Which is your favorite music genre? A validity comparison of Facebook data and survey data

Zoltán Kmetty¹, Renáta Németh²

1: Eötvös Loránd University of Budapest, Faculty of Social Sciences. Assistant professor, kmety.zoltan@tatk.elte.hu and Centre for Social Sciences – MTA Centre of Excellence, CSS-Recens Research Group,

2: Eötvös Loránd University of Budapest, Faculty of Social Sciences. Associate professor, Head of Department of Statistics, nemethr@tatk.elte.hu

Corresponding author
Zoltán Kmetty, kmety.zoltan@tatk.elte.hu. Eötvös Loránd University, Faculty of Social Sciences, 1117, Budapest, Pázmány Péter sétány 1/A, Hungary

Funding
This research was supported by National Research, Development and Innovation Office of Hungary (NKFIH), grant number FK-128981.
Abstract

Our study aimed to approach validity issues that arise both in the case of surveys and Facebook data. We conducted a novel parallel data collection method, rarely used before, which combines a face-to-face survey with the collection of personal FB data archives.

We show the research potential of using these alternative data sources together. We show that we can overcome some validity issues by cross-validating the two data sources by each other. We also show that if the researcher collaborates with the users instead of the companies and gets access to a part of the users' social media data archive, the problem of the "leaness" of social media data is eliminated.

Our chosen topic is music interest, a key indicator of cultural sociology. To our knowledge, there are no previous studies on the rate at which any population is categorized by Facebook to advertisers as interested in music genres, or on the relationship between self-reported interest, digitally expressed interest and ad-interest categories. Specific genres were detected which show remarkable different pictures when measured these different ways. We studied also dynamic patterns in FB users’ music interest.

We hope our data collection method and the presented validity approaches will initiate a future dialogue in digital data research in social sciences.
Introduction

Social sciences’ primary aim is to construct valid measurements. The validity of surveys has been criticized for a long time as they create an artificial environment while collecting data with some pre-specified purpose. In contrast, Facebook (FB) yields 'organic data,' that is, observational data of users' behaviors. However, validity is a concern in the case of FB, too. The biases introduced by shifts in algorithms, changes in platform usage or fake self-representation conform to social expectations raise possible validity issues. Further operationalization-related questions arise when processing FB-data. How to deal with these issues is not trivial at all.

In our study, we investigate whether there are transition paths between the two data sources (survey and FB) and whether we can overcome some validity issues and operationalization-related questions by using the two information sources in parallel to cross-validate them by each other. We conducted a novel data collection method: a face-to-face survey combined with the collection of personal FB data archive. The topic we chose was music interest, which is a key indicator in cultural sociology, and whose ‘digital trace’ has its own relevance since the Internet has been the primary locus of music consumption.

We hope that both the novel data collection method and our procedures to address validity questions help to realize the promise of FB data for social science research.

Facebook as a research tool

FB is the biggest social media site in the world, and it is growing continuously. They had 2.45 billion monthly active FB users in 2019 (Q3). Despite this, Facebook is not the target of researchers: several times more researchers study Twitter than FB. Preferring Twitter as a research platform is due to two reasons. Twitter data are easier to structure given that tweets
are short, and compared to FB, the number of possible actions a user can do is rather limited. Furthermore, it is much easier to get data from Twitter through its API-s. As a consequence of the Cambridge Analytica scandal, FB practically cut off data access even for researchers (Freelon 2019), only contents of the public sites are possible to load. Facebook makes an effort to build relationships with academics, see, e.g., their collaboration with Social Science One, which offers proposal-based researchers access to their data. However, this opportunity is open to just a few, and research topics contrary to the company's interests may not be welcome.

Even so, there are some good examples where researchers could overcome the above problems. There are plenty of studies, which concentrate on users with public pages. Public pages are appropriate for some specific research questions, for example, to study politicians and parties (e.g., Caton et al., 2015). However, even if one extends the scope on the comments sections of these pages, public sites show only a narrow slice of FB.

