

4.5 Summary of analysis

I. We used the DiD method (Eq. 1) to estimate the average treatment effect on individuals affected by COVID-19. DiD is a standard method of investigating and estimating effects in quasi-experiment settings [19].
II. While the DiD method is one of the most appropriate ways to estimate the average treatment effect, it cannot be used to explore heterogeneity in treatment effect based on other confounding variables [115]. To address this issue, we estimated the FEs analysis represented by Eq. 2.
III. In real-life scenarios testing and supporting assumptions for DiD estimation is challenging, especially when the treatment is staggered. To address this issue, newer methods like staggered DiD, with more flexible assumptions, provide a robust framework to estimate the average treatment effect in staggered adoption scenarios (Eq. 3). Equation 4 is an extension of Eq. 3, accommodating the linear trend model.
IV. Equation 5 investigates the moderating effect of social network size and social communication on music listening behaviors.

5 Discussion and future research directions

In the following, we discuss several theoretical and practical implications regarding the impact of the COVID-19 pandemic on online music listening behaviors and how digital media decision-makers may need to intervene with the new design strategies to ensure that they remain effective under COVID-19 and other future circumstances.

5.1 Implications for academia

5.1.1 Online music listening behaviors

The first strength of our contribution stems from analyzing online music listening behaviors through the context of the COVID-19 pandemic. Employing specific real-world events or daily experiences is an alternative method to predict users' behaviors. A growing body of music recommendation research includes information about time, sessions (morning, evening, night), feedback, and location to formulate users' contextual behaviors [59]. The previous literature has also discussed various possibilities for determining users' emotional music selection based on real-world events. For example, researchers have exploited individuals' music listening behaviors in the context of past and future real-world events [97], determined the mood of public sentiment [67], and discussed the best way to benefit listeners' psychological wellbeing [120]. Our research increases current knowledge of online music listening behaviors by analyzing the causal relationship between the COVID-19 pandemic and the consequent changes in quantity, novelty, variety, and mainstreaminess in consumption on a global scale that has not been studied previously.

According to our research, music listening behaviors have been affected by three components of the COVID-19 pandemic: the outbreak as a real-world event, the weekly new COVID-19 cases, and the stringency of lockdowns. The results of our study provide evidence that in its early stages, the COVID-19 pandemic negatively affected online music listening and that individuals' music listening decreased by approximately 15% compared with pre-pandemic time. Unlike the common belief that there was an increase in music streaming, we found that music listening continued to decline with the rise of weekly COVID-19 cases and strengthening lockdown policies following the beginning of the COVID-19 pandemic. In addition, the rising number of COVID-19 cases and restrictions resulted in less variety and novelty and more mainstream listening among music listeners.

By utilizing the staggered DiD method, we were able to present Box plots that depict the distribution of data before the onset of COVID-19 and for various groups affected by COVID-19 during different weeks (comparing the never treated group to groups in weeks 10 to 18). This type of visualization is beneficial for identifying changes in the data's central tendency, variability, and skewness. The use of never treated data made it possible to make these comparisons, as discussed in Section 4.1. We encourage readers to refer to the Box plots for all dependent variables (Fig. 4). Overall, the Box plots demonstrate that the users' music listening quantity decreased due to the impact of COVID-19 and turned to less novelty and variety in music consumption. Furthermore, the music listening to mainstream artists also increased.

We believe, our research opens up the possibility that a range of music recommendation systems, such as Last.fm and Spotify, will be able to take advantage of these causalities to determine the impact of COVID-19 on music preferences and make better recommendations.

It is widely agreed that user behavior research is essential during the current pandemic and for potential future crises [17, 54, 101]. The behavior of users during a global crisis that has massive influences requires reexamination, for example, to develop health guidelines for people who are isolated from their communities due to quarantine [17]. Music is nominated as the second most common method humans use to control their emotions [82]. However, we found that users did not turn to streaming services to listen to or discover music during the first wave of the COVID-19 pandemic to the level they had in the past. As an alternative, researchers who worked on video games during the pandemic discovered that individuals enjoyed playing video games both to escape the gloomy nature of their daily lives and maintain a sense of uncertainty within the game environment [16].

One possible explanation for the decline in music streaming is that music is generally consumed as part of a combined activity instead of a standalone activity [101]. Statistics cited in [101] indicate that nearly 29% of all music consumption occurs in the car, 30% occurs at work or while performing routine tasks, and 54% of consumers listen to music while commuting to work. In addition, reduced participation in events suitable for music listening, such as outdoor activities, parties, and galleries due to the COVID-19 pandemic, may be responsible for decreased music consumption. The analysis of the stringency index in our study, which indicates the level of government restrictions in various countries, such as closing schools and workplaces and imposing travel restrictions, also confirms the negative impact of COVID-19 on the quantity, novelty, and variety of music consumption.

