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Integrating digital traces into mixed methods design

An application to the study of online music listening using survey, interview and streaming history data collected from the same individuals

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Abstract

We present a mixed methods research design that integrates individual-level traces of online content consumption with survey and interview data, all collected from the same sample of tens of thousands of people. We explain how the pairwise combination of these information sources solves methodological puzzles often encountered when measuring cultural practices and preferences. We provide a concrete illustration for the case of music listening on streaming platforms, and show that survey respondents and solicited users do not stream the same music. We illustrate how the mixed data collected make it feasible to infer the social properties of non-respondents, and hence to assess bias in studies based exclusively on self-reported survey data. We provide empirical evidence that unlimited access to all kinds of recorded music on platforms does not blur the social boundaries between repertoires across respondents, and we show that artists have distinct audiences whose differences are both related to generation, gender, and educational attainment. Finally, we describe how we used digital traces in individual interviews to foster spontaneous expressions of aesthetic judgments, which are known to be challenging to collect. We conclude by discussing the current limitations of the design, the potential applications of these results in the field of cultural sociology, and the feasibility of adopting similar experimental designs to investigate other social phenomena.

Keywords: Cultural practices – Digital traces – Interviews – Mixed Methods – Music consumption – Nested data – Streaming platforms – Online surveys

Introduction

The increase in the digital recording of a wide range of ordinary practices, via cell phones, mobile devices or social platforms (Lazer et al., 2009), represents a new opportunity for the study of human behavior. Indeed, it provides access to data of an observational nature, at an unprecedented scale, both in terms of quantity (higher number of individuals whose practices are observed, higher number of practices observed over longer time periods) and quality (fine-grained information on the types and modalities of practices). The advantages of these new sources, heralded as an empirical revolution for social scientists (Burrows and Savage, 2014; Marres, 2017; Salganik, 2018), has initially led to numerous studies solely based on such materials (Bakshy, Messing and Adamic, 2015; Lewis, Gonzalez and Kaufman, 2012; Onnela et al., 2007; Salganik, Dodds and Watts, 2006).

In parallel, other scholars have commented on the multiple limitations associated with digital traces of people's activity, including noise, lack of information on the conditions in which these data have been collected and subsequently treated/filtered, uncertain meaning that can be extracted from the data, risks of generalization of digital observations to similar non-digital practices, etc. (Bastin and Tubaro, 2018; Boyd and Crawford, 2012). Another type of limitation inherent to this sole observation of practice is that, while providing a broader and more reliable account of what individuals actually do, it does not offer information on the variety of meanings associated with such activities, hence limiting the possibility of explaining what people do to only digital recordings of what they did, and falling into the well documented traps of revealed preferences approaches (Grüne, 2004; Moureau and Vidal, 2009; Sen, 1973). In addition, these studies are generally lacking key information on the individuals studied, such as

gender, age, occupation, level of education, or social background (Ollion and Boelaert, 2015), usually meaning that classic social factors cannot be tested.

A solution to overcome these limitations and still take advantage of digital traces is to combine them with other traditional methods of the social sciences in new mixed-method designs. The conjugation of the strengths of large-scale observations of digital practices to those of classic measures of social characteristics, attitudes and meaning-making such as surveys and interviews, seems a promising future for a grounded explanation of social activities.

The use of mixed methods research (MMR) in scientific inquiry boasts a rich historical lineage (Maxwell, 2016), and the large body of papers, journals, meta-reviews and handbooks focused on this matter provides useful typologies and debates to understand its strengths and challenges in the study of social phenomena (Bryman, 2006; Clark and Creswell, 2008; Greene, Caracelli and Graham, 1989; Leech and Onwuegbuzie, 2009). Scholars in this field converge on two fundamental principles that help distinguish between and within mixed and non-mixed methods research. To be considered mixed-methods, a research design must either use data of different types – generally according to the context of data production: questionnaire vs interview vs observation – or use different types of analysis of this data – generally differentiated according to their statistical or non-statistical treatment. Among MMR designs, a secondary principle of differentiation, when several sources of information are combined, is whether these data are available for the same individuals (e.g. Tucci, Fröhlich and Stock, 2021), or for groups deemed similar (e.g. Bourdieu, 1979).

The case of multiple sources for the same individuals is generally the most fruitful, as it allows studying interactions of different social dimensions at the individual level, limiting issues of unit heterogeneity (Goerres and Prinzen, 2012). However, such data collection protocols are

difficult to design for practical, technical, and ethical reasons (Leahey, 2007; Pearce, 2012), and most of the mixed methods studies that collect different types of data from the same people are one of two types of combination: (1) a questionnaire survey is conducted with a set of people (chosen randomly or not), followed by interviews with a subset of respondents; and (2) an ethnography of a group is conducted, and is complemented with interviews or a questionnaire survey to all or a fraction of its members. While the first design makes it possible to map out structuring differences and investigate more closely socially distant individuals, an important limitation is that the collected data are exclusively of a declarative nature, which does not directly provide information on what people actually do (Jerolmack and Khan, 2014). On the other hand, ethnographic studies give access to the direct observation of people's actions, and can be contrasted or complemented with declarative data (LaPiere, 1934; Weller, 1994), but it is more difficult to generalize the findings, while the size and the social heterogeneity of the population studied is often limited (Lamont and Swidler, 2014).

Integrating digital traces in MMR designs can solve some of these issues. By recording signals of actual practice rather than relying on self-reported statements, these data offer a nice trade-off between the two aforementioned approaches: they constitute a more reliable source on actual behavior than declarations collected in surveys and interviews; their scale and lower cost offer a powerful alternative to direct observation (Mohr et al., 2020).

A recent trend of work is heading towards this direction (Eck et al., 2021; Parry et al., 2021; Stier et al., 2019), but such a journey faces serious challenges. First, a significant hurdle arises from the divergence among the providers of these sources, typically situated on opposite sides of the public-private boundary. Most individual digital traces are collected by private companies, whose research and development sectors, though academically trained, tend to be oriented

towards economic goals and are closer to fields like physics or computer science, that have a longer history of partnership with the private sector. Conversely, the knowledge and time necessary for the design of large-scale surveys including standardized measures of important socioeconomic characteristics, as well as carefully crafted interview campaigns conducted by trained interviewers, lie essentially within the field of public academic social sciences, where scientific goals are generally orthogonal, if not opposite, to the private sector. Second, academic social scientists interact rarely and are reluctant to collaborate with non-social sciences (Renisio, 2017). A third reason, that can be seen as a delineation within social sciences of the second, is that the skills necessary, on the one hand, to handle and analyze large-scale platform data or survey questionnaires and, on the other hand, to carry out interviews and observations, are a structural division within our academic communities. From early on, future social scientists are incentivized by a series of institutions to define themselves as either belonging to the “quants” or “quals” tribes (Renisio and Sinthon, 2014). And, more often than not, research teams tend to reinforce this trend rather than act against it.

The case of music listening

In the field of study of cultural practices, the case of music consumption highlights both the duality of the empirical needs of the social sciences (of an observational nature, to know what people actually listen to; of a declarative nature, to know who these people are, what they say and think about different kinds of music), as well as the rarity of their combination in empirical research. Two major research currents can be distinguished along these lines.

The first one, long established, analyzes the social stratification of musical tastes based on information obtained mostly from questionnaires (Bennett et al., 2009 ; Bourdieu, 1979;

Coulangeon and Lemel, 2007; Prieur, Rosenlund and Skjott-Larsen, 2008; Sullivan and Katz-Gerro, 2006) or more rarely interviews (e.g. Le Guern, 2017). These sources provide detailed, self-reported information on individuals' characteristics, listening practices and musical tastes, but are declarative only, which poses the dual problem of the reliability of retrospective accounts (Prior, 2009) and the biases generated by the unequal social desirability of different repertoires (Krumpal, 2013).

The second trend, driven by the emergence of online music consumption, studies the uses of platforms and algorithmic recommendation, and relies upon users' streaming history data collected by these platforms. Previous studies have examined differences among users in terms of the amount of music streamed, or the number of unique songs and artists streamed within a common period (Louail and Barthelemy, 2017; e.g. Zhang et al., 2013). Additionally, some studies have focused on the impact of recommender systems on the diversity of content streamed by users (Anderson et al., 2020; e.g. Beuscart, Coavoux and Maillard, 2019; Villermet et al., 2021). While this research is much richer empirically than traditional studies in terms of actual data on practice, it suffers from a lack of information on user characteristics and preferences. In particular, it is rare to be able to access dimensions such as socio-professional category and level of education, despite these being established by the literature as central in the stratification of cultural consumption.