Another form of research uses applications or browser plug-ins that participants must install (e.g., Haim, Nienierza, 2019). Using this method, researchers can follow what the participants are exposed to (e.g., content of their timeline) but do not see the participant’s reaction.

Finally, one can solve the accessibility problem by asking participants to download a copy of their FB profile archive (which option is provided by FB) and to give the researchers that part of these summaries, which are in line with legal regulations. These data may contain posts shared, comments/reactions given, (anonymized) friend list, responses to events, pages liked, etc. Contrary to the previous case, this way, we do not have data on the content the user reacted to, but we have access to her/his reactions/comments. Furthermore, we have data regarding also the past behavior of the participants. In our study, we followed this way of data collection.
The last two solutions require the researcher to contact the study participants in some way, which induces further technical challenges and needs resources. However, this procedure has benefits as well: researchers can introduce a proper sampling strategy when choosing whom to contact (which may result in higher reliability). Additionally, contacting the participants gives the opportunity to ask them for further information. This approach allows the combination of FB data with a classic survey. In our study, merged data contains both self-reported information and online digital traces, which creates a rich dataset of users' attitudes and behavior.

The use of the personal FB data archive is very novel in scholarly research. We found only four previously published examples (Astudillo et al., 2018, Eslami et al., 2018, Marino et al., 2017, and Thorson et al., 2019) among which only the last one pertains to social sciences: their authors investigated political interest and exposure to content on FB. From the participants’ FB data, they used the list of pages the participants have ‘liked’ and the interest categories assigned to them.

We conducted our study because we are convinced that surveys combined with the collection of personal FB data archives provides a great opportunity for social sciences. We will show that this solution not only gives us access to FB data but also yields a merged dataset that is richer than the two datasets individually.

Social media data are often criticised and contrasted with survey data for being quite "lean" in information (e.g., Groves, 2018). According to the critics, one can get many attributes of respondents through survey questionnaires, while social media data contain only a few information on the user (e.g., the words of a tweet/post). In our study, we will also show that if the researcher collaborates with the users instead of the companies and get access to the users' FB data archive leanness in no longer a problem. A good example of the richness of
this data source is its temporal dimension: we can follow how our users "grown in up" via FB, and observe the changes in their behaviour, attitudes, networks.

**Internal validity of data - known problems in different types of datasets**

Internal validity (simply ‘validity’ in the following) of data depends on the accuracy of the measurement, on the fact whether we have actually measured what we supposed to measure. It is a basic concept of survey methodology (see e.g., Lavrakas, 2008). Just to mention some of the most relevant validity problems facing by surveys recall bias, context effect (wording of the question, etc.), interviewer-related measurement error etc. Validity (moreover, objectivity) of surveys has been criticised for a long time also from a more general epistemological point of view: it has been argued that survey questions are simplistic, incapable of grabbing the complexity of social reality, and are actually a construction of the researchers’ own views (e.g., Potter and Shaw, 2018).

FB data, being not self-reported but observational, do not bear these issues. However, they are biased from other reasons: by shifts in the algorithm (Vitak 2017) or by changes in user behavior (e.g., young users tend to leave FB, Perrin, 2018). Moreover, general epistemological issues arise here as well, even because of its observational nature: we have to interpret behavior without the opportunity to ask questions from the observed users. We need some measures which make the unstructured flow of data analyzable, and these measuring instruments are usually not validated with respect to some gold standard. A good example of this is textual sentiment scores aggregated over documents that aim at measuring happiness.

Finally, there are issues present in both data sources. Social desirability bias known in survey research also affects users’ self-representation on FB (Gil-Or et al., 2018).

Surveys combined with FB data at an individual level are not only richer but also more robust. Self-reported and observational data on the same phenomena give us the opportunity
for validation. The most common method for validating FB data is through independently conducted surveys when aggregated data are compared to each other (see, e.g., Zhan et al., 2019, on a health behavior study). Individually-linked survey and FB data are more accurate (although more expensive and technically more difficult) solution for validation.

