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Disruptions in Music Listening Behaviors During Lockdowns

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Abstract

This study examines how individual music listening behaviors evolved during the COVID-19 lockdowns in France, focusing on both listening volumes and rhythms. We combine passively collected individual listening history data, provided by a music streaming service and covering the 2019-2023 period, with survey data collected from the same users ($n \approx 10000$). Using the Dynamic Time Warping method, we develop a typology of listening trajectories during the first lockdown. The results reveal significant and heterogeneous changes in listening behavior, with approximately one-third of respondents experiencing a significant decrease in listening volume, while a quarter experienced an increase. We then analyze the evolution of the intervals between consecutive music listening sessions — so called inter-session times — to assess disruptions in individual listening rhythms. We uncover an unprecedented shift in the listening rhythms at the onset of first lockdown, reflecting varying degrees of disruption in daily life rhythms. For half of the individuals this disruption lasted more than four weeks. Finally we show that age, educational attainment and household structure unevenly influence the reorganization of music listening activity during this period, shedding light on the social differentiations at work in the reorganization of an ordinary activity during this crisis period.

Code and data —
https://gitlab.huma-num.fr/pgallinarisafar/icwsm-2025-disruption-in-music-listening

Introduction

As governments around the world adopted lockdown policies to mitigate the spread of the COVID-19 pandemic, most of the population was required to stay at home. Stay-at-home mandates were also accompanied by the widespread closure of numerous institutions, including schools, workplaces, shops, and cultural places that typically provide spatio-temporal boundaries between different spheres of activity. Thereby, the disruption of the socio-temporal frameworks which regulate human activities led to significant changes in routines and daily schedules for millions of individuals; as their statutory, relational, and cultural activities were restricted, individuals had to reorganize their daily lives to accommodate these changes.

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This pandemic-induced reorganization of human activities has been documented thanks to digital traces of activity collected by internet platforms and phone operators. With mobility severely restricted, digital traffic surged as more activities moved online or saw significant increases in usage (Feldmann et al. 2020, 2021). This included communication (both professional and social), but also intensified engagement with online entertainment (e.g., video-on-demand, video games), or informational activities.

The temporal reorganization of human activities

Beyond the surge in internet traffic and the increased use of digital communication tools, the drastic shift in usage patterns highlights the extent of the temporal reorganization of human activities during this period. This shift spans across various digital activities and has been observed at multiple scales. For example, studies based on highly aggregated data have shown that most of the increase in internet traffic occurred during non-traditional peak hours — due to casual activities like online searches, social network use, video-on-demand, streaming or gaming — and that phone-calling had intensified during workdays, while also shifting to later hours (Feldmann et al. 2020, 2021; Trevisan, Vassio, and Giordano 2021; Seufert et al. 2022; Castaldo et al. 2021).

Studies based on individual digital traces (coming from activity trackers or smartphones) have also revealed notable shifts in fundamental activities like sleep, walking, exercising, and communication. For example, people generally slept more, with data showing later bedtimes and wake-up times compared to pre-pandemic routines (Ong et al. 2021; Massar et al. 2022; Rezaei and Grandner 2021). Likewise, physical activities such as walking or exercise reduced, shifted to different hours of the day, and became more irregular (Luong, Barnett, and Aledavood 2023). Peer-to-peer communication — both messaging and calls — was more frequent, especially during the evening and at night (Seufert et al. 2022), particularly for women (Reisch et al. 2021). A common finding across these studies is the blurring of weekday and weekend patterns, with daily routines increasingly resembling those typically observed on weekends.

Variability and social differentiation in temporal reorganization

Social sciences studies have emphasized the disparities in pandemic experiences between different social groups. Those span areas such as income and employment, physical and mental health, mobility patterns, as well as social practices, including communication, network relationships, and digital, cultural, or leisure activities. The significant decrease in the perception of time scarcity during the first lockdown, as evidenced in the UK (Roberts 2020; Ludvigsen et al. 2023), the US (Roy 2024) or in France (Charlap 2021; Paye 2021), was unevenly experienced, as the relaxation of temporal constraints exhibited marked social differentiation.

As the pandemic lockdowns weakened collective routines, they disrupted the structure of everyday life, prompting individuals to reorganize their practices around new anchor activities (Greene et al. 2022). Cultural practices, which help structure daily routines, create temporal coherence (Chauvin et al. 2021), reorganize leisure time, and maintain social relationships, can thus be understood as resources that supported adaptation and coping during the pandemic (Roberts 2020). However, the capacity to mobilize these resources was not evenly distributed, as it varied significantly between social groups, shaped by life configurations and social characteristics (Charlap 2021; Chatot, Piesen, and Viera Giraldo 2021; Roberts 2020). Although there is evidence of differentiation, to our knowledge, there are only few studies that have combined the analysis of the reorganization of ordinary practices during the pandemic - using passively and continuously collected individual-level activity data - with an in-depth examination of the social inequalities driving these changes (Ong et al. 2021; Rezaei and Grandner 2021; Luong, Barnett, and Aledavood 2023; Voss et al. 2023).

The heterogeneous effect of lockdown on music listening behaviors

As a widespread cultural practice deeply embedded in the everyday rhythms of activity, online music listening provides an excellent example of the 'missed rendez-vous' between computational approaches and social sciences — an opportunity to bridge disciplines to gain a socially nuanced understanding of the reconfiguration of ordinary activity rhythms during this extraordinary period. Indeed, several authors have primarily focused on demonstrating the causal effects of COVID-19 on music consumption, applying diff-in-diff methods to large datasets collected across different countries. These studies reveal a wide range of effects on music consumption patterns, including a decline in both the listening time and the diversity of the music listened to (Ghaffari et al. 2023); changes in the audio characteristics of the music played (Kalustian and Ruth 2021); shifts in playlist use and music sharing and peer-recommendation behaviors (Maloney, O'Neill, and Gray 2021); and correlations between music listening patterns and mobility (Kim, Askin, and Evans 2024). However, these works are primarily content-oriented and none of these studies has focused on the rhythmic dimension of the music listening activity. Few of them even mention this dimension, and none delves into the heterogeneous and socially differentiated reconfigurations at work in the changes they describe.

