





## Unveiling social desirability scales by comparing individuals' responses to an online survey with their streaming history data

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in collaboration with Yann RENISIO CNRS researcher at CRIS (Sciences Po, Paris)





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The work presented in following slides is the result of a pluridisciplinary collaboration with (by alphabetical order) Amélie Beaumont, Jean-Samuel Beuscart, Samuel Coavoux, Philippe Coulangeon, Robin Cura, Brenda Le Bigot, Manuel Moussallam, Yann Renisio and Camille Roth.

Other active participants to the RECORDS project include Myriam Boualami, Pierre Gallinari-Safar, Noé Latreille, Darick Lean, Marion Maisonobe, Kristina Matrosova, Alvin Opler, Anne-Cécile Ott, Anne-Sylvie Pharabod, Jérémie Poiroux, Bruno Massoni Sguerra and Dougal Shakespeare.

# **Context Objectives of the RECORDS project**



1. Re-thinking categories in sociology of cultural consumption Switching from declarative data collected at the level of music genres ("I like rock and jazz") to mixed, declarative+observational data (digital traces) of effective consumption, collected at the level of tracks/albums/artists ("which rock and which jazz? how much? how long?")

2. Measuring the diversity consumed on streaming platforms Evaluate the relevance of statistical models linking social properties and music preferences that have been built on declarative data only

3. Measuring the effects of algorithmic recommendation What are the measurable effects of a recommendation system among its users, after several years of use/exposure?

4. Investigate the relationship between declared music preferences and music streaming practices Measure over- and under-representations and potential influence of legitimacy in displaying tastes

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in this talk

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### Context The increasing importance of streaming in the global recorded music market

#### World



About 600M premium accounts users

3 to 5 million premium account users in France

Sources: IFPI, Global music reports 2022, 2023 + SNEP decoding (IFPI data)

France

# First study // Use cases of a mixed methods research design that integrates digital traces, survey data, and nested sampling

> Yann Renisio, Amélie Beaumont, Jean-Samuel Beuscart, Samuel Coavoux, Philippe Coulangeon, et al.. (2024) Integrating digital traces into mixed methods designs: An application to the study of online music listening using survey, interview and stream history data collected from the same people*Under review* (hal-04448365)



### **RECORDS** data collection

- mixed
- iterative
- nested

+ Translation of the survey in DE, NL + Diffusion in 5 European countries GB, DE, BE, CH, NL/ + EN translation of + Large-scale the survey automated + PCS2020 module experiments ; + weighted sampling/ personalize questions in the + in-app push-notifications survey 4th iteration

2024

3rd iteration Spring 2023

465k

(16k -- 3.5%)

2nd iteration Winter 2021 30k (1,120 -- 4%) Online survey (CAWI) design and diffusion

> 1st iteration Autumn 2019 2k users invited (~4% responses)

Export individual streaming history data of {respondents + control group}

> Data analysis ; for consenting respondents only, join their stream and survey data

'Augmented' individual interviews

Data integration and improvement of the components (survey questionnaire, interview guide,

### **RECORDS** data collection

- mixed

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-



Control group (n≈16,000) : made of users randomly sampled among all those who were solicited to take the survey

#### Use cases of the pairwise combination of data sources

Streaming data (observed / logs)

Comparing respondents and non-respondents

Qualifying digital practices and situate them socially

Accessing reasons for undeclared practice

Experimenting in interviews ; testing (dis)taste predictions made from streaming data

Survey data (declarative / questionnaire) Purposeful sampling of interviewees

Interview data (declarative / text transcripts)

Enrich and contextualise survey declared information

### Illustration (1/2)



### Streaming data (observed / logs)

Comparing respondents and non-respondents

Qualifying digital practices and situate them socially

Exp tes

#### Survey data (declarative / questionnaire)

Purposeful sampling of interviewees

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### Illustration (2/2)



### Streaming data (observed / logs)

Comparing respondents and non-respondents

Qualifying digital practices and situate them socially

Exp tes

#### Survey data (declarative / questionnaire)

Purposeful sampling of interviewees

> Renisio et al.. (2024) Integrating digital traces into mixed methods designs: An application to the study of online music listening using survey, interview and stream history data collected from the same people. Under review (hal-04448365)

# Second study // Unveiling social desirability scales

> Thomas Louail and Yann Renisio, Unveiling social desirability scales by comparing individuals' responses to an online survey with their streaming history data. *In preparation*.