Another validity analysis covered by our study aims to compare FB's algorithmically inferred interests to the user's "real" interest expressed through "likes" and reactions. FB's algorithms are optimized to generate interest categorization available for targeting advertisers. Inferred interests are also used to determine the content of the users' newsfeed (DeVito 2017). Content of the newsfeed affects the users' knowledge and views - however, exact methods of the algorithms are trade secrets, although high-level patent descriptions are available.

To sum it up: we aimed to investigate associations between the users' (1) self-reported interests and activities, (2) digitally expressed interests (liked pages and reactions to pages), and (3) inferred interests. Each of these measures bears its own interpretative limitation and validity weaknesses, but we hoped that joining these to investigate would help us understand social phenomena better.

Music taste

Music taste and music preference play a central role in cultural sociology. Bourdieu (1983) used music taste as one of the key indicators of cultural consumption in his homology thesis. Peterson also used music preferences to study the omnivorization process in culture (Peterson 1992, Peterson and Kern 1996), and music is used to measure cultural capital too, like in the classic work of DiMaggio (1982). The big advantage of music preference compared to other cultural indicators that it does not depend heavily on the financial situation of the household; everyone can access to every type of music. There are several ways to measure music taste in surveys, from likert scale questions, through rank lists. A common point of these methods is
to define the music genres, and it is not obvious that people have the same understanding of what the genre categories mean (Park et al. 2015), and what are the boundaries between these categories (Beer and Taylor 2013). It is also a possible way to ask respondents to evaluate certain bands (Ferrer et al. 2013) or listen to specific songs, but these approaches also induce several validity questions. Why even these bands/songs are chosen, are they a good representative of a genre, how many bands/songs are needed to measure a dimension etc. As the Internet plays a crucial role nowadays in music listening, the measurement of music taste has become possible through digital traces (Greenberg and Rentfrow). Several online platforms were used to measure music taste, like Twitter (Park et al 2015), LastFm (Berkers 2012), or Facebook (Nave et al 2017). Nevertheless, as far as we know, there are no studies on the relationship between digital trace data and survey data regarding music preference, our study is the first step in this field.

Data

Our study uses a novel joint data source of combined Facebook and survey data. As Facebook restricted the use of their API to access a large number of Facebook data (Freelon 2019), new methods have to be developed by social scientists on how to access FB data for social science research. The new generation of studies collects the data through the users, not the tech company (Halavais 2019). Our study is one of the first attempts using this new track in computational social sciences.

One hundred fifty respondents took part in our study. The basic demographic characteristics of the sample are available in the appendix Table A1. The sample is non-probability quota sample, with quotas for age category and gender. All the respondents were Hungarian, living in the eastern part of the country, mostly in big cities. The fieldwork was done in 2019 between April and September, by a professional market research company.
After informed consent was obtained, respondents were asked to log-in to FB on the interviewers' notebook and to download their FB profile archive in JSON format. We did not ask for access to the full Facebook activity data because of privacy issues. Our database does not contain private messages, search histories, and marketplace activities. Still, the data covers a wide range of Facebook activities: posts, comments, likes and reactions, pages, friends, profile, and ads data. The full friend list contains 116 000 names (anonymized), there are 83 000 page-like from more than 50 000 unique pages, and the database contains more than 1 800 000 reactions as well as all posts and comments of the participants. The data covers the whole time period of the participants' Facebook usage. To ensure confidentiality, the raw FB data were anonymized: R code run by the interviewer in front of the respondent, and the code replaced person names by random IDs. The researchers only have access to the anonymized data. In this paper, we are using the page likes and the ads data from the archives. Besides sharing their Facebook data, participants had to fill out an online questionnaire. Questions about politics, media usage, self-representation, mental health, spare-time activities, and music preferences were asked from the participants. As we have a convenience sample, we cannot investigate reliability or external validity of our statistics. However, their internal validity can be assessed through a comparison of survey and FB data.