The RECORDS project is an attempt to connect these two strands, through a collaboration between social scientists and computer scientists working in public research institutions, with the research department of Deezer, a music streaming service that is one of the market leaders in France. The initial motivation was to bring together, in a framework that would provide the necessary conditions for public-private exploratory research (especially methodological

experimentation), teams of people with different skills and a shared interest for the social dimension of music preferences. On Deezer, as on most streaming platforms, users can navigate huge music catalogs that contain millions of tracks and artists, in fact almost all the recorded music listened to in France today. While these platforms have been around for some time now, and are nowadays the main source of access to recorded music,¹ little is known about the variations of *effective* listening practices and their relation with individuals' social properties such as age, gender, or education level.

In the next section we present the MMR design we implemented. It supported the collection of information of different types (observational, longitudinal data encoded in streaming logs; self-declared information in online surveys; detailed information in extensive interviews) for a large sample of thousands of volunteer participants. We then present some of the benefits resulting from the pairwise combinations of these three sources. Finally we discuss the main contributions, limitations, and perspectives opened by this design, in the field of cultural sociology and beyond.

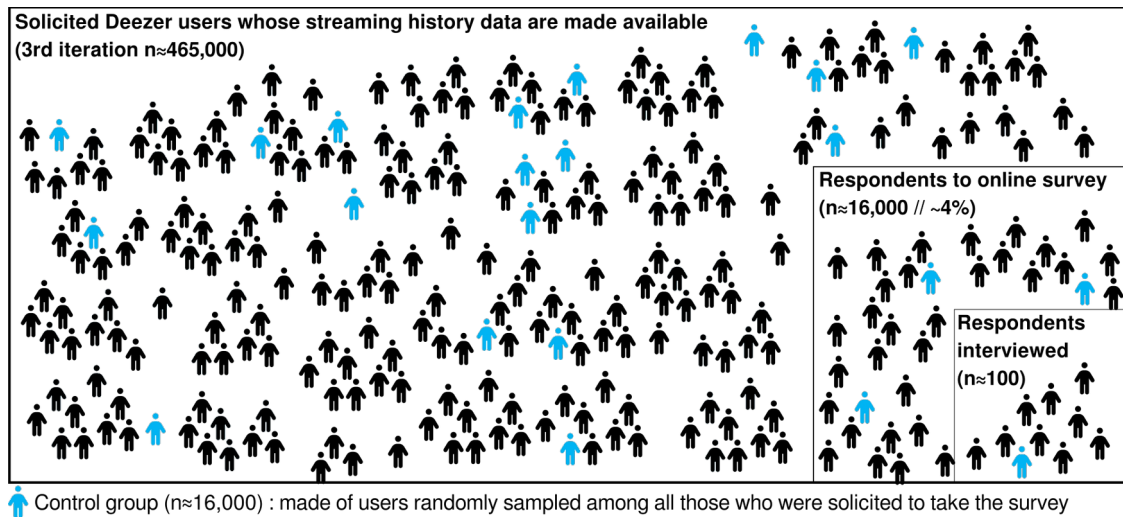
Materials and Methods

This research relies on three distinct sources of data: the Deezer platform, an online survey, and interviews, following an *explanatory sequential design* (Clark and Creswell, 2008) with four salient characteristics: nested, sequential, iterative, and scalable (Figure 1). We first present the specificity and challenges of this design and then explain further the content of each of the sources.

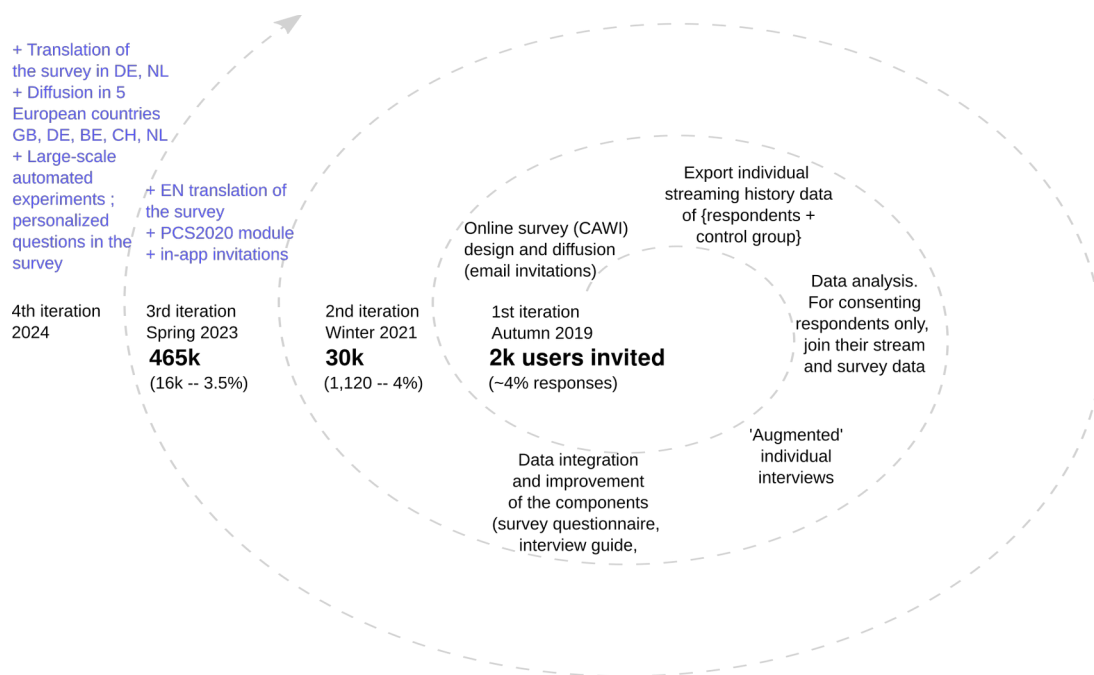
¹ According to the report “Engaging with music 2023” by the International Federation of Phonography Industry, https://www.ifpi.org/wp-content/uploads/2023/12/IFPI-Engaging-With-Music-2023_full-report.pdf

First, as shown on [Figure 1 \(a\)](#), our three sources and corresponding user samples are *nested* (Lieberman, 2005): each of the interviewees is a user who responded to the online survey, and all survey respondents are users whose streaming history data had been extracted and made available to the research team beforehand. Second, the MMR design is *sequential* (Leech and Onwuegbuzie, 2009): chronologically, our protocol starts with the sampling of users to solicit from their streaming history data; we then obtain answers to our survey questionnaire among this sample; and finally, we interview some of these respondents. Third, our design is *iterative* (Pérez Bentancur and Tiscornia, 2022): altogether, the basic data collection steps described in the aforementioned sequence constitute an iteration, and all these steps are repeated and refined in subsequent ones based on previous analyses, as illustrated by [Figure 1 \(b\)](#). Finally, the design is *scalable*, allowing us to expand each iteration to a larger scale by an order of magnitude.

Figure 1: Principles of data collection



(a) A nested approach: population and data are nested to access three different sources of information for the same population.



(b) An interactive approach: data is collected in successive iterations of increasing size, each of them consisting of the same sequence of operations. The number of Deezer users invited to take part in the survey is written in bold. This iterative approach made it possible to improve the MMR design components and add new features along the way (in blue), and to scale up the size of the population invited to take the survey.

Abbreviations: BE = Belgium, CAWI = Computer-assisted web interviewing, CH = Switzerland, DE = Germany, EN = English, GB = Great Britain, K = 1,000, NL = the Netherlands, PCS2020 = "2020 Socio-Professional Classification"

The combination of the three sources raised both ethical and technical challenges. Ethically, our team collaborated with both the Centre national de la recherche scientifique (CNRS) and Deezer data protection officers (DPOs) to ensure the compliance of our data collection protocol with the requirements of the General Data Protection Regulation (GDPR, see the dedicated subsection below). To ensure the pairing of our sources, the survey questionnaire played a key role: the first question asked the solicited users to consent to the research team's use of their platform data in conjunction with their answers, while the last question of the survey asked consent for respondents to be recontacted for an interview. We only used answers from survey respondents who gave consent for their data to be analyzed by the CNRS, and only contacted respondents who agreed to both demands for interview. From a technical perspective, the primary challenge was addressed by the Deezer research and development team, who provided us with a unique anonymized identifier (a "hashed id") facilitating the linkage of platform data, survey responses, and interview transcripts, while preserving the anonymity of the respondents.