The rhythmic dimension of music listening patterns, along with its social embedding, deserve greater attention. Music listening not only mirrors the broad rhythms of daily activities but also serves as a medium for structuring daily routines and supporting different activities (DeNora 2000). Music listening primarily serves as a companion activity: people listen to music alongside other activities, during journey-to-work commutes, in parallel or in the downtimes of fixed activities, at work, and during social meetings (Bosacki and O'Neill 2015; DeNora 2001). Among all cultural practices, it is likely the most widespread and deeply rooted in the rhythm of activities that structure daily life. As such, it provides an excellent entry point for linking previously mentioned findings across multiple scales of analysis. Studying change in rhythmic pattern of the individual music listening during the pandemic could therefore contribute to offering a more comprehensive view of the intensity of temporal restructuring in human activity. From a methodological point of view, bridging computational approaches with previous works focused on the variability of temporal reorganization across social groups, would illuminate both macro-level patterns and the nuanced differences driven by social characteristics.

In the following of this paper we aim to address this gap by investigating how much music listening changed during the COVID-19 crisis in France, in particular during the lockdowns. More specifically, our research questions can be formulated as such: How music listening behaviors evolved during the pandemic, both in term of volume and rhythm? (RQ1) How much different were these evolutions from one person to another? (RQ2) How these differences are embedded in society? (RQ3).

Data and Methods

Data and Data Collection Methods

We analyze a longitudinal dataset of online music listening provided by Deezer, a leading music streaming platform in France, covering the period from January 2019 to July 2023. As of 2024, Deezer ranks as the third-largest music streaming service globally, with 16 million active users across 180 countries and a catalog of 90 million tracks. The dataset includes individual listening histories enriched with responses from an online survey completed by over 10,000 Deezer France subscribers. These anonymous participants, who identified Deezer as a primary source of recorded music, provided explicit consent for their survey responses to be analyzed alongside their listening data.

For each anonymous user and each listening event of any given song, the data collected by the streaming company include the timestamps and the duration of each listening event. In the following of this paper we will focus on the evolution of individuals' weekly listening time – how much time each user spent using the streaming service each week – and on the time elapsed between two consecutive listening events (so called the inter-event time). From each individual's listening history data we will compute the distribution of her/his individual weekly listening times and the distribution of the time elapsed between two consecutive listening sessions, that is the distribution of the inter-event time. The distribution of weekly listening times highlights fluctuations in the intensity of musical engagement, capturing shifts in the overall listening behavior. The time elapsed between consecutive listening sessions is a proxy for capturing the temporal organization of the listening activity, offering insights into rhythms and disruptions in daily routines due to the pandemic.

The online questionnaire survey, overseen by the Data Protection Officer of the lead research institution, allowed us to collect standard sociodemographic variables, including age, gender, educational background, occupation, and income, without gathering any personally identifiable information or sensitive content. These self-reported data enable a deeper analysis of the statistical relationships between users' listening behaviors and their social characteristics, compared to relying solely on the basic gender and age information provided during registration (Ghaffari et al. 2023). For this study, we examine individuals' educational level (highest diploma obtained), gender, age, household structure, socio-professional category (derived from occupation and related variables using the procedure detailed in (Amossé 2022)), and the contexts in which they report listening to music. We aim to analyze individual time series of weekly music listening durations to identify distinct patterns in listening behavior (measured in hours) during different stages of the pandemic. Although for many people listening activity is organized on a daily basis (with important listening contexts, such as the commute to work or partying, that are not the same on weekdays and weekends), in this study we focus on potential reconfigurations of music listening time on a weekly scale under the effect of exceptional events, the lockdowns, that lasted several weeks to several months. For each user, we construct a time series $(t_1, t_2, ..., t_l)$ where t_i represents their listening time during week i, over a time window of length l. To ensure comparability across users, regardless of the overall intensity of their listening activity, we apply z-normalization to the time series. This normalization also facilitates subsequent calculations (Mueen and Keogh 2016).

Methods

Dynamical Time Warping On these time series we apply a method named Dynamical Time Warping (DTW) using the "dtw" function of the R *dtw* package (Giorgino 2009). For a couple of time series (X, Y) the DTW distance is defined as the minimal sum of the correspondence costs between the two series, considering all possible correspondences that respect alignment constraints. The formula is generally written (Mueen and Keogh 2016) :

$$\text{DTW}(X, Y) = \min_{\pi \in \Pi} \sum_{(i,j) \in \pi} d(x_i, y_j) \tag{1}$$

where Π is the set of all possible alignments (paths) between the sequences X and Y, and $d(x_i, y_j)$ is the Euclidean distance between points x_i and y_j. Therefore, the DTW distance is obtained by finding the minimal sum of correspondence costs along an optimal path through a cost matrix, while respecting predefined alignment constraints (see the Appendix for more details).

We focus on survey respondents who registered on Deezer before the beginning of 2019 to avoid potential biases from those who joined Deezer later, as their experience with the platform and its features may differ due to the discovery process. This represents 9821 individuals, after excluding around 1,000 users with too few listening sessions to compute dynamic time warping (DTW) distances.

To provide an initial insight into how individual listening patterns changed at the onset of the first lockdown, we calculate intra-individual DTW distances over time using a sliding window approach. We segment each individual's listening time series into a sequence of overlapping windows S_i, where each window spans two consecutive months and starts one week after the previous one, from January 2019 to the end of 2020. For example, S_1 covers the period from 01/01/2019 to 28/02/2019, S_2 covers 08/01/2019 to 07/03/2019, and so on. We then compute, for each individual, the Dynamic Time Warping (DTW) distance between each pair of windows separated by eight weeks — e.g., between S_1 and S_9, S_2 and S_{10}, S_3 and S_{11}, etc. Finally, we compare the average "self" DTW distance between the March-to-May periods in both 2019 and 2020 — the latter encompassing the first lockdown in France.

In parallel, we calculate the DTW distance between individuals' time series for a sub-period that encompasses the first lockdown in France (from the beginning of March to the end of May). After computing the distance matrix we applied a clustering algorithm analogous to k-means but adapted for time series data, using DTW Barycenter Averaging (DBA) to compute the cluster centroids (Montero and Vilar 2015). This approach enables us to identify and extract three distinct temporal listening behavior profiles across the users. To explore the relationship between these clusters and the sociodemographic characteristics of the users, we employ a multinomial logistic regression model. In this model, the cluster assignment serves as the dependent variable, while various sociodemographic attributes - such as age group, gender, household composition, and the listening contexts self-declared by the users - were included as predictors. This approach allows us to estimate the likelihood of a user belonging to each behavioral cluster based on their profile. By interpreting the resulting odds ratios, we can assess which features are significantly associated with a given listening dynamics profile, offering insights into how demographic and contextual factors shape music consumption over time. The regression was computed using the "multinom" function of the nnet R Package (Venables and Ripley 2002).