**Indicators and basic statistics**

In the survey, we measured nine music genres, using a 1-7 scale. One means absolutely do not like the genre, and seven means really like it. In the sample, Pop was the most popular music genre, and Classical music got the lowest score (see Table 1). There was one special Hungarian music category, called 'mulatós' (no recognized translation exists). It is a mixture
of Roma wedding music and techno. Listening to 'mulatós' correlates with lower socio-economic status (Kristóf and Kmetty 2019). Many of the bands and singers of this music genre belong to the Roma minority in Hungary. The Hungarian elite does not regard 'mulatós' as something of value, stigmatizing its consumers as having 'bad taste,' failing to understand its role and context (Kovalcsik 2010).
Table 1. Self-reported music genre preferences in the survey

|                          | 1     | 2     | 3     | 4     | 5     | 6     | 7     | Mean | S.E. |
|--------------------------|-------|-------|-------|-------|-------|-------|-------|------|------|
| Classical music          | 30.1% | 19.9% | 15.8% | 12.3% | 10.3% | 3.4%  | 8.2%  | 3.0  | .16  |
| Electronic music         | 13.9% | 18.1% | 13.2% | 13.9% | 16.7% | 11.8% | 12.5% | 3.9  | .16  |
| Hip-hop                  | 8.2%  | 10.3% | 18.5% | 19.2% | 22.6% | 11.0% | 10.3% | 4.1  | .14  |
| Jazz/blues               | 12.4% | 24.1% | 15.9% | 20.0% | 11.0% | 9.0%  | 7.6%  | 3.5  | .15  |
| 'Mulatós'                | 29.7% | 11.7% | 13.8% | 14.5% | 9.0%  | 11.0% | 10.3% | 3.4  | .17  |
| Pop                      | 2.1%  | 4.8%  | 6.9%  | 15.2% | 29.0% | 17.2% | 24.8% | 5.2  | .13  |
| Rap                      | 11.7% | 15.2% | 13.8% | 16.6% | 19.3% | 11.7% | 11.7% | 4.0  | .16  |
| Rock                     | 13.8% | 13.8% | 13.1% | 11.0% | 15.9% | 9.0%  | 23.4% | 4.2  | .18  |
| World-music              | 7.8%  | 6.4%  | 14.2% | 21.3% | 17.7% | 17.0% | 15.6% | 4.5  | .15  |

We decided to create a joint category for the hip-hop and rap genres. Our Facebook page categorization is based on bands (see later in detail), and it is not easy to decide in some cases if a band is a hip-hop band or a rap one. The correlation between the two survey items is 0.7, which also indicates a strong link between the corresponding categories. We calculated the average of the variables. The mean value was 4.1 with a 0.14 standard error.

The page like data contains two types of information, the date of the page like, and the name of the Facebook page. However, in the page's profile data, a categorization of the given page is also available, which is created by Facebook. The 150 respondents liked 52,701 pages.
Three thousand eight hundred three pages were categorized as music, which is higher than 7 percent. If we add, that 80 percent of the page categorization is other or unknown, this value turns out to be quite high. We focus on these pages in our study. Two BA students - who study sociology - categorized these 3803 pages manually. Every page was coded by one coder. We use the same genre typology what we had in the survey, so we have distinguished 8 genres (hip-hop and rap in a joint category), and we had another category for genres like Latin or soul. There were 455 additional pages, which we were unable to put in any genres. Festivals and radio stations were in this group and also some pages, which did not relate to music in any way (false FB-classification).

Table 2. Classification of the liked Facebook pages classified as music (N=3803)

| Genre          | Percent | Valid percent |
|----------------|---------|---------------|
| Classical music| 2.8%    | 3.8%          |
| Electronic music| 17.4%  | 23.7%         |
| Hip-hop/rap    | 8.4%    | 11.4%         |
| Jazz/blues     | 2.2%    | 3.0%          |
| 'Mulatós'      | 1.7%    | 2.3%          |
| Pop            | 18.3%   | 24.9%         |
| Rock           | 20.4%   | 27.7%         |
| World- music   | 2.3%    | 3.1%          |
| Other music    | 14.6%   |               |
| Not music genre| 12.0%   |               |
The three most frequent music genres were rock, pop, and electronic music. There were relatively few pages being categorized as classical music, jazz/blues, world- music, or 'mulatós'.