Platform data

The information from the platform constitutes the starting point of each iteration: it is from this pool of users that individuals were solicited for the questionnaire.

The data provided by Deezer for this project are a by-product of the information collected by streaming platforms as part of their activity, independently of the purposes of our research. It consists of three main sources: (i) *catalog metadata*: this relational catalog contains information about all the tracks made available to users, at the levels of song, album, and artist, along with the content of all the playlists available on the platform; (ii) *user data*: this includes

the birth year and gender that users self-declared when registering on the platform, the date of their registration, as well as the list of items users added to their “favorites” collection by clicking on a heart-shaped icon; and (iii) *streaming history data*: this is the complete list of all timestamped stream events ever generated by the user account, that is who (user account id) is listening to what (catalog metadata id), when (time the song is played/skipped/stopped), how (device type, mode of access, i.e. editorial or personal playlist, search bar, algorithmic recommendation, etc.), and where (type of internet connection and location derived from an IP-based geolocation third-party service).

Concretely, this means that, for the 2023 iteration, where 465,000 users predominantly from France were solicited to answer the survey, we used the streams of 32,200 users: the 16,038 solicited users who answered the survey and, as control group, a random sample of 16,162 solicited users (see Figure 1A). The decision to use a sample rather than the entire population of solicited users was a practical one: the volume of the streams for this sample represents already more than 10 GB of information for the 18 months preceding the survey date. For each of these users, we then know with high precision which songs they listened to, as well as the birth year and gender they reported when registering. For each of these songs, we know its artist, the moments, and the duration of listening. For convenience, and following legal definitions, we only considered a user to have listened to a song if the duration was at least 30 seconds.

Online survey data

Our online survey questionnaires were sent via the email that Deezer users indicated for their registration to the platform, or, in the case of the 2023 survey, via “push notifications” directly on the app, with extra solicitations in case of non-response. The overall response rate was very

low, with only 4 per cent of solicited users completing the survey, creating important limitations in the generalization of our results (see the section on “Limitations” in the conclusion). Nonetheless, due to the large number of users who were solicited (465,000), and the richness of the answers collected, the 2023 survey questionnaire gathered 16,038 answers, with a median response time of 15 minutes. This volume of answers, while not ensuring the representativeness of the larger population of users, opens the possibility to compare the platform activities of users on many dimensions, providing insights on cultural consumption.

In our MMR design, the primary objective of the online survey was to gather comprehensive self-declared socioeconomic information from Deezer users, including variables such as education level, household size, place of residence, marital status, employment status, occupation, income, as well as details about the country of birth and occupational categories of their parents when the respondent was aged 15.

In addition, the survey gathered declarative preferences and listening practices information, aligning with traditional quantitative studies in the sociology of cultural practices. This served a dual purpose: comparing our survey responses with other surveys and contrasting these answers with the respondents’ streaming practices recorded by the platform. In the 2023 iteration, this information was divided into four modules.

The first module focused on the devices and internet services respondents used for listening to music, exploring the frequency and contexts of this activity both online and offline. The second module delved into the music genres respondents declared they listened to, their preferences among these genres, and their opinions on specific artists representative of different genres. The third module centered on the use of Deezer, encompassing different navigation and recommendation/discovery features. Here we also inquired about the number of individuals

regularly using the account, providing a basic yet incomplete criterion to identify accounts declared as shared in subsequent analyses of individual streaming practices. The fourth module focused on cultural and leisure practices more broadly, covering areas such as TV, radio, cultural outings, among others. This module replicated several questions from the 2018 edition of “Pratiques culturelles”, a reference survey on this topic in France (Donnat, 1998, 2009; Lombardo and Wolff, 2020).

While the comparison of declared and observed practices has proved to be a promising locus of theoretical investigation (see the conclusion and discussion), its methodological and technical challenges have led us to focus here on the information on individuals’ characteristics (declared number of users of the account, gender, birth year, and level of education), rather than their declared tastes or practices.

Interview data

Finally, individual interviews were designed to increase and enhance information on individuals for whom we had already gathered streaming and survey data. The goal was to gain access to a less constrained description of the individual’s perceptions of their music consumption, as well as *in vivo* reactions to listening to music.

We developed an interview framework that included four modules. The first explored the contexts and configurations of users’ listening experiences (such as equipment, usual locations and times for music listening, associated activities), while also situating the streaming activity within the overall music listening activity of the interviewee. The second module examined music browsing and selection, with a particular focus on the use of algorithmic features, and on the users’ creation of their own classifications, such as playlists and favorites. The third module

aimed at identifying users' musical tastes and dislikes, investigating their musical socialization through family, marriage, peer groups, or the workplace. In the final module, we asked interviewees to react to three songs that we selected beforehand, drawing on their streaming history data.

A first set of thirty interviews took place between May and July 2021 among respondents of the 2021 survey questionnaire, conducted by seven researchers of our team, using video conferencing due to the pandemic context. Respondents who had agreed in the questionnaire to be contacted for interviews were offered a gift voucher worth EUR 30 as an incentive. The interviews, lasting an average of one and a half hours, were recorded and then coded by the interviewers using MaxQDA software. Transcriptions of the interviews were entrusted to professionals. The coding grid resulted from a collective effort to finely sift the collected material and identify themes and initial analytical avenues. The first ten interviews were coded by two team members blindly, a method that revealed differing approaches to the material. We therefore decided that each interview would be coded by one person only, then re-read by a second one to complete the initial coding.

Simultaneously, each interview was summarized in a portrait created by the interviewer, outlining the main information about the interviewee and forming a separate corpus for an alternative understanding of the material beyond the more transversal coding. Interviews of the respondents of the 2023 survey questionnaire are ongoing, aiming for a final number of one hundred interviews covering a broad social spectrum of users (see [Figure 3](#)). In this paper, the interview extracts are all from the 2021 iteration.

Compliance of the data collection protocol with General Data Protection Regulation

Above all, the GDPR requires complete information to be provided to persons whose data are collected and processed. In particular, every processing of personal data requires a legal basis (the lawfulness of the processing) and a purpose. The GDPR preserves arrangements for public scientific research, in particular with the legal bases of “legitimate interest” and “mission in the public interest”, the latter being the legal basis on which public scientific research mostly relies when processing personal data. In this case, the participation of a private company in the consortium meant that the legal basis for the processing could not be a public service mission. After joint consultation, the DPOs of the project consortium’s partners opted for “legitimate interest”, which can be understood differently depending on the partners involved. The DPOs were very vigilant about the nature and quantity of personal information collected in the survey, as the GDPR imposes a principle of data minimization (one should only collect what is necessary for the purpose of the data treatment, and nothing more). Each survey indicator therefore had to be justified by the project manager to the CNRS DPO. It should be noted that none of the information collected in the survey is considered sensitive data as defined by the French Commission Nationale de l’Informatique et des Libertés (no data on religious beliefs, or political affiliation, health, sexual preferences, etc.). The data anonymization procedure has been checked by the DPOs (the data processed by the partners contains no directly identifying personal information, such as an email address, social security number, postal address, etc.). The risks of de-anonymization by combining data have been mitigated, for example by collecting the respondent’s postal code rather than the municipality code, when asking about the place of residence (the postal code is less identifying because it is common to several

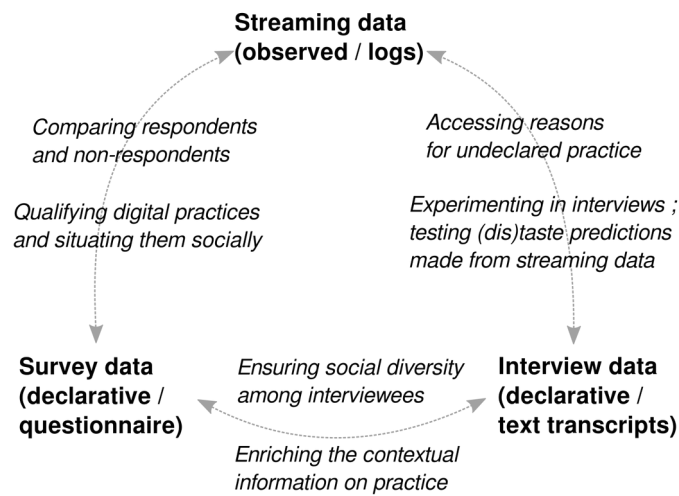
communes when these have small population sizes). A web page providing participants with complete information about the processing of their personal data was prepared in collaboration with the CNRS DPO, and linked from the survey welcome page.²

Results

The three sources of data collected in our process complement each other and allow new results to emerge. We present their combination pairwise (as illustrated by [Figure 2](#)), progressing from the most classic to the most original pairing experiments we conducted.