Inter-event Time To further explore the change in music listening rhythms during the lockdowns, we focus on the time intervals between consecutive listening sessions. This approach is inspired by a broad body of research that examines time gaps between events to uncover patterns in human, natural, and mechanical activities. Previous studies have analyzed the time between consecutive emails (Barabási 2005; Malmgren et al. 2008), SMS (Wu et al. 2010), tweets (Jeong and Moon 2017), website visits (Halfaker et al. 2015), online game sessions, and song listening (Mongiardino Koch and Soto 2016) to better understand the dynamics of human activities mediated by digital interfaces and the social systems they are embedded in.

By studying the evolution of the time intervals between consecutive music listening events (Inter-Session-Time IST) during the lockdowns, we aim to characterize shifts in the temporal patterns and routines of an activity that is usually deeply embedded in the rhythms of public and private life. Since people often listen to music while doing something else (DeNora 2000), we assume that a shift in the listening rhythm pattern provides information on the rearrangement of activity rhythms during the lockdown. In other words, we hypothesize that shifts in the listening patterns may constitute an original proxy to measure disruptions in the rhythmic patterns of daily life.

Wasserstein Distance To focus on more informative variations in listening behavior, we filtered out time intervals of less than 10 minutes between two consecutive listening events. These short intervals likely represent brief interruptions within a session and are not relevant to our study, which aims to capture changes in the rhythms of broader activities associated with music listening. To examine the longitudinal evolution of an individual's distribution of inter-session times (IST), we apply a sliding window as follow: we segment the year 2020 into 52 overlapping two-month time windows with one week sliding window. Then, for each individual, we compute the Wasserstein Distance (WD) (Piccoli and Rossi 2014) between their IST distribution in the current window and a corresponding reference distribution. For a given time-window this reference distribution is constructed by randomly sampling an equivalent number of data points from a vector formed by concatenating all the user's IST values from the same time period, across different years. For instance, for a given user and a 2-month window in 2019, the reference distribution is created by concatenating their IST values from the same window in 2020, 2021, 2022, and 2023, and then randomly sampling m points from this vector.

We compute the WD between each window and its reference window, repeat the random sampling process 500 times, and retain the mean of all the WD distances. This approach enables us to compare an individual's listening rhythm during a specific period (represented by their IST distribution in the current window) to their "average" behavior during similar periods across multiple years. The resulting measure provides a longitudinal, individual-level indicator of behavioral continuity while controlling for potential seasonal effects. The Wasserstein Distance is computed using the *wasserstein1d* function from the R *transport* package (Schuhmacher et al. 2024). Further details on the calculation of WD for IST distributions are provided in the Appendix.

Results

Figure 1A gives the social characteristics of the 9821 anonymous users whose listening history data and survey responses are analyzed in the following. While the sample is not representative neither of the entire French population — women are underrepresented and respondents from the Upper class and those aged 35–54 are slightly overrepresented — nor of the global population of the platform users — because of social selection bias when recruiting participants in no-incentive surveys — it still offers sufficient diversity to explore social differentiation across the measures performed in this research. Further details on the survey can be found in (Renisio et al. 2024).

Before investigating the reconfigurations at work in the context of the COVID-19 pandemic, we first observe on Figure 1B that not only there is strong inter-individual variability in average weekly listening time, but also and most remarkably strong intra-individual variability in weekly listening times. On this plot all individuals are ranked from left to right by decreasing order of their average weekly listening time in 2019. For each of them we plot in black the average value while the bars correspond to the standard deviation of their personal distribution of weekly listening times. This plot, limited to a pre-pandemic period, conveys two important information : first, for all people we observe some strong fluctuations (with the standard deviation of the same order of magnitude as the mean), with some weeks filled with much more music than some others. Second, some individuals (those on the left) spent much more time listening to music than some others (on the right).

To analyze the relationship between the different phases of the pandemic and inter-individual variability, we have plotted on Figure 1C the distribution of the users' average weekly listening time for five different periods ; before the first lockdown in France, during each of the three lockdown periods, and after. We observe no clear differences between the different periods: the median value remains approximately constant (around 5 hours/week) and the distributions are stretched, with for all periods some individuals listening to music ten or twenty times more than some others. Either no substantial change in individual music listening rhythms was observed during the COVID-19 pandemic, or the increase in listening time for some people was offset by a decrease for some others

To settle this issue we construct for each single user her/his time series of individual weekly listening times, and we apply Dynamical Time Warping (DTW) in order to compare the users' listening patterns, cluster them, and relate this classification to socio-demographic properties of individuals (see Methods for details).

Figure 2A presents the distribution of intra-individual DTW distances computed between pairs of two-month windows separated by eight weeks (e.g., between S_i and S_{i+8}), over the period from March to May in both 2019 and 2020. This comparison allows us to assess changes in the temporal consistency of individual listening behaviors across these two periods, with 2020 encompassing the first lockdown in France. We observe a slight shift in both the median and