### Motivation (1/2) Build on the gap between practice and declaration of practice

- Digital traces are sometimes presented as able to replace survey data (on the long run), because considered a better proxy for actual practice than the declarations and self-reports collected in surveys often sought to capture (Parry et al. 2021)
- When the two sources are available and used together, it is often to 'improve'/enrich one with the other (Stier et al. 2019)
  - correct social desirability biases in survey data
  - reduce noise in observational digital traces
- Our approach: rather than 'triangulating', we want to use the measure of discrepancies to build new indicators to compare measurement categories
  - compare discrepancies for different categories of content
  - highlight social norms related to these categories
- Two well-known cases of social desirability biases: Body Mass Index; Voter abstention

### Motivation (2/2) Application to music listening and preferences

 The case of music consumption makes it possible to elaborate on the numerous studies that have highlighted the statistical affinity between the music preferences declared by respondents and their social positions,

e.g. (Coulangeon 2003) for France ; (Peterson & Kern 1996) for the US ; (Chan & Goldthorpe 2007) for the UK

- In particular it has been long documented that:
  - Classical music is more often declared to be listened to by the upper classes;
  - Rap, on the contrary, is more often listened to by the working classes;
  - Jazz and Metal are somewhat intermediary between these two genres: C > J > M > R
- Would we retrieve this order if we compared the genres according to how much they are over-/under-declared when compared to how much they are streamed?

### Survey snapshots (1/3) : Asking users' explicit consent



Français

Veuillez répondre à cette question.

J'accepte que mes réponses à ce questionnaire soient exploitées par l'équipe du programme RECORDS piloté par le CNRS (https://records.huma-num.fr)

Oui			
Non			

Cors SciencesPo deezer Français Veuillez répondre à cette question. J'accepte que mes réponses à ce questionnaire soient exploitées par l'équipe du programme RECORDS piloté par le CNRS (https://records.huma-num.fr) Oui Non Produit par Qualtrics [2]

100%

12:29

 $\rightarrow$ 

### Survey snapshots (2/3) : Asking about listening habits and music genres



	0	
12:29 (Plusieurs rép	onses possib	Jes)
Musique Latino	Jazz	Rap français
Musique de Film	Blues	Reggae
К-рор	Musiques Arabes	Dance & EDM
Musiques Asiatiques	Rock	Variété française
Musiques Africaines	Indé / Alternatif	Folk & Acoustique
Musique Classique	Electro	Hip Hop / Rap
Musique Brésilienne	RnB	Country
Soul / Funk	Métal	Рор
<b>←</b>		$\rightarrow$
Pro	duit par Qualtrics	s 🖸

### Survey snapshots (3/3) : Asking about listening habits and music genres

Orange

deezer	CILLS	OBSERVICTORIE SOCIOLOGIQUE	

English - United Kingdom V

Are there any of these genres that you never listen to on Deezer?

Rap	
Soul & Funk	
Metal	
Classical music	
Dance & EDM	

Rank these genres you listen to from favorite to least favorite



5

Dance & EDM

12:29	all 💻
Are th	English - United Kingdom v
never	listen to on Deezer?
Rap	
Soul	& Funk
Meta	l.
Class	sical music
Dano	ce & EDM
Rank favoril	these genres you listen to from te to least favorite
1	Classical music
2	Metal
3	Soul & Funk
4	Rap
5	Dance & EDM

# The population of survey respondents

Iteration n°2 // January 2021 30k users of Deezer located in France email invitation to take the survey no incentive N=1.4k respondents (~4%)