An important feature of online music consumption is that services have made the music experience more personal [46, 103]. In fact, digital platforms have changed the way people listen to music and turned music listening into a more individual activity [58]. However, in response to the initial COVID-19 restrictions and isolation requirements, people have since turned to activities that engender a stronger sense of socialization and community [42]. Researchers have also observed a "migration of music

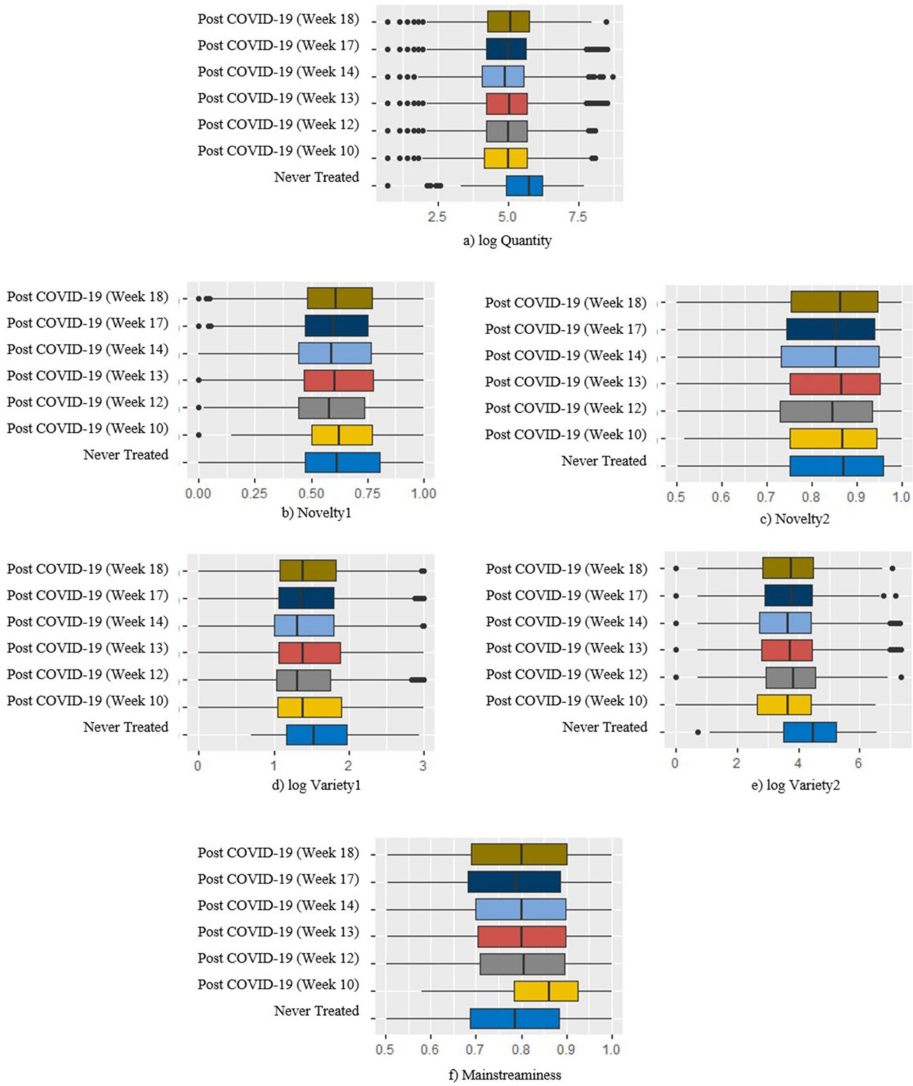

Fig. 4 Box plot of music listening behaviors among the never-treated group and groups week 10-18

consumers from audio-based to video-based streaming services" since platforms like YouTube permit more active participation than audio-based platforms like Spotify and Pandora [54]. During the initial stages of the COVID-19 pandemic, various music clips were created to supplement pre-existing music as a response to the crisis [120]. Aside from the novelty and significance of "coronamusic" during the lockdowns of 2020, much of this music pertained to music videos [48]. Consequently, "to fulfil emotional coping goals, engagement with music may have become more attentive, immersive, multimodal, and active", independent of significant reductions in measurable listening time [54].