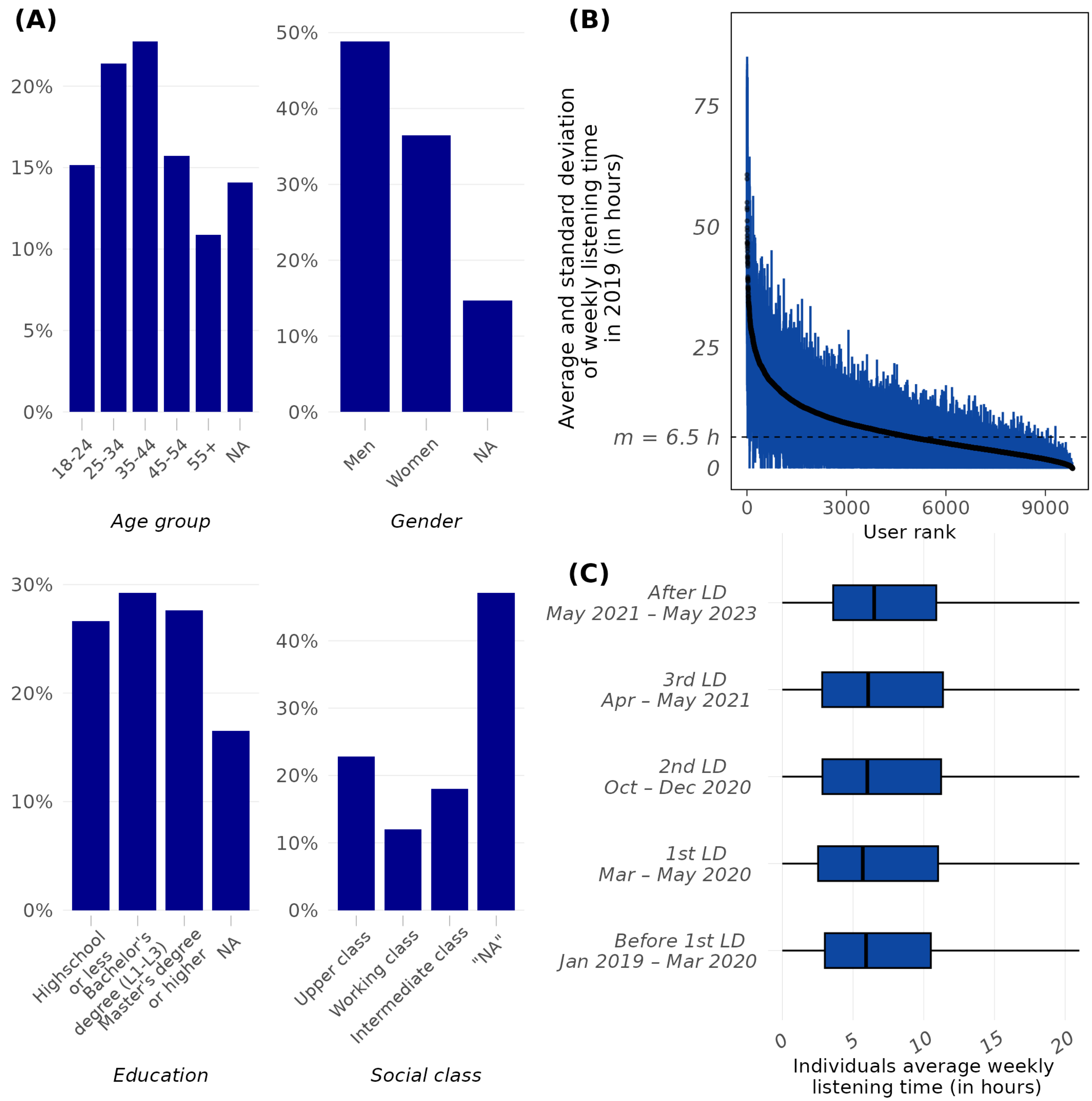

Figure 1: **Social properties and intensity of the online listening activity of the surveyed individuals.** (A) Sociodemographic characteristics. For gender, we asked survey participants to specify their gender identity and excluded from the analysis those who did not identify as either male or female. (B) Rank-plot of the individuals' average weekly listening time (in hours) — black dots — along with the standard deviation — blue bars — for the year 2019. (C) Distributions of the individual average weekly listening time (in hours), calculated for five different periods: before the COVID-19 pandemic; during the three distinct lockdown periods in France; and after.

the overall distribution: intra-individual DTW distances between successive months are slightly higher during the period encompassing the first lockdown (mean = 8.48, median = 7.42, SD = 5.33) than during the same months in 2019 (mean = 7.21, median = 6.26, SD = 4.98). This suggests that, on average, individuals exhibited less temporal consistency in their listening behavior in 2020 compared to the same period in 2019, providing a first indication of a disruption in