We summed up the number of page likes per music genre for each respondent and merged it with the survey data. Within the 150 respondents, 11.3% did not have any music page likes. The mean of the music page likes was 39, the median was 13, and the standard deviation was 110. The distribution was highly skewed; one of the respondent’s had 1137 page likes. We will analyse this variable in more detail in the next section. We also calculated a dummy variable for all the genres. We coded 0, and 1 page likes into 'not linked to the genre' and all values above 1 into 'linked to the genre'. In the following, we call this variable 'digitally expressed interest'. It is not obvious which cut-off point to choose to define digitally expressed interest. We decided to code 1 page like into 'not linked to the genre' because the genre boundaries are not clear cut, and we can assume that our coders might have put bands to different categories from where respondents would have classified them.
The number of musicians is different in every music genre, and this has an effect on the mean value. There are more pop bands than classical music artists. So the mean value alone is misleading. The dummy variable presents a more valid picture of the music preferences. Based on that - pop music is the most preferred genre, and hip-hop/rap category is closer to the leading genres, compared to the analysis based on the mean value.

The third data source we use in this paper is the ads interest data. Facebook categorizes every user for sales for advertising. This is an algorithmic classification of the users based on their

| Music Genre       | Mean | Std error | Max | More than 1 page likes (%) |
|-------------------|------|-----------|-----|---------------------------|
| Classical music   | .8   | .35       | 51  | 10.7%                     |
| Electronic music  | 6.8  | 2.76      | 398 | 47.3%                     |
| Hip-hop/rap       | 6    | 1.25      | 136 | 42.7%                     |
| Jazz/blues        | .7   | .32       | 47  | 8.0%                      |
| 'Mulatós'         | .5   | .17       | 22  | 10.0%                     |
| Pop               | 13.9 | 2.47      | 230 | 66.7%                     |
| Rock              | 9.8  | 2.39      | 281 | 53.3%                     |
| World-music       | .7   | .29       | 41  | 7.3%                      |

Table 3. Music genre page likes on respondent level
own likes, activities, and used keywords and also based on their friends' preferences (DeVito 2017). The algorithm is a black-box; we can only observe the result of the categorization. Thorson et al. (2019) have proved that political news exposure is strongly correlated with the ads categories users are classified.

Overall there were 18 689 ad interest categories in the sample. There are high-level categories like jazz music, more specified subcategories like British hip-hop, and specific musicians and bands, too, like Eminem or Adele. We used the high-level categories as they contain all the lower-level categories. So if someone is classified in the British hip-hop category, he/she would also be categorized in the hip-hop category. The list of used interest category names is available in the appendix (table A2). We could extract 7 music genres. We didn’t find any interest group for the 'mulatós' preference. This reveals a very important problem. The category selection of Facebook limits the measurability of certain interest groups. This is especially true for categories not typical in the main Facebook countries (primarily the US).

We aggregated the ads interest data - called "inferred interest" from here on - to respondent level and merged it with the survey. Seven percent of the respondents were not linked to any music category through inferred interests, and 5 percent were assigned to all music genres. An average respondent was linked to 3.8 genres. Eighty-one percent of the respondents were assigned to rock music, 68-68 percent to pop and electronic music, 73 percent to hip-hop/rap, 32 to jazz, 30 to world- music, and 24 percent to classical music.

There are two other data sources of Facebook archives that could be used for analysing music preferences. One of them is the reactions of the users. If they like a post on a page of a musician, we can map this activity. However, the explanatory analysis of this dataset showed that only around half of the respondents used any reactions at least ten times. So this dataset tells us more about people's Facebook usage habits, than their music preferences.
The user’s post database also contains information about music preferences. In their posts, people can share what music they like, or what music they listen to. A typical form for this, if they share what music they listen through a music streaming applications like Spotify or Deezer (it is a Hungarian one). Nevertheless, the preliminary analysis of posts data revealed that this kind of Facebook usage is rare, and we cannot map the music preferences of our sample through the user's post data.