² <https://records.huma-num.fr/gdpr-en/>

Figure 2: Some benefits of the pairing of the three sources



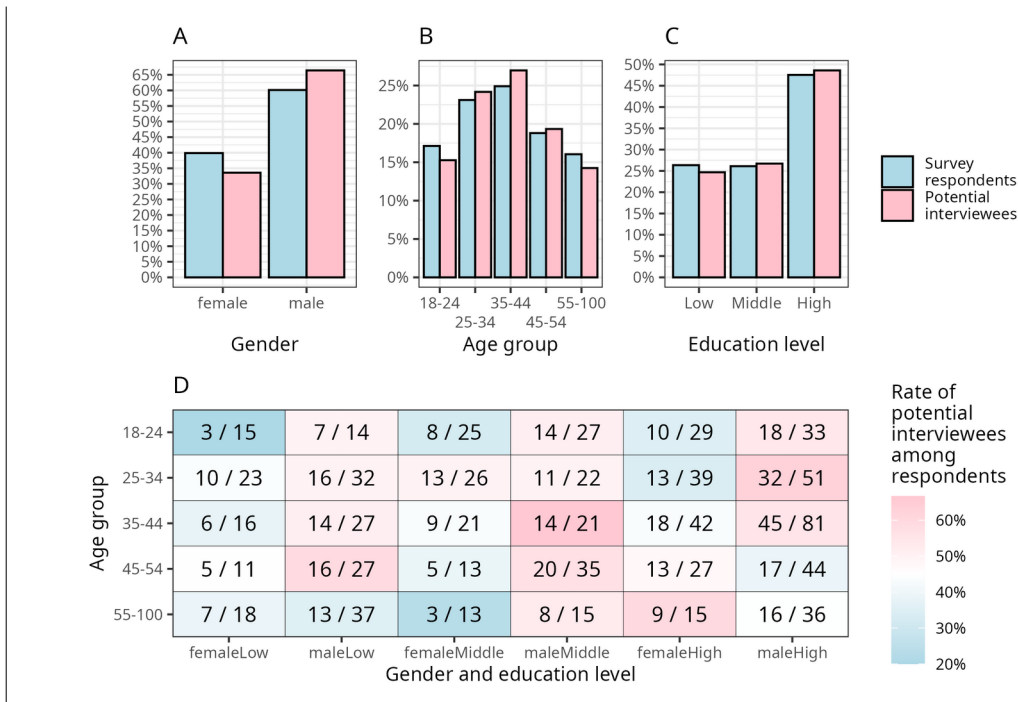
Surveys and interviews

The benefits and limits of using paired surveys and qualitative interviews represent one of the most explored topics in the mixed-methods literature (Harris and Brown, 2019), including in the sociology of culture (Silva, Warde and Wright, 2009). This association helps gather both systematic information from surveys on large and potentially diverse or representative populations, complemented and nuanced by the richness of respondents' own description of their practices. This section aims to underscore two aspects that proved especially valuable for our research design. First, the technique of "purposeful sampling" was employed to create a stratified sample from the pool of interview volunteers, with the goal of maximizing the social diversity of people interviewed (Palinkas et al., 2015). Second, interviews served to unveil the ambiguity or plurality of meanings inherent to questionnaire responses. This insight was instrumental in refining the survey questionnaire from one iteration to another.

A. Ensuring social diversity among interviewees

Survey respondents are quite different from the French population with respect to age, gender and education, with highly educated, middle-aged men being overrepresented (see [Figure 3](#)). This bias is related to inequalities in online content consumption and online skills (Hargittai, Piper and Morris, 2019), as well as music consumption (Katz-Gerro, 1999), on the one hand; and to self-selection into online surveys (Blasius and Brandt, 2010), on the other hand. This trend is accentuated in the sub-sample of individuals who volunteered for an interview. This subgroup strongly overrepresents highly educated men aged between 25 and 44 (a demographic that closely mirrors the profile of our research group members). Gender appears as an influencing factor in interview agreement: men make up 60 per cent of the survey respondents but 66 per cent of those willing to do an interview. [Figure 3D](#) highlights the interplay of age, gender, and education levels, illustrating how these combined dimensions lead to sample deformation. Given the substantial impact of these three dimensions on cultural practices (Bryson, 1997; Carter, 2006; Lizardo and Skiles, 2016; Noûs, Robette and Roueff, 2021), our objective was to encompass a broad spectrum of combinations of these factors within our sample of interviewees.

Figure 3: Differences in social characteristics of online survey respondents, according to their willingness to take part in an interview



(A) Gender, (B) Age group, and (C) Education level distribution. (D) represents a combination of the three factors and the number of interview volunteers over the total number of respondents in the group.

Field: 835 respondents to the 2021 online survey who declared gender as male or female, an age between 18 and 100, and a level of education.

Reading: (D) Out of the 81 respondents who declared being male, aged between 35 and 44, with a high level of education, 45 (56 per cent) gave their consent to be contacted for an interview.

Note: Level of education is divided into 'High-school certificate or less' (low); 'More than high school, less than Master's degree' (middle), 'Master's degree or higher' (high). For the youngest group (age 15–24), if education levels were not 'high' they were replaced with the highest socioeconomic status of parents.

To achieve this, rather than sending interview invitations to survey respondents randomly sampled among those who volunteered for an interview (as we did for our surveyed population), we defined 30 categories by intersecting the three variables (age, gender, education). The goal was to conduct at least one interview per category in the 2021 iteration.

Each interviewer then received an ordered list of individuals to contact within a specified group. For instance, among men aged 25 to 34 with lower education levels, the interviewer was

asked to contact the first individual on the list. After one week, a reminder was sent. After two weeks, without an answer, the next person on the list was contacted, and so forth. The assignment of these thirty groups to interviewers was randomized, with the exception of women with lower levels of education: to prevent introducing a gender difference alongside a class distinction, female interviewers within the team were specifically tasked with conducting interviews within these particular groups. We have effectively conducted one interview for each of the 30 groups identified in the 2021 iteration, forming the pool from which excerpts are drawn for presentation in the following sections.

B. Enriching the contextual information on practice

The interviews played a crucial role in identifying survey questions that may carry a different meaning than originally anticipated. For instance, Valentin and Laure (two of the interviewees) responded “no” to the survey question “Do you listen to music while working?”. However, during the interviews they both described a consistent exposure to music while at work:

Valentin: I work in restocking at a supermarket with morning hours, which means that from noon onwards, the entire day is available.

Interviewer: During this work, do you sometimes listen to music or not?

Valentin: No. At work, no. I even think it’s prohibited, just to stay alert ... Well, I do listen to music: there are speakers in the store. But there, clearly, it’s not me who chooses.

Laure: Actually, in our department, we work in the operating room, and so, it’s like in the car, it’s the one who is driving or, in this case, the surgeon, who has the right and priority. So often, to maintain concentration in the room, it’s the surgeon who somewhat chooses his playlist. But if it doesn’t appeal to everyone, well, we make him feel that he also works as part of a team and that it’s not acceptable. So, we try to find compromises.