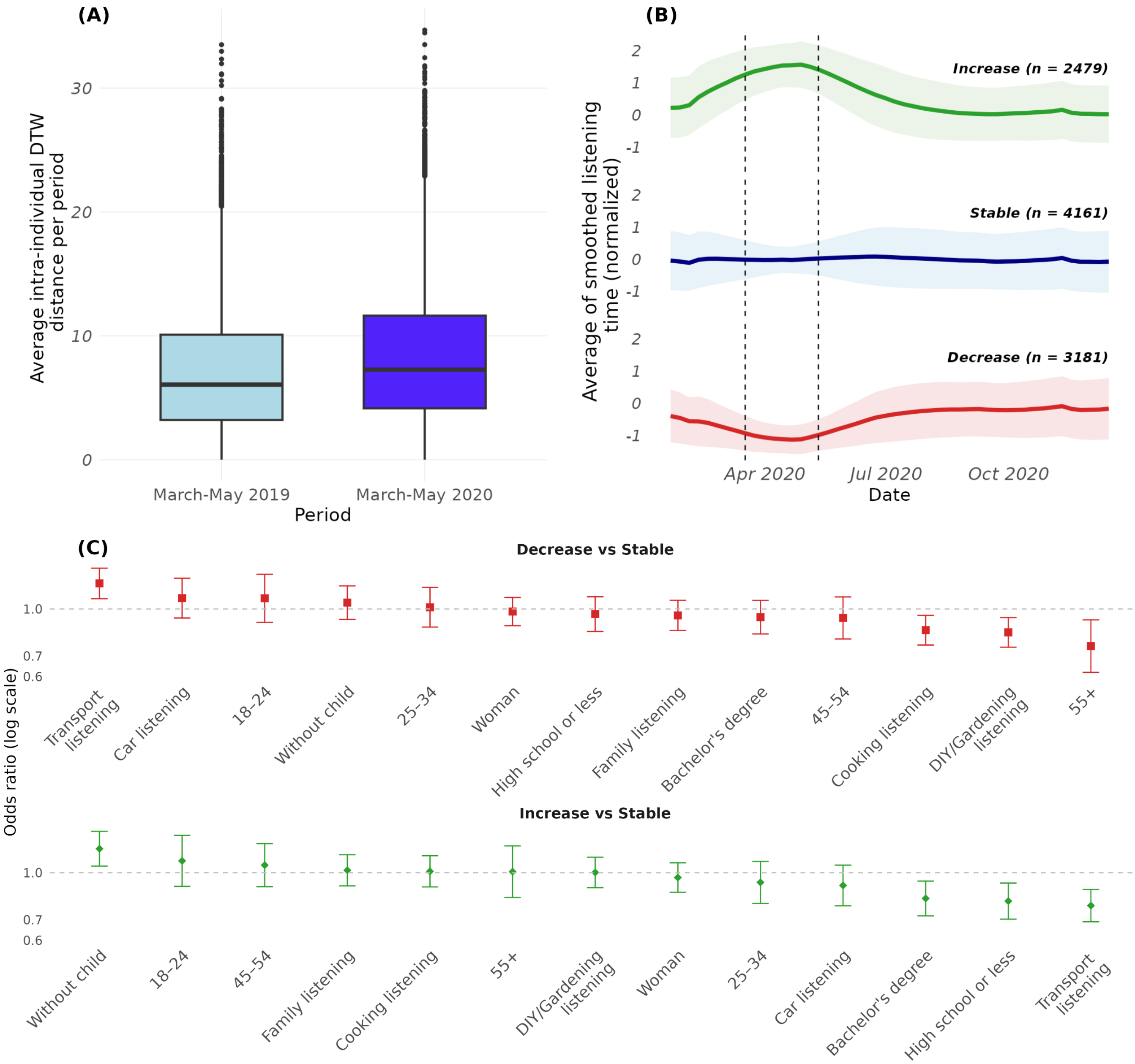

Figure 2: **Evolution of music volume listened by the surveyed individuals during the lockdown and social differences.** (A) Boxplot of average intra-individual DTW distances computed from sliding two-month windows, each compared to the one starting eight weeks later, during the March–May periods of 2019 and 2020. The 2020 March–May period covers the first lockdown in France. (B) Mean normalized weekly listening time, at the onset of the first lockdown, derived from the DBA clustering of the Dynamic Time Warping distance matrix. Dashed lines represent the start and end dates of the first lockdown in France. (C) Odds ratio resulting from the multinomial regression models applied to three clusters previously determined. The "Stable" cluster serves as the reference category for calculating the odds ratios.

the rhythm of individual listening activity during the first lockdown.

In order to better understand the perturbations patterns, in Figure 2B, we show the average weekly listening time series of clusters of users, determined from the DTW distance matrix obtained when applying the DBA algorithm on a time-window covering the first lockdown (see Methods). The average time series of the three clusters exhibit distinct variations in the listening trajectories throughout 2020. The first group includes individuals whose weekly listening activity remained relatively stable during the first lockdown (Cluster 2, n = 4161, in blue). The second group comprises those who experienced a decline in their listening activity (Cluster 3, n = 3181, in red). Finally, the last group consists of individuals whose listening activity increased during the lockdown (Cluster 1, n = 2479, in green).

Taking advantage of the information self-declared by users in the survey, we now focus on social differences in cluster membership. The following paragraphs describe the results of multinomial logistic regressions, which estimate the association between each category within each variable and the probability of respondents belonging to a given cluster rather than to the reference category (the "Stable" cluster), all else being equal within the limits of the model. These results are summarized in Figure 2C.

- Respondents with a high school diploma and those with a bachelor degrees are less likely to belong to the "Increase" cluster relatively to the "Stable" one, compared to those with a Master's degree or higher (respectively *OR* = 0.81, $p < 0.01$ and *OR* = 0.83, $p < 0.01$)
- Respondents aged 55 and over are significantly less likely to be in the Decrease cluster compared to those aged 35–39 (*OR* = 0.77, $p < 0.01$)
- Respondents who declared listening to music while cooking, tinkering or gardening are less likely to be in the 'Decrease' cluster (*OR*: 0.86, $p < 0.01$; *OR*: 0.84, $p < 0.01$; *OR*: 0.91, $p < 0.05$)
- Respondents who declared Listening to music on public transport are more likely to be in the 'Decrease' cluster (*OR*: 0.78, $p < 0.01$).

Beyond the total time spent listening to music each week we now analyze how much the individual rhythms of the listening activity have been disrupted during the lockdowns. By individual rhythm we refer to how the online music listening activity is integrated into the individual's life time. We first calculated the Wasserstein Distance (WD, see Methods) between all 2-month time windows of all individuals, and subsequently computed the ratio between the self distance (i.e the mean of the WD calculated between all the time-windows of a single individual), and the non-self distance (i.e the mean of the WD calculated between the time-windows of a given individual and those of all the others). Figure 3A represents the histogram of this non-self/self WD ratio, which shows that for over 90% of users the ratio is larger than one and thus that the intra-individual WD is smaller than the inter-individual WD. In other words, when it comes to the temporal distribution of the listening activity, most respondents are more similar to themselves over time than they are to others, no matter the fluctuations from one period to another. The individual distribution of inter-activity times then constitutes a 'signature' of the individual listening rhythm. This finding is consistent with previous studies using the same method to characterize the individual rhythm of other digital activities (e.g. web browsing sessions (Halfaker et al. 2015) and tweeting (Jeong and Moon 2017)).

We then measured how much these individual distributions of the inter session time were disturbed during the lockdowns. We plot on Figure 3B the evolution over time of the distribution, among users, of the mean of the intra-individual WD. Each inter-individual distribution of the mean is represented by a vertical boxplot, that corresponds to a 2-month time-window. We see that the first lockdown has been the period of greatest disturbance throughout the entire period going from 2019 to 2024, both in terms of the median value of the mean (bold line) and the third and fourth quartiles. The first lockdown was an period of unparalleled reconfiguration of individual listening rhythms.

The plot also shows that the disruptive dynamics were limited to this specific period, which corresponds to the time when government-imposed activity and mobility restrictions were at their strictest in France. On Figure 3C we plot the same time series of boxplots, this time by grouping the users according to their age, and we see that people over 45 experienced less disruption in their listening rhythms during the first lockdown compared to younger respondents.