Online music listening trends cannot be attributed to a shift to more niche markets due to the decline of novelty and variety and the increased preference for mainstream artists found in our research. Likewise, the demand for nostalgia consumption showed a positive increase in response to the COVID-19 lockdowns [117]. Our study on novelty and variety consistently showed that during our research period in the early phases of the pandemic, COVID-19 significantly and negatively affected the desire for unusual or novel items, and users preferred to stick to their previous preferences and mainstream artists. Consumers generally love variety and different kinds of music can reflect users' musical preferences [28]. However, individuals often choose only one or two styles of music from their favorite playlist in specific situations [64]. A recent Spotify report indicates that listeners' musical habits turned to relaxing and calming music at the start of COVID-19 pandemic [65].

In response to the stress and isolation caused by the early stages of COVID-19 pandemic, music had the opportunity to provide a positive and therapeutic experience based on an individual's needs [88]. While our study emphasizes that the COVID-19 pandemic adversely affected online listening behaviors during our research period, future research could explore the factors affecting music consumption within the COVID-19 context, such as lack of genre and listener knowledge and unsuitable recommendations. Using the experience of the COVID-19 pandemic, context-aware music recommendations could offer users more significant opportunities in certain places, times, and according to their COVID-19 preferences [e.g., see 32, 33]. This also relies on artists' partnerships with academics for effective music intervention in disaster situations [105]. More radically, "academics could join musicians in activism and even direct action on health and other matters" [6].

Our study's examination of individual characteristics aligns with previous research investigating the impact of gender and age variables on music listening behaviors. Specifically, our findings indicate that males tend to listen to more music than females, seeking out a greater level of novelty and variety. Previous research supports these results, highlighting differences in music preferences between males and females [89]. Evidence suggests that males prefer less mainstream music genres, while females favor melodic and popular genres [14]. Specifically, females tend to exhibit a preference for mainstream music genres such as pop [25, 27], folk [49] [91], and classical music [26, 113]. A more detailed discussion can be found in [25, 26, 77].

Although the present study does not delve into the underlying reasons for these gender differences, previous research has suggested that socialization and cultural factors may be at play. Specifically, males often use music to establish their group affiliation and identity, and to impress others, which may explain their tendency towards non-mainstream music [27, 78, 107]. The desire to impress others is a social motivation that can demonstrate their knowledge and appreciation of more obscure or niche music genres. Females, however, conform to social norms and are more likely to approach music more instrumentally and socially, as opposed to using it for identity construction or impressing others, which is the case with males. Therefore, females prefer more mainstream and sociable music genres [14, 25, 27].

Our analyses also yielded several other noteworthy results. While the impact of COVID-19 was negative on three aspects of music listening, quantity, novelty, and variety, this impact was more significant on males than females. This finding could be due to various reasons, such as differences in gender-specific roles and responsibilities at home during the pandemic, variations in the types of music preferred by males and females, or discrepancies in the amount of leisure time available to males and females. For example, females prefer listening to music over playing computer games, while males prefer playing computer games [78]. The differences in male and female adolescents' leisure behaviors may be due to gender stereotyping and may be explained by differences in socialization practices [38]. Considerable research cites in [72] indicates women listen to music more often than men to get enjoyment, pleasure, relief from emotional stress, or to lessen loneliness e.g., [23, 69, 107]. In contrast, males were more likely to use music to support their social identity [69, 106]. However, other studies have inconsistently demonstrated that the psychological benefits of singing and listening to music do not appear to be affected by gender [68]. The COVID-19 pandemic provides the opportunity to re-examine the music listening behaviors associated with the personal characteristics of the listeners.

Considering the age of the listeners, we could not find any specific differences in the impact of new COVID-19 cases and music listening. However, with the increase in the stringency index, including school closures, working from home, and many other restrictions, older adults showed a more considerable decline in music consumption than younger listeners. We examined specific age groups to understand this effect better. With the increase in the stringency index, young adults (20-39) listened to more music than adolescents (under 20); however, users over 65 years old listened to significantly less music. Among the benefits of music listening, young adults seek to regulate their mood and connect with others, whereas older individuals listen to music to maintain personal growth [43, 69]. Our finding that the negative effect of the stringency index on online music listening was greater among older adults is supported by the study of [72], in which retirees reported the lowest impact of music on their wellbeing during the COVID-19. Because earlier COVID-19 challenges caused more social dissociation and isolation in older people than in other age groups, their emotional health was negatively affected, and music was no longer as beneficial as it once was [18].