The apparent discrepancy between the responses in the questionnaire and the descriptions provided in interviews seems to be tied to the interviewees' interpretation of the statement "listening to music" in the survey. The survey question is interpreted with respect to intentionality: not as "Is there music playing when you work?", but as "Do you actively choose to listen to music, and what music do you listen to, when you work?". This tension is tied with power relations at work: owing to their subordinate positions at work, the two respondents are subject to the musical preferences of some of their colleagues. This interpretation seems reinforced by the testimony of another interviewee, Muriel, who answered "yes" to this question. Muriel, holding a supervisory position in her workplace, sheds light on how she manages the broadcasts of her preferred radio station (FIP) in the workshop she oversees:

Muriel: So, I control it from my phone, the radio, yeah. But yeah, it's a speaker that we've set up, so what's annoying for... let's say... for many people I work with is that we're in a company where there's noise, [... and] music adds noise for some, and ... But for me, not at all! (laughter) [...] And when I like it, I turn it up! (laughter) [...] So it's true that some people endure it, but that's how it is, it's something, you know, in our profession ... [...] Even if we don't have the same tastes. ... So, you have to be tolerant with music at work.

In this scenario, the interviewee asserts her musical preference over her colleagues, a decision that seems to generate tensions but remains non-negotiable for her. Tolerance, in this case, is expected to be exercised by her subordinates. While we cannot claim that her colleagues would have declared, had they been asked in a survey, that they do not listen to music at work, the contrast with the two previous accounts leans towards associating control of content and hierarchy in the disparity of meanings attributed to musical exposure.

A similar benefit of combining interviews and questionnaires surfaced when comparing the music actually streamed by survey participants with the music they declare listening to in the

survey (see the discussion). For instance, classical music was frequently said, in interviews as well as in discussions with colleagues in seminars, to be played less often on Deezer and more on other devices (including platforms or radios dedicated to that genre, physical records, etc.), than any other music genre. To ensure that the differences we measured were not influenced by potential ambiguity in our survey, we introduced a supplementary question in the 2023 iteration: after participants selected the genres they listen to, they were asked to select those they were also listening to on other media and platforms besides Deezer.

Although conventional, the triangulation of information gleaned from surveys and interviews has proven instrumental in acquiring insights into our research subjects. Employing a snowball sample technique, as well as adopting a random sample design, would not have provided coverage of individuals with such diverse social profiles in interviews. Furthermore, the juxtaposition of data from questionnaires and interviews unveiled potential contradictions. These contradictions, in turn, prompted the generation of new hypotheses and facilitated the refinement of the data collection in subsequent iterations.

Digital traces and surveys

A less common pairing of sources involves combining survey answers with digital traces. Integrating these two sources helps mitigate each of their limitations. The deficiency in measuring actual practices in surveys is offset by the wealth of observational data obtained from traces, while the absence of social qualifications in traces can be complemented with the sociodemographic data collected with surveys. In the following sections, we first show how having access to the streaming history data of a large sample of solicited users made it possible to compare the streaming practices and streamed content of the population with those of users

who responded to our survey. We then explain how we leveraged this mixed material to gauge the association between various social characteristics and music consumption.

A. Comparing respondents to the population of solicited users

Random sampling is the most efficient technique to reach statistical representativity of the target population in questionnaire surveys. However, the assumptions of randomness are rarely met because of large non-response rates: if not answering a survey is not a random phenomenon, then the conditions required to generalize the results are not met. This imperative was clearly not met in our case, with a response rate lower than 5 per cent. This very low rate echoes a more general trend of disaffection for surveys going, for example, from 66 per cent in 1991 to 27 per cent in 2019 in the case of the International Social Survey Programme (Greaves et al., 2020) or from 28 per cent to 7 per cent from 1997 to 2017 in the case of the Gallup Poll Social Survey (Luiten, Hox and Leeuw, 2020).

By construction, researchers know little if anything about non-respondents. Collaborating with a digital platform to survey its users introduces a transformative shift similar to techniques from census or sampling based on registers, where samples are drawn from a population with already available information. In our case, the availability of content consumption data and basic demographic information self-declared by all users when they register to the platform (birth year and gender) makes it possible to measure how these factors (gender, age and music streamed) are distributed among respondents *and* the broader population of solicited users.

[Figure 4](#) highlights remarkable differences in the music streamed by both groups. To leave aside the effects of age (different generations listen to different artists and genres) and also the important fluctuations among the least-played artists, we focused here on the 200 most popular

artists among each of the two groups, respondents and our control group (a random sample of solicited users), who all declared an age between 35 and 44 years old (the largest age group among respondents). We calculated which artists were over/under-represented in each group, by calculating for each artist i its rank r_i among the respondents (the most streamed artist has rank 1, the second most streamed rank 2, etc.) and its rank r'_i in the control group. For each artist we calculated the rank ratio r_i/r'_i and plotted in blue (resp. red) those for which $r/r' < 1/2$ (resp. > 2). Looking at the artist names colored in red and blue, a clear pattern emerges: all the 26 artists most represented among respondents streams (in blue) are English or American rock artists or bands, most of whom started recording music in the previous century. On the contrary, all 23 least represented artists among respondents (in red) sing in French, and belong to the recent generations of French rap and RnB. Thanks to the coupling of streaming and survey data, we will see in the next section that such differences correlate with differences of social characteristics among the respondents.

Figure 4: Differences in artists' popularity between respondents and the solicited population of the same age group



Field: 7,830 solicited users (3,797 respondents and 4,033 from the control group) of the 2023 questionnaire, who declared an age between 35 and 44, and their streams between June 2022 and May 2023.

Reading: Among solicited users aged 35–44, the rock band Radiohead is the 44th most popular artist among respondents, but only the 132nd most popular artist in the control group. Conversely, the French artist Aya Nakamura is ranked only 119th among respondents but is ranked 48th in the control group.

Note: Popularity is defined as the rate of individuals who listened to an artist at least once during the period, and then converted into ranks. Only artists with rank ≤ 200 in either group are plotted. Artists' names appear only if the rank difference is > 10 or < -10 , and if the rank ratio is > 2 or $< 1/2$. These rank-ratios are suggested with the dashed lines, while the dotted line indicates equal ranks.

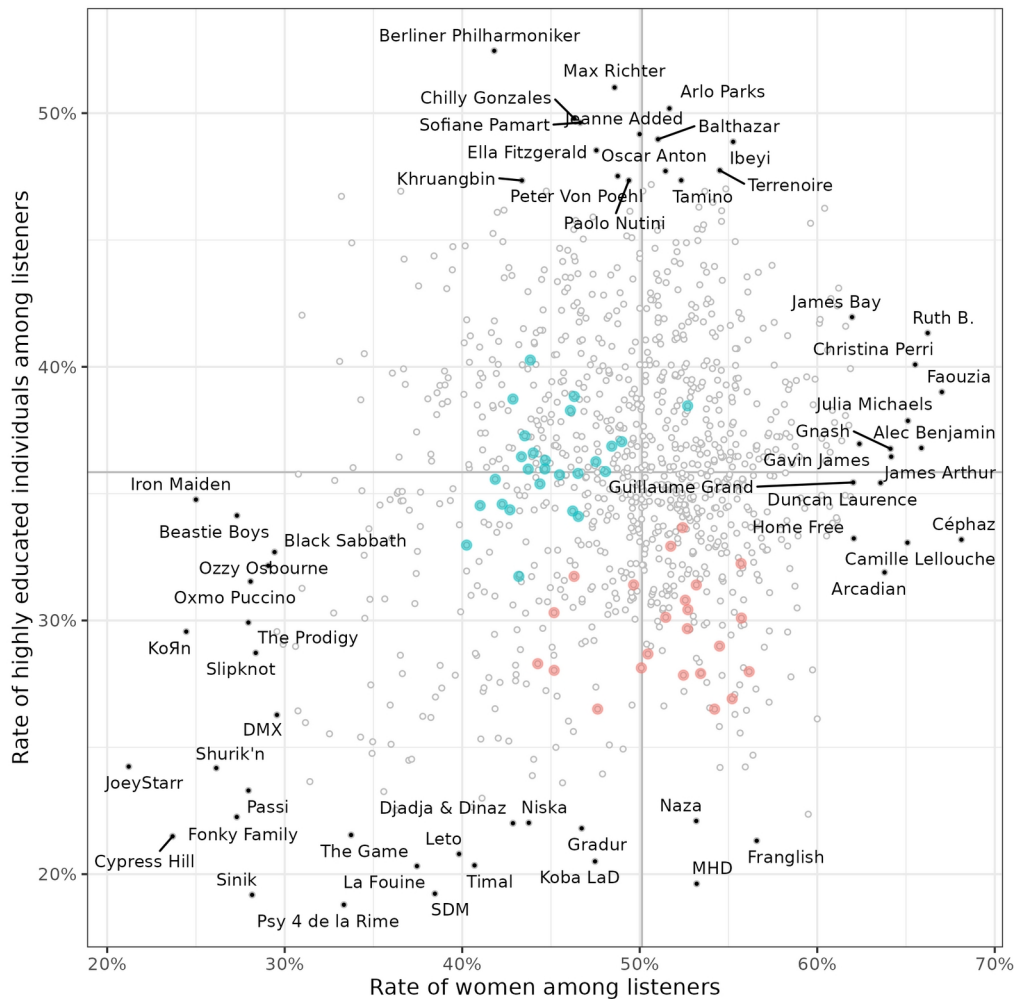
B. Qualifying practices and situating them socially