To capture the uneven duration among individuals of this disruption of their personal listening rhythm, we calculated for each individual a relaxation time, measured as the number of consecutive weeks following the start of the first lockdown during which the intra-individual WD (see Methods) exceeded its overall mean plus 0.2 times its standard deviation (to account for intra-individual variability, see Figure 1C). Figure 4A shows the cumulative distribution of this relaxation time among individuals. We can observe important variability with 25% of the sample presenting a value of 0 (no disruption). The mean is equal to 5 weeks, while the median is equal to 4, indicating a positive skew in the data. The standard deviation of 5 reflects the variability and highlights the presence of outliers. This relaxation time is not normally distributed, as illustrated by the Q-Q plot in (Figure 5) in the Appendix. However, the central portion of the distribution aligns closely with a normal distribution. Thus, to analyze the relaxation time in relation to sociodemographic variables (Figure 4B) and assess the significance of these differences, we adopt a two-step approach: we first perform an Anova test, to assess differences under the assumption of normality, and a Kruskal-Wallis test, a non-parametric alternative to ANOVA better suited for heavy-tailed distributions. Based on the results of the Kruskal-Wallis test and ANOVA, we state that individuals in the 25–34 and 35–44 age groups experienced significantly longer periods of disruption compared to other age groups, both in terms of the median (Kruskal-Wallis test) and mean (ANOVA) ($p < 0.001$). Women experienced a marginally longer period of disruption compared to men, with a mean difference of +0.34 weeks (ANOVA, $p = 0.076$). However, no significant difference was observed in terms of median values.

Finally to explore the interactions between age, gender, and parental situation in greater depth (Figure 4C), we recognize the constraints imposed by the deviations from perfect normality in the data. Consequently, we rely on a combination of T-tests, which assume normality, and Wilcoxon tests, their non-parametric counterparts, to compare groups in a more focused and granular manner. This analysis reveals differences that remain otherwise hidden. Notably, the 35–44 age category is the only group exhibiting a signif-

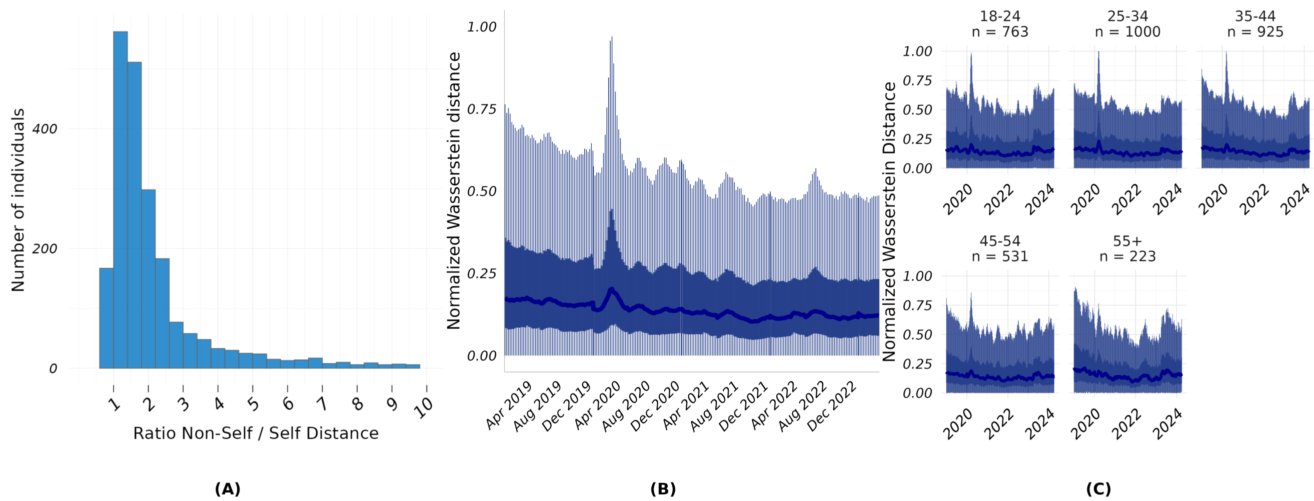

Figure 3: **Intensity of rhythmic disruption in the online listening activity of surveyed individuals.** (A) Distribution of the non-self/self distance ratio across users (B) Time series of boxplots showing the distribution of the normalized Wasserstein Distance (WD) used to quantify the rhythmic perturbation observed for each user (C) Time series by age class of the WD distribution.

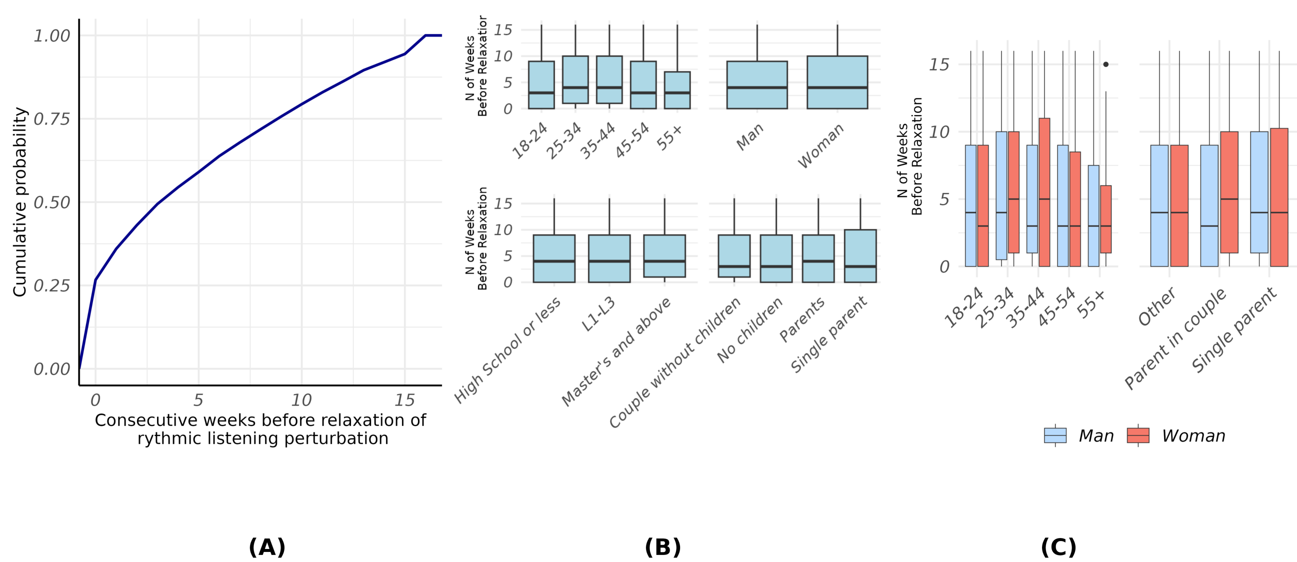

Figure 4: **Uneven duration of the disruption of individual listening rhythm.** (A) Cumulative distribution function of consecutive weeks of perturbation (B) Boxplot of the number of weeks preceding the stabilization following rhythmic perturbation, categorized by social characteristics (C) Boxplot of the number of weeks preceding the stabilization following rhythmic perturbation, categorized by age group and parental situation, further broken down by gender.

icant difference in the disruption relaxation time between men (mean = 5.03; median = 3; SD = 4.96) and women (mean = 5.86; median = 5; SD = 5.62). These differences are statistically significant according to the T-test ($p < 0.02$) and marginally significant with the Kruskal-Wallis test ($p < 0.08$). Similarly, gender-based differences emerge when considering parental situations. Men in couples living with children experienced significantly shorter periods of disturbance (mean = 5.06; median = 3; SD = 4.99) compared to women in the same situation (mean = 5.7; median = 5; SD = 5.29). These differences are statistically significant according to the T-test ($p < 0.02$) and the Wilcoxon test ($p < 0.04$) performed.