### Demographics of a (bad) sample



Femmes Hommes

### Highest qualification level (highest diploma obtained)



# Methods

- 1. Assign musical genres to the millions of tracks and artists streamed by the survey respondents
- 2. Systematically compare the weight of these genres in the individuals' streams with the listening habits they reported in the survey, and rank
- 3. Rank musical genres based on the intra-individual deviations between reported listening habits and actual streams
- 4. Apply the same method to artist preferences

# Methods

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# Tracks, artists and genres (1/2)

People listen to songs/music pieces and artists, whose qualification by one or more genre labels (rock, jazz, rap, etc.) is debatable

> Genres are problematic and ill-defined categories
\* no consensus on a definition (Robette & Roueff 2014)
\* they aggregate very different products (Nault et al. 2021)
\* their boundaries evolve over time (Levine, 1988)

=> more formally, there's no unique and well-defined function *F*:  $t \rightarrow g$  that would associate a finite number of genre labels *g* to each track (or artist) *t* 

BUT almost the entire scientific literature in sociology of music preferences is written at the level of music genres...

Highbrow: classical and jazz Middlebrow: rock Lowbrow: dance and rap

 $\rightarrow$  There exists a very large number of reasonable choices for the labeling function F









# Tracks, artists and genres (2/2)

Over the past 12 months prior to the survey, for the 16k respondents to the 3rd iteration of the survey :

313k distinct artists streamed at least once

3M unique tracks

=> Manual labeling is out of reach

Different systematic approaches to labeling:

- from online collaborative databases (e.g. musicbrainz, wikidata)
- from the content of user playlists named after a music genre
- from the content of editorial playlists named after a music genre
   from the programming of French radio stations dedicated to a given music genre (France Musiques, Radio Classique, TSF Jazz, etc.)
   ...

In the following, to simplify we reduce a music genre to a set of artists whose tracks are often associated with this genre in playlists curated by professional editors (employed by the streaming platform)

Assumption: a strong result on possible deviations between genres, in how people declare and/or listen to them, should hold whatever the procedure chosen for assigning genre labels to musical items









## An expert-based and statistical approach

We rely upon the editorial playlists proposed by the platform that are named after a music genre



Emotional orchestral music 33 titres



Chamber Music Essentials 50 titres



Classical Music For Studying 451 titres



Le meilleur du classique - Best of classical music 133 titres



Classics - Classical Music - Music to Study By - Concentration - Música 79 titres



Namaste: Classical Music for Yoga & Meditation 74 titres



Film Music for Reading - Classical Music Reading 134 titres



Classical Music - Music to Study By -Concentratio 69 titres



Focus: Classical 47 titres



Classical Music: The 50 Greatest Tracks 50 titres

# An expert-based and statistical approach

We rely upon the editorial playlists proposed by the platform that are named after a music genre



Les Hits DNR

Calm Down · Rema

Pan Motivation

Les Hits de la Due



Chicha Lounge





001- 0--

## An expert-based and statistical approach

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# Consistency of the lists of artists per genre

- 80% of artists are tagged, representing ~91% of respondents' streams in the last 12 months
- The most frequently featured artists in these editorial playlists named after a genre are easily identifiable as popular artists of that genre →

rank	classical	jazz	metal	raphiphop
1	Lang Lang	Ella Fitzgerald	Metallica	Drake
2	Berliner Philharmoniker	Miles Davis	Iron Maiden	Eminem
3	Daniel Barenboim	Louis Armstrong	Megadeth	Kanye West
4	London Symphony Orchestra	Nina Simone	Slipknot	Travis Scott
5	Max Richter	John Coltrane	Judas Priest	Post Malone
6	Ludovico Einaudi	Stan Getz	Black Sabbath	Dr. Dre
7	Wiener Philharmoniker	Herbie Hancock	Slayer	Snoop Dogg
8	KHATIA BUNIATISHVILI	Diana Krall	Pantera	Future
9	Martha Argerich	Billie Holiday	Sepultura	50 Cent
10	Alexandre Tharaud	Frank Sinatra	КоЯп	Lil Wayne
11	Yann Tiersen	Chet Baker	Motörhead	Migos
12	Үо-Үо Ма	Norah Jones	Disturbed	Kendrick Lamar
13	John Williams	Bill Evans	Ozzy Osbourne	Jay-Z
14	Joep Beving	Duke Ellington	System of a Down	Nas
15	Riccardo Muti	Nat King Cole	Accept	DJ Khaled
16	Alice Sara Ott	Sarah Vaughan	Helloween	J. Cole
17	Anne-Sophie Mutter	Gregory Porter	Arch Enemy	2Pac
18	Dustin O'Halloran	Ray Charles	Anthrax	Booba
19	Hans Zimmer	Tony Bennett	Nightwish	XXXTentacion
20	Hélène Grimaud	Sonny Rollins	Scorpions	Chris Brown