Our study indicates that subscribers in music streaming platforms tend to a higher degree of music consumption and possess more diverse and novel music preferences. Previous research has similarly suggested that subscribers are more inclined to listen to more music and explore novel music than non-subscribers [8, 30]. Furthermore, research by Hagen [45] indicates that subscribers utilize the platform's social and interactive features, such as creating and sharing playlists, increasing their overall listening time. Consequently, subscribers are more likely to use the platform's unique experience to discover new and diverse music and as a way to share music with others. In addition, our study on the impacts of COVID-19 on music streaming platform subscribers, for the first time, reveals that as the stringency index increases, subscribers listen to music with more novelty and variety than non-subscribers. The strategy of focusing on subscribers may have saved music streaming platforms during the COVID-19 shock in the industry.

Another notable finding of our research is that individuals who have been using Last.fm for an extended period tend to listen to more music and have more diverse and novel music listening behaviors, as indicated by the age of their account. This can be attributed to the gradual evolution of their music preferences over time. Research has suggested that registration time could positively affect music listening behaviors [e.g., 27, 56]. Nonetheless, it is worth noting that the impact of registration time on music listening behaviors may differ in the COVID-19 context. Therefore, further investigation is necessary to comprehend this association during the COVID-19 pandemic, as our analysis did not reveal any moderating effect of this variable.

5.1.2 Social network size and social community motives

One of the key observations of our research is that there were significant differences in individuals' inclinations towards using Last.fm as a social network site during the early stages of the COVID-19 pandemic. We found that individuals' social activities moderated their online music listening behaviors during the start of the COVID-19 pandemic – those with social network connections listened to more music than those without connections. Additionally, users who utilized Last.fm as a way to join a community and interact with other users listened to more music with more novelty and variety, not only in general but also during lockdown times. It is likely that social communication and network motivations encourage users to utilize music streaming platforms more frequently than those who use them only to listen to music. During the early stages of the COVID-19 pandemic, social networking and community motives influenced how people listened to music or chose the theme for their emotional feelings. Despite our focus on music listening, the topic of social networking opens up a whole new area for future research.

To our knowledge, existing research has not considered social networking activities alongside online music listening behaviors within the context of COVID-19. Our research connects the limitations of face-to-face socializing and the increased tendency to use social network sites during the COVID-19 pandemic with music listeners' motives to use Last.fm's socializing features. This methodology helped us distinguish socially active users of Last.fm during the COVID-19 pandemic and study their music listening behaviors more nuancedly. We found that during the research period, the negative effects of COVID-19 on online music listening were more pronounced for those who did not use Last.fm as a social networking tool to communicate with the Last.fm community. In contrast, as an indicator of governments' lockdown policies during the outbreak of the COVID-19 pandemic, the stringency index had a significant and positive effect on online music listening when it interacted with social communication. Streaming platforms that rethink the design of their services can benefit from integrating social networking features, much like Last.fm positioning itself as a social music platform.

Since the start of the COVID-19 pandemic, various industries have been affected both positively and negatively. The positive implications are clear in some industries, such as IT and software; however, the online music industry was reversely impacted [99]. The majority of COVID-19 response strategies were developed in conjunction with the transformation of traditional business models [61]. Specifically, technology transformation has also been examined in the human-computer interaction community [16]. The significant impact of digital and technology transformation is due to the innovative design of products and services that enhance users' experiences. For example, the live streams conducted during the early stages of the COVID-19 pandemic increased feelings of physical and social presence [80]. Based on the perception of Last.fm as a social network site centered around music listening, we suggest that online streaming platform business models focus on how users discover, share, and discuss music. We propose that social communities can be utilized as effective business models to boost the performance of online music platforms throughout the remainder of the COVID-19 pandemic. The design of music streaming platforms such as Spotify and Apple Music could be examined as a future research topic to see how social dynamics might affect them [66, 103].

In recent years, the expansion of social networks has led to several significant changes in the music streaming industry to fill the gap in online communication [29]. Over time, features of online streaming services have developed to resemble those of social network sites (e.g., Facebook, Twitter). Users can listen to songs and follow users, watch their favorite songs, post, and reply. While some social features are designed to promote the online music community, for example, the "friend feed" feature provided by Spotify, [63] found that participants in their study on music listening behaviors were not interested in using this feature to stay in touch and listen to music; rather, they listened to music with their friends only when co-located. These results suggest there may be more design gaps in the social elements of online music platforms than a lack of interest in socializing behaviors, for example, co-listening [103]. In spite of the widespread use of social networking sites that revolve around shared interests, social networking is generally not seen as dependent on online music listening, meaning its vast benefit to online music services is underrated.