Discussion

We sought to explore how music listening behaviors were reconfigured during the COVID-19 lockdowns in France. To do so we have used two complementary approaches and data that, up to our knowledge, are among the most complete used in this type of research, due to the number of participants, the granularity of the listening history data, and also the availability of survey-collected variables that are rarely (e.g. household structure) or even never (e.g. diploma, usage contexts) available in conjunction with digital traces of activity. As discussed in the introduction, music listening nowadays mostly serves as a companion activity, deeply rooted in the broader rhythms of daily life. We thus argue that disruptions in listening patterns — both in terms of listening time and rhythmic structure — serve as indicators of disruptions in daily routines, extending beyond just music streaming.

In the first approach we have applied DTW on the individuals' series of weekly listening times. Our results highlight different types of discontinuities, and unequal chances among the social groups to experience increase or decrease of global listening volume. About sixty percent of respondents experienced significant changes in their weekly music listening volume, with roughly one-third showing a decrease and one-quarter showing an increase. In the second approach, we have focused on individual listening rhythms, as captured by the distribution of inter-session time. Our analysis revealed that unparalleled disruptions of these individual rhythms occurred during the first lockdown. Half of the participants experienced disruption of their own characteristic rhythm during a period exceeding four weeks, while a quarter faced disruptions lasting more than ten weeks. Our analysis thereby highlights a significant shift in music consumption behavior, a shift that appears to be essentially confined to the first lockdown period (RQ1), which in France was the most stringent one in terms of mobility and outdoor activities restrictions. We also characterized the differences between individuals in these behavioral shifts, and shed light on the diversity of their evolution (RQ2). Finally, we also highlighted social differentiations in these disruptions (RQ3), and showed in the first approach that the evolution of listening time was influenced by factors such as diploma, age and household structure. In the second approach we showed that the duration of the perturbation of the listening activity was primarily shaped by age, with slight influences from gender and parental configuration.

These two approaches provided complementary information on the disruptions, both highlighting slight but consistent differences between social groups. The regression analysis, which aimed to characterize each cluster based on sociodemographic features, revealed a notable effect of household structure: individuals living with children were less likely to belong to the 'Increase' cluster, suggesting that parenthood may have constrained music listening engagement during the lockdown. However, the structure of the sample limited our ability to explore more nuanced, intersecting effects. Certain combinations — such as men living with children —- were underrepresented, making it difficult to test potential interactions. Nevertheless, we suspect that gender may interact with other factors and shape listening behavior in important ways.

Indeed, Figure 4C, which stems from the second analytical approach — focused on the duration of rhythmic disruption as captured by shifts in inter-session time distributions — suggests that the effect of parenthood on music listening during the first lockdown was shaped by gender. More precisely, mothers appear to have experienced slightly longer periods of disrupted leisure time compared to their male counterparts. This result may be rooted in the persistent gendered inequalities in the division of domestic, parental, and care responsibilities. These structural inequalities were further exacerbated by the closure of schools, nurseries, and other support infrastructures during the lockdown, which blurred the boundaries between work, family, and personal time placing disproportionate pressure on women(Charlap 2021; Landour et al. 2023). This finding resonates with broader evidence of gendered inequalities documented in cultural consumption (Feder et al. 2023; Ludvigsen et al. 2023), leisure time (Roberts 2020; Roy 2024), mobility patterns (Luong, Barnett, and Aledavood 2023), and communication practices (Ohme et al. 2020). Furthermore, previous research based on mobile phone data showed that women returned to prepandemic rhythms - such as circadian cycles, mobility, and communication - more slowly than men (Reisch et al. 2021). The fact that older respondents were less likely to experience disruptions in their music listening behavior (in terms of volume and rhythms) is consistent with surveys showing that they generally faced less pressure and reorganization of their activities (Grossetti et al. 2021; Lazcano, Doistua, and Madariaga 2022; Feder et al. 2023; Jonchery and Garcia 2023). This is particularly true for the 55+ age group, who are less likely to have young children, engage in social out-of-home activities (except for work), or maintain large social networks, and are generally less precarious. In contrast, younger individuals (18-34) experienced the most significant disruptions in their social networks (Grossetti et al. 2021) and daily activities(Roberts 2020; Greene et al. 2022; Saals, Boss, and Pot 2022) with many aged 18-25 returning to their parents' homes during the first lockdown. Such changes could explain the salient disruption in their music listening rhythm, as illustrated in Figure 3C.

We also showed that participants with higher diploma positions are more likely to experience an increase in their listening activity. This can be understood in light of studies showing that the digital shift of cultural practices induced by the pandemic has deepened sociocultural inequalities. As previous research has shown, the lockdown may have nurtured cultural engagement, but primarily among individuals who were already highly engaged, like those with higher levels of education or social position (Feder et al. 2023; Ludvigsen et al. 2023). All in all, as previous research showed that cultural practices could be seen as resources that helped in coping with the negative effects of the pandemic (Greene et al. 2022; Ludvigsen et al. 2023), we believe that our results also highlight certain dimensions of social differentiation in the experience of the pandemic, which are rooted in preexisting inequalities.