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### The more respondents stream a given music genre, the more they declare to listen to that genre

- This holds whatever the music genre considered



### And individuals who claim to listen to a genre listen to it more than those who claim not to listen to it

- It is true regardless of the music genre



# Measuring intra-individual discrepancies

We define in a non-ambiguous way an inconsistent statement:

If individual i declares listening to genre G and not genre G', there is inconsistency if this individual listens to more G' than G Additionally, the intensity of this difference is obtained by the ratio of the times he/she spent streaming the two genres: t(G)/t(G')

For example, an individual who claims not to listen to classical music and to listen to rap will be considered inconsistent if he listens to more classical music than rap.

If he has listened to 3 hours of classical music and 1 hour of rap, the intensity of this difference will be 3/1

# The unequal social desirability of musical genres

However, we observe rather the opposite: the majority of respondents who declare listening to classical music and not rap, listen to less classical music than rap

Conversely, almost all individuals declaring to listen to rap and not classical music have a streaming practice that align with their declaration

A gradation can thus be observed between the pairs of genres.



### The unequal social desirability of musical genres

By aggregating these results, we retrieve a ranking of genres often discussed in the literature, but based solely on the discrepancies between survey responses and digital traces (rather than on the social properties of respondents).



# Methods

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# Excerpt of the online survey

B4. Quels genres musicaux écoutez-vous ? (Plusieurs réponses

-		
	Rap trancais	
-	rtup nunguis	

Pon	
Rock	
Electro	
🗌 Jazz	
RnB	
<mark> S</mark> oul / Fun	k

🛃 Hip Hop / Rap

				je déteste	je n'aime pas	je ne connais pas	pas d'avis	j'aime	j'aime beaucoup
rvey		Georges Brassens		0	0	0	0	۲	0
•		Jean-Jacques Gol	dman	0	$\bigcirc$	$\bigcirc$	0	۲	0
	1. <u>2</u> .	Michel Sardou		0	0	$\bigcirc$		$\bigcirc$	$\bigcirc$
ez-vous ? (Plusi	eurs réponses	Renaud		0	0	0	0	۲	$\bigcirc$
		Calogero		0		0	0	0	$\bigcirc$
🕑 Variété franç	aise	Céline Dion		0		0	0	0	0
Musique Cla	osique	Johnny Hallyday		0	0	0	$\bigcirc$	0	$\bigcirc$
Reggae	B5-rock. Ou	e pensez-vous	des artistes de	e Rock suivant	s?	<u> </u>	0	<u> </u>	0
Métal									0
					je ne connais				0
Indé / Altern			je déteste	je n'aime pas	pas	pas d'avis	j'aime	j'aime beaucoup	
🗌 Musique de	U2		0	$\bigcirc$	0	$\bigcirc$	۲	0	0
🗌 Folk & Acou	Metallica		0	۲	0	0	0	0	0
□ Musique Lat	Imagine Dragons		0	0	0	0	0		0
	Oasis		0	$\bigcirc$	0	$\bigcirc$		$\bigcirc$	
	The Beatles		0	0	0	0		0	
	Led Zeppelin		0	$\bigcirc$	0	$\bigcirc$		$\bigcirc$	
	Luke Carlson		0	0		0	0	0	
	Radiohead		0	0	0	$\bigcirc$	0	۲	
	Queen		0	0	0	0		0	
	AC/DC		0	0	0	0	0		
	Twenty One Pilots	5	0	0	0	0	0		
	The Clash		0	0		0	0	0	
	PJ Harvey		0	$\bigcirc$		$\bigcirc$	0	0	
	Téléphone		0	0	0	0		0	

B5-variete. Que pensez-vous des artistes de variété française suivants ?