Although social networking could provide many advantages for the music streaming industry, these platforms still have gaps. For example, to ensure that a website is design-oriented and in compliance with different marketing strategies, service providers need to foster social connections on their sites to encourage social interaction and consumer consumption simultaneously [29]. Emerging music streaming services enable users to connect and share ideas rather than merely listen to music. Some prominent examples of this service are Wavy.fm[3], Hype[4], and Localify[5]. Our research suggests that, as the music streaming industry aims to monetize music consumption, social networking components can effectively regain market share through new revenue streams.

Our research provides us with the opportunity to re-examine the design of content streaming services in two ways: (1) by including social features in streaming services and (2) by integrating social technologies (such as ICTs) into streaming services. In the first instance, it is plausible that our results can be generalized to other experience products, such as online videos, books, software, and other digital content. Furthermore, it would be helpful to study user behavior regarding social connections and communication motives in services other than music in greater detail, such as online gaming communities (e.g., Xbox Live Communities), online book communities (e.g., LibraryThing), e-sports streaming platforms (e.g., Twitch), and online fitness communities (e.g., ikePlus.com). In the second instance, mainstream social network sites such as Facebook and Twitter are increasingly used to consume content, including listening to music and viewing videos. The interconnectivity between social network sites and streaming services is undervalued because neither is a dependent technology.

In Table 17, we present a summary of the contributions of this research and future research directions based on the opportunities the research provides. Potential research questions support each research direction.

5.2 Implication for practice

Based on our findings, we present the following practical implications. By emphasizing the social dynamics of online platforms, music streaming services and other digital platforms, such as video hosting services and software solutions, can respond to the current pandemic and future crises. In addition, owners of digital platforms seeking to increase consumption should consider the implications of social media strategies. It may be beneficial to take advantage of listeners' social and community motivations to encourage digital media consumption and engagement, resulting in more website revenue. Means of doing so could include better online advertising or more profitable freemium packages. We found that during the initial stages of the COVID-19 pandemic, people's online music listening habits varied depending on the characteristics of individual listeners. Platform providers are encouraged to

[3] https://wavy.fm

[4] https://hypem.com

[5] https://localify.org/

Table 17 Future Research Directions

Research Area	Contribution	Potential Research Questions
Research Area 1: *Impact of COVID-19 on online music listening behavior*	We identified the contextual online music listening behaviors in response to the first wave of the COVID-19 pandemic from a set of variables much broader than used in previous studies. In addition, the social dynamics of the streaming platforms were discussed as the moderator of the impact of COVID-19 on music listening.	RQ1. What other variables measure, moderate, or mediate online music listening behaviors? RQ2. How did the Last.fm users' listening patterns during the COVID-19 pandemic differ from those on other platforms?
Research Area 2: *Factors affecting music listening behaviors within the COVID-19 context*	While our study emphasized that the first wave of the COVID-19 pandemic adversely affected online music listening behaviors, future research could explore the factors affecting music consumption within the Covid-19 context, such as lack of genre, listeners' knowledge, and unsuitable recommendations.	RQ3. What is the reason behind the changes in online music listening behaviors?
Research Area 3: *Social dynamics of online platforms*	There is a potential for future research to examine the socializing features of online platforms similar to social networking sites (SNSs) and how those features can be translated into opportunities for streaming platforms in different ways.	RQ4. What role does design initiative play in influencing user behaviors on streaming platforms? RQ5. How can platform owners develop more proactive approaches when responding to issues instead of simply accepting them as exogenous forces?
Research Area 4: *Insights from sentiment analysis*	When conducting our research, we noted opportunities to review changes in music sentiments, such as in the lyrics. This matches noted changes in song titles that replicate the sentiments of the society during a real-world event [67]. The qualitative aspects of shouts on Last.fm indicate that the communication features of Last.fm primarily facilitates discussions about music [74]. As a promising direction for future research, we also suggest analyzing listeners' comments on Last.fm during the Covid-19 pandemic and examining the ensuing changes.	RQ6. What are the changes in the sentiment of song lyrics consumed within the context of the Covid-19 pandemic? RQ7. What are the changes in the sentiment of communications within the music community after the COVID-19 pandemic?