Methodological limits Previous research on the music listening activity during the pandemic used the difference-in-differences (diff-in-diff) method (Massar et al. 2022; Ghaffari et al. 2023; Kalustian and Ruth 2021) to formally establish causal influence of the pandemic. In contrast, our analysis does not adopt this framework. As a result, although our indicators display temporal correlations with key phases of the COVID-19 crisis, we cannot assert that the observed changes were caused by the reconfiguration of daily life activities — such as those during which people listen to music — and thus, indirectly, by the pandemic itself. However, the temporal correlations we observed, including the return to pre-pandemic listening patterns at the end of the lockdown, strongly support the hypothesis that the disruptions we highlighted are linked to the restrictions imposed by the lockdowns. These results are consistent with previous research which also suggested that observed shifts in digital practices were closely tied to the unprecedented reorganization of daily life caused by restriction measures (Castaldo et al. 2021; Feldmann et al. 2021; Luong, Barnett, and Aledavood 2023).

Conclusion

Through this study, we have exposed variations in the cultural habit of music streaming, across social position, gender, age, and household structure. These variations, rooted in social inequalities, show differences in how daily life was disrupted during the pandemic. Future research could investigate how changes in music streaming behavior relate to shifts in other daily habits, such as mobility patterns, exercise routines, or leisure activities like gaming and reading. By exploring these connections, researchers could assess how much cultural practices, such as listening to music, serve as proxies for capturing broader disruptions in daily routines. Furthermore, since music can function as a resource for adaptation and coping during challenging times, understanding its role could offer deeper insights into the dynamics of resilience and adjustment during events like the pandemic.

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Paper Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? Yes
   (e) Did you describe the limitations of your work? Yes
   (f) Did you discuss any potential negative societal impacts of your work? We believe that, due to the nature of our research, it cannot have any negative societal impact
   (g) Did you discuss any potential misuse of your work? No (but we did not identify any potential misuse of our work)
   (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes
   (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
   (a) Did you clearly state the assumptions underlying all theoretical results? Not applicable
   (b) Have you provided justifications for all theoretical results? Yes, but our results are empirical rather than theoretical
   (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Not applicable
   (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Not applicable here, we did not intend to propose formal mechanisms of explanation for the outcomes observed.
   (e) Did you address potential biases or limitations in your theoretical framework? Yes. We explained that the population under study is not representative neither of the whole French population, nor of the whole population using the streaming platform (because of social selection bias in no-incentive survey participation).
   (f) Have you related your theoretical results to the existing literature in social science? Yes.
   (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes we did in the conclusion.
3. Additionally, if you are including theoretical proofs... Not applicable.
   (a) Did you state the full set of assumptions of all theoretical results?
   (b) Did you include complete proofs of all theoretical results?
4. Additionally, if you ran machine learning experiments... Not applicable.
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)?
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)?
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)?
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)?
   (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made?
   (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance?
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...

(a) If your work uses existing assets, did you cite the creators? Yes.
(b) Did you mention the license of the assets? Yes.
(c) Did you include any new assets in the supplemental material or as a URL? No.
(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? Yes.
(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes.
(f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see **?**)? No, in this version we did not discuss it. However in future versions we will provide a URL to access aggregated individual data for a sample of the 11437 users of the music streaming platform whose data (survey+listening history) are analyzed in this paper, enabling the reproduction of the results discussed in the paper.
(g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see **?**)? Not in this version.

6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...

(a) Did you include the full text of instructions given to participants and screenshots? Yes (see the code and data repository — link on the first page). There are two types of data analyzed in the paper. The first type are listening history data passively collected by Deezer. By definition, there is not any instruction given, as those are data passively collected by the company. The second type of data are survey data. They were collected in a no-incentive, online questionnaire taken by registered users of the music streaming platform. The survey is GDPR-compliant and we collected the explicit consent of the participants to the treatment of their data. These include anonymous responses to the survey and their listening history data on the streaming platform.
(b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? Yes.
(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? Not applicable.
(d) Did you discuss how data is stored, shared, and deidentified? The complete information about the data collection process (including storage and GDPR-compliance measures) are provided in (Renisio et al. 2024).

Appendix

DTW Dynamic Time Warping (DTW) identifies the optimal path that aligns two time series by minimizing the total distance between their points. The optimal path can be efficiently determined using dynamic programming, which evaluates the following recurrence relation that defines the cumulative distance $\gamma(i,j)$ as the distance $d(i,j)$ found in the current cell and the minimum of the cumulative distances of the adjacent elements:

$$\gamma(i,j) = d(x_i, y_j) + \min \begin{cases} \gamma(i-1, j-1), \\ \gamma(i-1, j), \\ \gamma(i, j-1) \end{cases} \tag{2}$$

where $\gamma(i,j)$ represents the cumulative distance at point (i,j), and $d(x_i, y_j)$ is the distance between the points x_i and y_j. The function $\min\{\gamma(i-1,j-1), \gamma(i-1,j), \gamma(i,j-1)\}$ ensures that the optimal path is calculated by considering the minimum cumulative distance from the adjacent elements (Keogh and Pazzani 2001). To reduce the computational complexity and ensure realistic alignment (in the context of our study), we use the Sakoe-Chiba band constraint (Sakoe and Chiba 1978) to limit the warping path to a narrow region around the diagonal of the cost matrix, with a window size constraint set to five, which determines the maximum allowable deviation from the diagonal.

Inter-session time

To perform this analysis, we excluded from the study all respondents for whom at least one window contained fewer than 25 listening sessions during the period. After examining the distribution of the final number of individuals based on different thresholds, we determined that a threshold of 25 sessions was a reasonable choice, as it allowed us to maximize the number of individuals in the subsample while ensuring that the data for each respondent was sufficiently robust for meaningful analysis. This resulted in a subsample of near 4000 respondents.

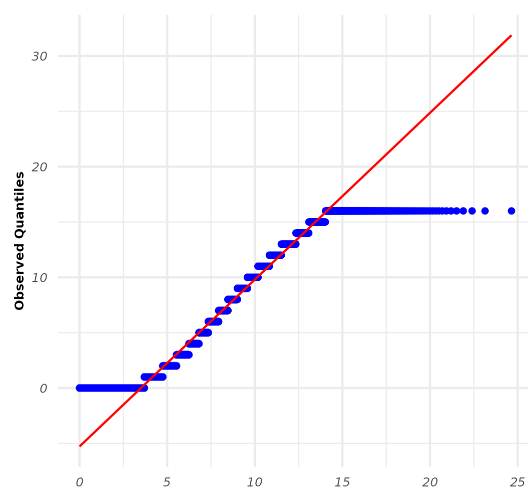

Figure 5: Quantile to Quantile plot to assert the normality of the distribution