Recent works have suggested that the platformization of listening, along with access to vast catalogs of music at little or no cost, would shift the principles of social differentiation from what we consume to how we consume it (Webster, 2019). However, the results we obtained when analyzing the music actually streamed for an entire year by approximately 16,000 survey respondents, seem to highlight the persistence of the relationships between individuals' social attributes and the music they listen to.

We illustrate this point in [Figure 5](#) and [Table 1](#). [Figure 5](#) maps the most played artists among our respondents aged 35 to 44 in a space defined horizontally by gender (percentage of female listeners among all the users who streamed the artist at least once), and vertically by education profile (percentage of listeners with at least a Master's degree).

We observe that the top of the figure, corresponding to the artists streamed by the most highly educated users, is predominantly occupied by artists who interpret or compose classical music (such as the Berliner Philharmoniker orchestra, Max Richter, Sofiane Pamart, etc.), while artists located in the bottom of the figure (who are the least streamed by respondents with the highest educational profile) are predominantly associated with French hip-hop music (La Fouine, SDM, Psy 4 de la Rime, etc.). The variation is substantial, ranging from 20 per cent to 50 per cent of highly educated listeners among all the users who streamed these artists at least once.

Figure 5: Gender and education profile of the most popular artists' audience



Field: 1,483 respondents to the 2023 online survey, aged between 35 and 44 years old in 2023, who declared being the only user of their Deezer account, male or female gender, and their level of education. Artists are limited to the 1,066 that at least 15 per cent of this population listen to.

Reading: The classical Berliner Philharmoniker orchestra has the highest rate of highly educated listeners, while the French hip hop band Psy 4 de la Rime has the lowest rate of such listeners.

Note: Popularity is defined as the rate of individuals who listened to an artist at least once. “Highly educated” is defined as having declared at least a Master’s degree. Name of artists appear if they are among the top/bottom 15 most “feminine”/“highly educated”. Blue and red dots indicate the corresponding artists labeled in Figure 4.

Similarly, we observe significant variations in the gender composition of the artists’ audiences, ranging from 25 to 60 per cent. Among the artists who have the most masculine audiences (on the left of the plot), we find exclusively male artists, predominantly associated with genres like metal, rock, and hip hop. On the opposite side (mostly feminine audiences, on the right), we

observe a more balanced mix of male and female artists, with a higher prevalence of pop, RnB, and French (non-rap) genres.

Finally, we also colored in red and blue the artists previously labeled in [Figure 4](#), that is, the top artists who are over-represented among respondents (in blue) and those most represented among non-respondents (in red) in the same age group. The clear separation between these two groups of artists in a space defined by the social properties of the sole respondents suggests that the differences in the music streamed by these two populations correlates with differences in gender and (especially) level of education. In other words, based on the streaming practices of our sample of solicited users and the social characteristics of the respondents in this sample, it seems that the population who did not respond is likely to be composed of more women and particularly of less highly educated individuals.

To extend the analysis to different generations, we focused on the 5,000 survey respondents of the 2023 iteration who declared as male or female, an age above 24, and being the sole user of their Deezer account. We then divided them into four age groups (25–34, 35–44, 45–54, and 54+) and determined for each of these groups the 100 most popular artists during the year preceding the survey. We then ranked these artists according to the proportion of their listeners who declared having a Master's degree or higher diploma. [Table 1](#) presents for each age group the top 10 and bottom 10 artists according to the rate of highly educated individuals among their listeners.

Table 1: Top and bottom 10 artists based on the proportion of highly educated listeners, among the 100 most popular artists of four age groups of survey respondents

Rank	Age: 25–34	Age: 35–44	Age: 45–54	Age: 55+
1	Lana Del Rey	Juliette Armanet	Benjamin Biolay	Nina Simone
2	Taylor Swift	Lana Del Rey	Véronique Sanson	Neil Young
3	Billie Eilish	Amy Winehouse	M	Led Zeppelin
4	U2	Radiohead	The Beatles	Françoise Hardy
5	Ariana Grande	Billie Eilish	Daft Punk	Creedence Clearwater Revival
6	Glass Animals	Julien Doré	The Rolling Stones	Simon & Garfunkel
7	The Kid Laroi	The Beatles	Radiohead	Bob Dylan
8	Lizzo	M	Bruce Springsteen	Bernard Lavilliers
9	Daft Punk	Milky Chance	David Bowie	Serge Gainsbourg
10	Thérapie TAXI	Taylor Swift	Clara Luciani	Fleetwood Mac
...
91	Soolking	Major Lazer	GIMS	Vianney
92	Naps	Kungs	a-ha	George Michael
93	Kofs	Slimane	Maroon 5	Sia
94	Dadju	Eminem	Kendji Girac	Kate Bush
95	Tayc	Kendji Girac	Rosalía	Phil Collins
96	Booba	GIMS	Lil Nas X	The Weeknd
97	Soprano	Sean Paul	P!nk	GIMS
98	Alonzo	DJ Snake	Scorpions	Calogero
99	Jul	Soolking	Katy Perry	Louise Attaque
100	Ninho	Soprano	Calvin Harris	Kendji Girac

Field: 5,205 respondents of the 2,023 questionnaire, who declared an age over 24 and reported being the sole users of their Deezer accounts, identifying as either male or female, and providing information on their level of education.

Reading: Lana Del Rey has the highest rate of highly educated listeners among the 100 most popular artists by respondents aged 25–34 and ranks second among respondents aged 35–44.

Note: Popularity is defined as the rate of individuals who listened to an artist at least once during the period. “Highly educated” is defined as having declared at least a Master’s degree. Artists in bold are the ones who appear in several age groups.

First, the generational nature of music consumption is suggested by the absence of common artists between the youngest and oldest cohorts, whereas adjacent cohorts consistently share some of their top or bottom 10 artists (though that may also result from the change of the relative value of a diploma between distant generations). Although classical music interpreters

are not present on this popularity scale, a pattern akin to the previous figure persists: French hip hop is markedly under-represented among artists with the most highly educated audience, particularly in the two youngest cohorts. The artists in the top 10 of each age group predominantly enjoy critical acclaim in their respective genres (examples include Billie Eilish, Amy Winehouse, Radiohead, or Nina Simone, representing one in each age group), while artists in the bottom 10 are often associated with “low brow” listening in their genre (such as Booba, Kendji Girac, a-ha, or Slimane) (Boyadjian, 2019).

While these results might appear familiar and predictable, and the sample might be distorted due to the low response rate, these descriptions represent, to our knowledge, the first instance of integrating sociodemographic information from thousands of surveyed individuals with the systematic and automated recording of their *actual* consumption of cultural products over a long period of time. In contrast with self-declared statements on practices or opinions extracted from a handful of genres or artists in scholarly surveys, this approach can provide detailed insights into the relationship between actual practices and sociodemographic data.

Digital traces and interviews

The last pairwise combination of sources consisted in using digital traces to “augment” interviews. Integrating digital traces with interviews allows introducing information into the conversation that the interviewee may not be aware of, or had not thought relevant to mention. Because they have been passively recorded over long periods of time, streaming logs are considerably less subject to conscious control than survey responses. Our team of interviewers leveraged this opportunity in interviews through two primary methods. First, we gained access to a detailed, visual and customizable summary of information on each interviewee’s streaming

practices through AMPLI, a data visualization application designed by one of the team members (Cura et al., 2022). This tool proved valuable for both the preparation and the conduct of interviews. Second, the streaming data were used to identify beforehand songs that we anticipated the interviewee might love or hate. This approach let us test the accuracy of our predictions, and helped provoke vehement reactions to certain pieces of music or genres.