Table 17 (continued)

Research Area	Contribution	Potential Research Questions
Research Area 5: Methodological improvements	We conducted a study on Last.fm; generally, the development of streaming as a phenomenon and its evolution requires more research across various industries and disciplines. Furthermore, it would be helpful to study user behaviors in services other than music in greater detail, such as online gaming communities, online book communities, e-sports streaming platforms, and online fitness communities.	RQ8. How did the COVID-19 pandemic impact other user behaviors, such as gaming and video streaming? RQ9. How can the results of this study be generalized to different music platforms?

adopt recommendation strategies based on the type of user and the type of music produced in a particular context (in our case, the COVID-19 pandemic).

To fully align with the social dynamics of social network sites, digital platforms need to create more features such as live chats, live streaming, and multi-streaming to use the most of social dynamics. While the social characteristics of platforms are essential to increase the quantity of music listening, they are even more important in promoting novelty, variety, and listening to music outside of mainstream artists. In the design of a digital streaming platform, there could be more socializing features common to social network sites, such as indicating a friend online, tags in a comment or post, and sharing a co-experience (e.g., attending events in Last.fm). In terms of applications, it may be easier to achieve this goal if platforms offer more innovative features, such as displaying the number of listeners present or notifying the user when a friend selects to co-listen [103].

6 Conclusion

In this research, we utilized the unanticipated outbreak of COVID-19 as a real-world event to investigate the causal association between the pandemic and individuals' music consumption and discoveries. Shifts in mood caused by an event can drive changes in music listening behaviors. Therefore, context-aware music recommendation systems can boost recommendation results by capturing and representing contextual information compared to conventional recommendation systems. The emotional aspect of music relates to wellbeing theories. Thus, we addressed the need to determine whether users changed their song choices during the early phases of the pandemic. However, our results showed a decrease in online music listening by 15% due to the COVID-19 pandemic. With this in mind, we utilized the DiD method to study the causal impact of the COVID-19 pandemic on variety, novelty, and mainstreaminess. We additionally found that with the increase of weekly COVID-19 cases and strengthening lockdown policies during the first wave of the COVID-19 pandemic, the choices of music listeners became more mainstream with less variety and novelty. However, the results showed that even when the stringency index was extremely high, such as above 80%, individuals with social networks or those who used the Last.fm platform to communicate with others listened to more music with significantly more novelty and variety. As a final point, we discussed the implications of our research for academics and practitioners.

Appendix A

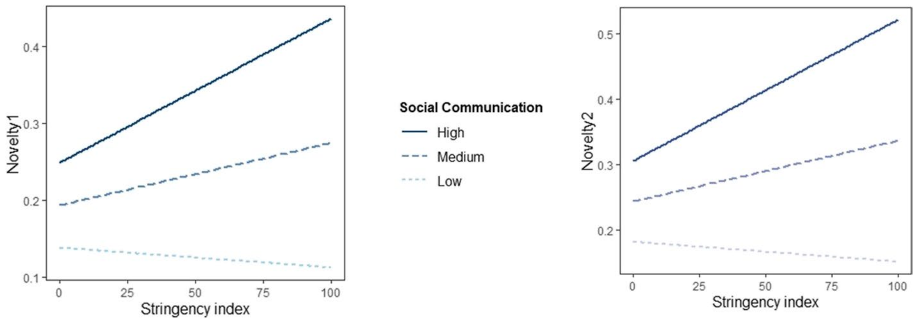

Fig. 5 Interaction plot of the stringency index and social communication (related to novelty)

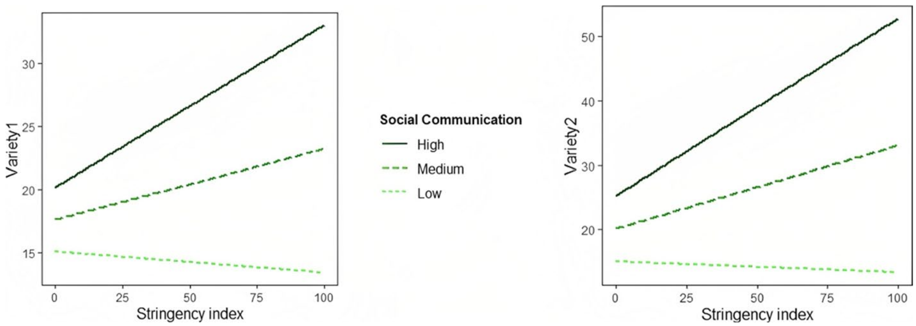

Fig. 6 Interaction plot of stringency index and social communication (related to variety)

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Data availability The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of Interests All authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

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