**Digitally expressed interest**

**Users without music page like**

People are using Facebook in several ways. If we operationalize music preferences through page likes, we have to assume that users follow their favorite musicians and bands. Eleven percent of the sample did not have any music-related page likes. It is an important validity question why don't they have any page likes. One possible explanation is that they do not have any interest in music, and this behavior is expressed in their (non)-activity. However, it is also possible that they don't use this functionality of Facebook, and/or they are just using Facebook lightly. We tested all of these explanations. First, we calculated the number of really liked genres based on self-reported interest data (6 or 7 on the scale) and analyzed the average of this variable within those who had music page like and within those who didn't. There was a small, and not significant (p=0.33) difference between the two groups (1.5 vs. 1.9). Second, we run a crosstab analysis to measure the relationship with Facebook activity. Seventy-five percent of the whole sample uses Facebook more than once a day. This proportion is 70 percent within those who don't follow any music-related page, and 76 percent within those who follow at least one page, so the difference here is also small and not significant. Third, we calculated the mean number of all page likes in the two groups. The mean value was 55 within the group with no music page like, and 620 in the other group and
this difference was significant (p=0.00) even in this small sample. To sum up the results, based on the three calculations, it seems that people with no music page like have strong music preference, they use Facebook actively, but they don't use FB page like function.

Correlation of self-reported interest and digitally expressed interest

One of the most important questions of this study is the relationship between the self-reported interest (survey) data and the Facebook based data. In the previous section, we introduced the basic distribution of the variables. The next figure presents the interest order position of the music genres from self-reported interest data and digitally expressed interest data. When defining the latter, we use the proportion of those who like at least two pages per genre.

Figure 1. Comparing self-reported interest and digitally expressed interest
Most of the genres are in a similar position in the two approaches. 'Mulatós' and Jazz are evaluated higher in self-reported data, while rock, electronic music, and hip-hop/rap categories are a little bit lower. There is one significant difference, the "world music" category. People like this genre based on the survey, but we can't measure this in the digitally expressed interest data. We calculated the (Spearman's rank) correlation of the survey items and the number of page likes per music genre.

Table 4. Correlation of self-reported interest data (row) and digitally expressed interest data (column)

|                | Classical music | Electronic music | Hip-hop/rap | Jazz/blues | 'Mulatós' | Pop | Rock | World-music |
|----------------|-----------------|-----------------|-------------|------------|-----------|-----|------|------------|
| Classical music| .26**           | -.09            | -.21*       | .04        | .12       | -.16*| .11  | .06        |
| Electronic music| .27**           | .20*            | -.13        | -.15       | .07       | -.12 | .20* |            |
| Hip-hop/rap    | .44**           | .05             | .32**       | .26**      | -.09      | .22**|      |            |
| Jazz/blues     | .15             | -.02            | -.04        | .11        | -.05      |      |      |            |
| 'Mulatós'      | .23**           | .24**           | .01         | -.08       |           |      |      |            |
| Pop            | .21*            | -.10            | .14         |            |           |      |      |            |
| Rock           |                 |                 | .38**       | .20*       |           |      |      |            |
| World-music    |                 |                 |             |            |           |      |      | -.02       |

*p<0.05  **p<0.01
The diagonal contains the correlation with the same genre. In most cases, the correlation is highest between the same genres, but there are some important deviations. The survey world-music preference does not correlate with the same FB item. We could have expected that based on the difference of the base statistics. The survey answer correlates with the electronic music page likes and the hip-hop/rap page likes. The world-music page like number correlates with the rock survey item. Also, an interesting result, that 'mulatos' survey item correlates with hip-hop/rap stronger than its own category. Overall the correlations are rather moderate; the highest value is 0.44

The evolution of music taste?

Facebook archives data provides a timestamp for every user activity. This gives a unique opportunity to study the dynamic pattern of social life and social activity. In the survey, we can measure the current music preference of the respondents. However, based on digitally expressed interest data, we can measure the development of music taste. Nonetheless, it is not evident how people use Facebook - do they start to follow/like all the music pages they prefer when they start using the platform or is this a slower process? It is also a question whether we can observe a socialisation process regarding taste in music.