# Artist overstatements and social desirability

To extend this principle on better defined 'objects', we tested the same hypothesis on artists. For each respondent, and for each pair of artists in the survey questionnaire, we hypothesized that if the respondent (implicitly) declared preferring A to B, he/she should listen to A more than B. We then aggregate the results by artist to calculate an artist's overstatement rate.

ie n'aime pas pas d'avis i'aime Céline Dion 0 Indochine  $\bigcirc$ 0 0 Serge Gainsbourg 0 0 Julien Doré 0 0 Alain Bashung 0  $\bigcirc$ Georges Brassens 0  $\bigcirc$ Henri Salvador 0  $\bigcirc$ **Jacques Brel**  $\bigcirc$ Christophe Maé

In parallel, for each artist in the questionnaire, we extract from rateyourmusic.com the ratings given by the website's contributors to the artist's albums, and calculate the average rating (weighted by the number of reviews) as a proxy for recognition.

!! Number of reviews varies greatly from one artist to another

Albu	M Showing all (25)		
	Dans ma paranoïa 2014		2.09
A.	Lacrizeomic 2014		2.45
A PAR	Je trouve pas le sommeil 2014		2.61
	Jul 2015		2.98
	Je tourne en rond 2015		2.42
	My World 2015		2.44
	Album gratuit 2016		2.95
the second second	Émotions 2016		2.50

Que pensez-vous des artistes de variété française suivants ?

# Hypothesis

The more an artist has good reviews, the more likely she/he will be declared as more appreciated than another artist, yet listened to more.

# **Overdeclarations of artists and social desirability**

Some fluctuations but a trend: the artists most often over-declared as appreciated (relative to how much they are listened to) are those whose albums are the best rated



## Still needs to be done

- Reproduce analyses using other genre labeling functions
- Does the propensity to conform to the norm vary significantly between social groups (gender, generation, socio-professional category, etc.)?
- Use different rating databases given to albums and (aggregated to artists) by both specialized media and internet users
- Reproduce calculations on RECORDS' 3rd iteration data
  - more volume (16k respondents)
  - better encoding of the socioeconomic status and educational attainment
  - filter listeners who declare listening to a music genre exclusively outside of Deezer (often heard: "people do not stream classical music, they listen to it on CDs with hifi material")
  - additional questions relative to genre appreciation and ordering
- Reproduce the analysis for users/respondents from different countries where Deezer is a big player in the market (Germany, UK and other EU countries)

# Summary and outlook

- First exploration confirm the value of working on the discrepancies between survey responses and digital traces to characterize social desirability scales
- Research protocol requires collaboration with an internet platform willing to survey its users
   + when these users give their consent, willing to provide access to their individual digital traces
- Compared to other approaches API ; data donation ; have users install apps that log their phone usage and web browsing cf. F. Keusch (2024) Quality of Digital Behavioral Data. *FORS-SSP Methods & Research Meeting* 
  - behavioral data recorded in natural conditions
  - very long time periods (several years for users who registered to the service long ago)
- The approach could be replicated to measure other kinds of digital consumption in streaming (e.g. movies and TV shows), and more generally any ordinary practice interfaced by digital platforms (eg. online shopping, book medical appointments, online dating, news consumption)
- Work needed to identify a proper level of aggregation of the personal data prior to their release, to guarantee privacy/anonymity of respondents
- Potential collaboration with FORS on the upcoming 4th iteration of the data collection
  - improve survey and data quality
  - experiments in survey methodology

# Thank you!



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