A. Enhancing interviews with rich data on the interviewees' practices

During the interviews, in more diverse ways than we initially anticipated, AMPLI allowed us to enhance our interactions with the interviewees. The app made the streaming history data of each interviewee easily searchable, with no prior technical knowledge needed. Interviewers could query the streaming logs with various filters, including time and place filters to identify listening trends and habits. The use of videoconferencing facilitated the real-time use of the tool: we could engage in the conversation while searching for specific data, mentioning it when the application provided information that aligned with, or differed from, the interviewee's ongoing discourse. On several occasions, these use cases fostered the mention of significant biographical events.

Interviewer: When I looked at your number of streams per year, from 2018 onwards it explodes, and that's also when Electronic Dance Music becomes one of your most listened-to genres.

Françoise: Yes, in 2018, well, it's not surprising, I didn't even remember: I had a burn-out. I'd been a caregiver for my father, my mother, and I was looking after my mother-in-law at the time. So I had a burn-out and ended up in a psychiatric hospital. I was listening to a lot of electronic music at the time, and I was terribly angry, really deeply angry. I've been in therapy ever since... [...] And now I listen to very little of it, or if I do, it just makes me happy, that's all. [...] I'd completely forgotten that I'd been listening to a lot of electronic music at the time.

This excerpt highlights the intricate connection between music, emotional states, and life events in Françoise's experience. It emphasizes the evolving and adaptive nature of music preferences, serving as coping mechanisms and expressions of inner emotions across different stages of her life (DeNora, 2000). Such insights might have remained undiscovered without the analysis of listening patterns made beforehand by the interviewer through AMPLI, that acted in this case as a crucial elicitation medium.

Another use case emerged during the interview with Jean-Christophe, a 29-year-old metal fan and customs liaison officer. Notably, he did not mention other musical genres in the interview until the interviewer prompted him to guess his top 15 artists as they appeared on AMPLI.

Interviewer: [After successfully mentioning most of his top artists, most of which are metal bands (Tool, Meshuggah, etc.), the interviewer evokes one equally listened to, but from a different musical genre (French hip hop)] ... And Freeze Corleone.

J.-C.: [Expressing surprise] Uh, yeah, ok. Yeah, yeah. So ... It's funny because it's not ... In my head, it's not the same ... It's not in the same part of ... Well, I don't know how to explain it. Uh... I don't listen to it the same way, actually. [...] Freeze Corleone, it's a bit like fast food. I like it, but basically, really basically, maybe not so much. Because ... in fact, he's an artist I'm not sure I'll be listening to in ten years' time. [...] It's not what inspires me as a drummer. And I listen to it with certain people, with buddies, with uh ... And yeah, in the car, I like it, it ... But uh ... it's not very ... Musically, it's not developed, we'll say it like that. Even lyrically. But uh ... Whereas Tool, well, they're a source of inspiration. And bands like Meshuggah, really instrumental bands. [...] Well, it's not that I'm ashamed, but musically, I am, a bit! Of ... of listening to [Freeze Corleone] (laughs). But then again, you should never be ashamed! I'm not very clear. I don't really know how to express myself, but uh ... But for example, Tool, I'm going to recommend it to all the people who are likely to like this kind of music and this band. The same goes for Meshuggah or Converge, things like that. But Freeze Corleone, no, I'm not necessarily going to recommend it like that. [...]

Interviewer: ... And Alkpote?

J.-C.: (Laughs) So we were talking about shame! (laughs) Now we're right in the thick of it! I'd never listen to it with my sisters or my mother, for example, in the car ... (laughs) But uh ... [...] It's entertaining! Well, that's what I wanted to say, that it's associated with entertainment. [...] For me, rap is also entertaining. Uh ... Beyond the

music, it makes me laugh. For me, it's comedy. It's so absurd and vulgar that I take it to the fifth degree and it makes us laugh, it makes me laugh!

Clearly, the interviewee wouldn't have mentioned these French rap artists if the interviewer had not brought them up during the interview. The expressed embarrassment and the multitude of justifications provided highlight an internalized judgment, akin to "I shouldn't be listening to this." This led him to explicitly articulate a socially marked hierarchy between music genres: he perceives this French rap niche genre as the "fast food" of music, a genre that he feels "shame" listening to and wouldn't recommend, unlike the metal bands that inspire him and that he actively promotes. Consequently, by juxtaposing self-presentation and recorded traces of past listening, fine-grained social judgments emerge during the interview, generating explanations for these practices.

The explicit use of their listening data was well accepted by the interviewees; it did not give rise to the expression of criticism or feelings of invasion of privacy, which some of the researchers expected. This can probably be explained in part by the fact that the data used in the interviews (most-listened-to-songs, artists, genres) is similar to the data provided by Deezer to its users, as part of their subscription, such as "monthly playlists of the personal tops" or "end-of-the-year" personal charts.

B. Predicting interviewees' (dis)likes

In the last part of the interviews, we aimed to explore our ability to predict the musical preferences and aversions of interviewees based on their own streaming history data. Our overarching goal was to assess whether streamed content could serve as a reliable indicator of individual likes and dislikes. Furthermore, we sought to determine whether, from the array of signs available in individual traces, we could effectively map the nuances of the types of music

enjoyed or disliked by individuals. Questions such as whether recurrent listening to a particular track or artist consistently signaled approval, and whether the absence of listening, systematic skipping, or even “banning” of a track always indicated dislike, were central to our inquiry. We also wondered whether dislikes for genres the user did not play were stronger than those for popular artists within a genre that the user otherwise listened to. In essence, we aimed to establish a gradient from favorite artists to those least liked, based solely on streaming history data.

With these questions in mind, for each interviewee we curated a personalized list of three tracks, anticipating positive, ambivalent, or negative reactions. Importantly, the interviewees were unaware of which tracks they would be listening to and commenting on. Overall, our highest success rates in accurately anticipating reactions occurred in cases of strong likes and dislikes. Specifically, this was observed when testing widely listened to and favored tracks, and very popular tracks in genres little or not at all listened to by the respondents, respectively. In the latter scenario, the reactions – sometimes vehement – often provided insights on the social principles fueling aesthetic judgments.

Predicting dislikes: reactions to listening to a musical extract, chosen to displease, on the basis of individual listening histories.

Alain, 66, former customer service manager, speaking about Djadja by Aya Nakamura: “Immediate destruction. This is something I wouldn’t call artistic creativity. It’s the opportunistic navel-gazing of a society focused on online social networks and all that goes with it. This charming *Djadja* certainly pleases a lot of people and undoubtedly makes a lot of people laugh on stage, but not me. No, but when you see the image she gives in public or through these things – it’s the big family of TV shows that show just how low human stupidity has sunk. It’s a horror. But I can understand why some people like it. But it’s about satisfying the greatest number at the expense of quality. There’s no quality there.”

Benoit, 46, engineer, on La Moulaga by Jul and Heuss L’enfoiré: “Well, that’s a total turn-off. Vococode, vocode or I don’t know ... Vocoding, ah no, it’s really not possible,

it's ... it's crap, well it's ... Ah I ... Yeah, really. Really bad, yeah, it's ... Ah no, that sound there ... that doctored sound of the voice, frankly, it repels me, but really. And it's a turn-off ... I mean, it really ... it makes my hair stand on end. Really, it's ... It's hell ... musical hell."

Nico, 35, care assistant in an EPHAD [residential care for the elderly], on Gambi's Popopop: "So I'm not the right audience! (laughs) Well, it's not my ... it's not too ... [...] A bit too much street rap, uh ... A bit too much of what's being done at the moment, you know. [...] That kind of sound, there are dozens of them doing the same thing. [...] and anyway, it's not ... it's not targeted for me. I think it really belongs to a community that's not mine. [...] People ... how can I put it? People from ... the suburbs, you know."