To measure the dynamic evolution of music taste, we created two complex variables. As we wanted to analyse a longer time period of music preference development, we omit those respondents, who started to use Facebook after 2012 - altogether 26 participants. In the second step, we selected the first seven years of Facebook activity of all users. As most of the users in our sample started to use Facebook between 2010 and 2012, we can assume that possible algorithmic changes do not cause too much bias in this data. Then we calculated for all the respondents the cumulative percent of their Facebook page likes within the elapsed
time. Furthermore, we also calculated the cumulative percent of music preference growth. So if someone preferred two genres within this whole seven-year period, but only one genre after the first year, the first-year cumulative percent was 0.5 in their case. We only include those in this analysis who had at least five music pages likes (N=85).

Figure 2. The Cumulative growth of Facebook page likes and ratio of preferred music genres

The blue line represents the growth of page likes. This figure has at least two important messages. At the start of FB use, people will not start to follow all their preferred musicians. So we cannot observe a strong kick-off increase here. Additionally, the growth of page likes do not show a linear trend for the whole period, but for the first 5 years, the trend is linear. The increase has a saturation point around year five. So after a linear growth, the growth rate is starting to decrease. This trend could be a general one but could also be caused by the age
distribution of the sample as it is biased toward young users, so this could be an age effect too.

The growth rate of music preference growth presents a different pattern, and it is far from linear. After two years of Facebook usage, we can map 61 percent of the genres a user likes, after 3 years, 74 percent, and after 4 years, 86 percent. We could assume that the growth rate is even steeper for older generations where music preference is more stable.

Based on the two trends, we can expect that the current music taste measured by the survey would correlate stronger with the "whole time period" Facebook page like data, than with the last few years of activity. To measure this, we calculated the number of page likes per genre from 2018 and then correlated these variables (Spearman correlation) with the survey responses (1-7 scale). This is the same analysis as we did for the whole time period in the previous section (see table 4). The correlation was lower in all cases between the same genres. In some cases (pop), the correlation turned from positive to negative.

These results have important validity aspects. If we want to analyse someone music preferences through Facebook page likes (digitally expressed interest data), the preferred solution is to use the whole timeline of the user, because a few year time-frame could be misleading, especially if we just use the last few years of activity, and don’t include the first (5) years of Facebook presence.

**Inferred interest**

The last part of the analysis focuses on the ads interest data and its correlation with the other measurement methods. The ads classification algorithm is a black box, but some available high-level patents give us some idea about how they work. The algorithm uses the page likes, search words, comments and shares, and even the interest of friends.
To our knowledge, no previous study has reported the rate at which any population is categorized by Facebook to advertisers as interested in music genres. Inferred interest overall shows a stronger preference level than the other measures. Eighty-one percent of our respondents were linked to rock music, and even the least popular classical music was linked to every fourth of our respondents. The next figure (3) gives an overview of the difference between the survey data and the inferred interest data.

Figure 3. Comparing self-reported interest and inferred interest

The basic tendency is the same, as in the case of page likes. Rock, electronic music, and hip-hop/rap genres were over-measured in the inferred interest data, compared with the self-reported interest. World-music position is completely different here too; it is preferred much more in the survey. We also have to highlight that the difference between the preferences of
genres was bigger here than in the case of the page likes. We expected the opposite before the analysis. It is possible that the algorithm overestimates the homophily of music preference, and this might cause a bias in this data.

**Discussion**

Our study contributes to the research on social media data by combining personal FB data archives with self-reported data. Our methodological experiences add to the technical feasibility of such studies, while our substantive results provide important results about validity issues of different measurement methods.

This paper is the first attempt to compare self-reported music preference with Facebook-based music preference classification. We primarily focused on operationalization-related questions and validity issues. The results overall showed that the different measures have only moderate correlations with each other. Some genres measured similarly, but there were significant differences too. A good example of the latter is world-music. It was the second most preferred genre of the survey, but based on FB data (both on digitally expressed and inferred data), it was at the lower end of the preference scale. We can assume that this music category is too wide, and people might not agree on what belongs here. However, it is also possible that they love this genre, but they can't express their preference, because the genre is under-represented on the Facebook. We know that the affordance of the platform and the algorithms forming the timeline can also affect the (expressed) interest of users. More research needed here to understand this difference better, but this result in itself also questions the validity of the survey item. A possible solution would be to list some artists pertaining to the genre or evaluate played song tracks.