Caroline, 39, nurse, on Tryo's L'hymne de nos campagnes: "Tryo, why I hate it, because I think it's a bit of a lie, this group, under the guise of committed lyrics, a bit hippie, it's still very commercial, and then a bit light ... I mean, I find that the lyrics aren't really ... I find that the lyrics are maybe a bit too simple and without an underlying meaning. Because I've listened to much worse things, but with an underlying meaning, so ... But here, no, Tryo doesn't even have an underlying meaning, so, no, I don't like it."

These arguments encompass a spectrum of critiques, ranging from the perceived lack of "artistic quality" and a decline in cultural standards (as expressed through terms like "stupidity," "too simple," and "commercial") to disapproval of specific musical elements (such as the "doctored sound"). These critiques occasionally converge into explicit references to contexts or populations linked to social class judgments (evidenced by mentions like "the greatest number" or "people from the suburbs"). Even judgments on specific musical features, like the vocoder, can be associated with artists listened to by a more popular audience, and act as "cultural distaste markers" (Boyadjian, 2019). These methods of elicitation of reactions by making interviewees react to specific music pieces (rather than traditional opinions following mentions of artists' name or genre) could provide, through the analysis of these "gut reactions", substantial insights on the thesis that "dislikes are used to construct boundaries primarily around markers of disadvantaged class status" (Lizardo and Skiles, 2016, p. 15).

Conclusion/Discussion

We have presented an original MMR design that sustains collaborative, public-private research on online music consumption. This project has enabled the collection of mixed, diverse data from the same individuals, at a larger scale than traditional studies. We have highlighted some traditional and more innovative use cases of the pairwise combinations of our three data sources – interview data, survey data, and digital activity traces collected by a music streaming platform. Our main contribution emerged from the combination of individual streaming logs, of observational nature, with traditional data collected in surveys and interviews, of declarative nature. Use cases include the identification of differences in content consumed between respondents and non-respondents; the measure of the relationship between the social characteristics of respondents and their actual, everyday listening practices; and the algorithmically driven elicitation of life events as well as aesthetic and social judgments. Another iteration of data collection, scheduled for 2024, will attempt to test on a larger scale some exploratory hypotheses and heuristics that have emerged along the way.

Limitations

Despite the insights provided by this design, at present a clear limitation is the non-generalizability of our results. This difficulty arises at five different levels. First, the population of Deezer users is unlikely to reflect directly the cultural practices of the general population: registering on such a platform supposes both cultural involvement and technical ease that is unlikely to be evenly spread among generations and social groups. Second, as we have shown, the population of survey respondents is also unlikely to be representative of Deezer users: while the response rate of 4 per cent is quite aligned with industry standards in customer online

surveys, inferences from our sample would not respect the assumption of randomness necessary for representativity. While large public surveys, thanks to their “mandatory” status, their economic means, and their face-to-face interview methodology, still maintain relatively high levels of responses (around 70 per cent for the French “Pratiques Culturelles” survey), the aforementioned general trend towards the fall in response rates seriously threatens the foreseeable representativity of questionnaire surveys. In that respect, our case is both a contribution to the study of differences among committed music listeners, and to the uncovering of the principles of distortion in survey answers. It also provides, at a larger scale, results more akin to ethnographic inquiries, where observed differences provide more reliable information than self-reports. Strategies of incentivization could be used to diversify the profile of respondents, as well as partnerships with public institutes for a more effective power of the solicitations. It is nonetheless likely that such setups come with their own recruitment biases to consider. Third, and consequently, while diverse in their declared social properties, our interviewees are still selected from this doubly unbalanced pool. As our goal was to identify contrasts between individuals of our sample, this problem is probably less central. Fourth, the practice of online listening does not cover the wider spectrum of musical consumption, and hence may not be generalized to radio listening, personal media, etc. In view of the evolution of listening practices and the rapid growth of streaming however, this difficulty is the most likely to fade out in the coming years. Finally, for some of the respondents, the Deezer account may be used by several individuals, distorting the information relative to the user. In this respect, platforms are quickly developing tools to detect such shared account usage, and these could be leveraged to filter out such data points. Those last two limits also emphasize the relevance of

MMR, which helps identify and sometimes even take into account such limitations through the cross-fertilization of mixed data.

Contributions to sociological puzzles

Beyond music listening and preferences, similar MMR designs could be reproduced in different fields of study, such as eating habits, with the development of online food shopping (Jenneson et al., 2022); online dating (Bergström, 2022; Lewis, 2013); visiting healthcare professionals (platforms for online medical appointments), or education pathways via centralized selection platforms (Frouillou, Pin and van Zanten, 2020).

Four broad sociological puzzles could benefit from such designs.

The first one is the social characterization of actual practices on a large scale. The joint use of social characteristics and digital traces is a promising venue for the multidimensional analysis of the relationships between social position variables and behavior in most sociological areas. If the challenge of statistical representativity is still to be overcome, digital traces provide an important improvement towards the measure of “what people do” in combination with social characteristics, at a larger scale than what classic observation techniques can offer. Our preliminary results on differences between respondents and non-respondents raise important warnings regarding the generalizability of conclusions drawn from surveys on cultural practices, especially if they are based on self-administered questionnaires, or when the response rate is low or non-communicated.

The second potential contribution of such design is the refining or building of empirical categories from the ground up. Whether when studying academic practices through the lenses of disciplinary categories, or social stratification through those of occupational categories,

researchers face both the fuzziness and the real effect of such institutionalized divisions. In our case of music consumption, the main theories (structural homology, omnivore theory, etc.) are generally assessed on the ground of survey data analyses that relate social position indicators with the self-reported habits and preferences for music genres. Such simplifications are problematic, as genres are volatile categories, encompassing heterogeneous products, with no consensus in the criteria or procedure to attribute one or several genre labels to a given song or artist (Lena and Peterson, 2008; Savage and Gayo, 2011). On the other hand, genre categories, institutionalized in various ways and used by many to define their own consumption or productions, do capture social differences (e.g. [Figure 5](#)). Our MMR design allows to circumvent such issues in two distinct ways: the first, following the logic of the “micro-class” approach, used artists as smaller and less ambiguous categories; the second consists of the elaboration of multiple complementary typologies of genres that can be translated into well-defined, algorithmic procedures (based, for example, on the content broadcast by professional radio stations dedicated to the genre, on editorial or personal playlists named after a genre, on encyclopedic platforms or music databases, etc.). We are convinced that important theoretical improvements will emerge in various sociological areas, if researchers use multiple reproducible competing typologies and test their sensitivity.

A third contribution could be the algorithmic unveiling of preferences through experimental settings. Preferences or tastes are important cogs in most theories of action, but the way in which they are measured tends to limit their accuracy (based on declarations, they fall into social desirability bias; based on observation, they inform more on behavior than on preferences). Our preliminary experimentation on reactions to music exposure in interviews has highlighted the potential of such elicitation for provoking “gut reactions” that reveal

entrenched social judgments. The observation of individual reactions to the exposition to actual content could allow current limitations in many domains of study to be minimized. In our case, we plan to systematize this process in the next iteration of the online survey. A promising avenue is to include a series of musical excerpts selected algorithmically, on the basis of the user's streaming history, and to record their appreciations both explicitly (via open-ended and scaled questions) and indirectly (by measuring, for example, the duration before they stop the music). In addition, the preliminary results we presented (see [Figure 5](#)) seem to confirm the relationship between individuals' social properties and the music they listen to. If this relationship were to be strong, an important research avenue would be to test the accuracy of predictions of the social properties of any user (including non-respondents) from their cultural consumption data (e.g. Hinds and Joinson, 2018; Krismayer et al., 2019).

Finally, such design could contribute to the detection of social norms. More generally, a notable advance provided by this design is the detection of empirical interstices, where different sources of data highlight apparent contradictions between what people declare doing, what we observe them doing, and how they describe these activities. This diverging information, often conceived in the literature as biases that MMR designs can help mitigate, seem in fact to convey important sociological meaning. In some cases at least, we observed that these discrepancies between observations, declarations, and descriptions constitute an important locus to investigate social norms, as these situations underscore tensions between internalized hierarchies and actual behavior. For this reason, digital traces should not replace self-reports or be seen as the ultimate type of information: it should be systematically compared with other types of material to unveil social tensions. Such comparison could inform most social phenomena currently under study.

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