However, the classification of musicians/bands into genres is far from obvious in some cases. A musician could have songs in different genres, and the genre boundaries are not clear in
some cases. That is why we merged the hip-hop and rap categories. We had resources in this project to annotate the liked pages by only one annotator. We are planning to run a second independent round of annotation on at least some part of the liked pages to check inter-annotator agreement.

It seems that the size of a genre (how many musicians/bands are in it) also affects the operationalization. Furthermore, we have to take into consideration that different genres could have different representation in FB. If a musician uses different platforms other than Facebook (like Soundcloud or Instagram), it might cause a blind spot for our measurement. Thus, the number of likes per genre might not be the best indicator to measure music preference. For this reason, we created a dummy variable, but this has two disadvantages. First, we lost the scale character of the indicator, which is a significant information loss. Second, we have to define a cut-off value. We chose to categorize 1 page like into 'not linked to the genre' - to decrease the effect of possible measurement error of page classification. However, there is no gold standard on how to deal with this issue. Nevertheless, even if we could agree on the cut-off value, we still have to deal with those users who don't have any music page likes. We tested three different hypotheses about the lack of music genre likes. In the analysis, we concluded that people without music page like, have overall strong music preference, and they use Facebook actively, but they don't use page-like functionality.

How we can use the algorithmically inferred data is also a validity question. It is based on Facebook’s own classification, which is a total black-box for the research community. We can try to define a higher-level classification by merging lower-level ad interest categories into higher-level ones; however, we would still be exposed to the unknown classification algorithm. The digitally expressed and the inferred data showed a strong correlation with each other (above 0.9) - but this is not a surprise; we know that FB includes the page-likes in its algorithm. However, it was not expected that the self-reported music taste would correlate
stronger with the page-likes than the ads interest. We only have weak assumptions for explaining this. One of the possible explanations is based on the fact that Facebook uses the friends’ interest in order to classify the users (e.g., Thorson 2019). The theoretical background for this decision is the well known social science phenomenon that friends share the same interest (see the thesis of network homophily (McPherson et al 2001). Nevertheless, the homophily level is not the same for all the interest categories, like music, sport, or politics. If the algorithm uses an equal level of homophily factor for all interest groups, it might cause a bias in the classification. Fine-tuning of the algorithm could also result in an over-estimation of music preference. It is always an open question which type of error we want to minimize in a classification model. By choosing a more gentle cut-off point, we classify some users into a category that he/she does not like. On the contrary, a strict cut-off point results in failing to classify some user into a music genre which he/she likes. If we want to minimize the latter error (which is completely logical from a business perspective), we tend to overestimate the level of music preferences. The higher degree of music preference level in ads data may show indirect evidence for such an assumption.

Another important validity problem arose in the case of the algorithmically inferred data. We did not find any ad interest category which fits the 'mulatós' genre. The category selection of Facebook limits the measurability of certain interest groups. Although big data theoretically makes it possible to reach smaller subpopulations, it is not obvious how we can find measures to analyse these groups if this group is not classified by the Facebook algorithm.

Besides observing behaviour of small subpopulations, big data also makes it possible to analyse the dynamical patterns of people's behaviour. Our results showed that music page like increased linearly in the first five years of users' FB-usage, but the growth rate started to decrease afterward. Using only the first three years of page-like data, we were able to estimate quite well the whole range of full-period music preference of the user. We can assume that the
initial time interval long enough to estimate music preference would be even narrower for older generations where the music taste is more stable (Way et al. 2019). This result has an important operationalization outcome too. If we want to analyse someone’s music preferences through Facebook page-likes (digitally expressed interest data), the preferred solution is to use the whole timeline of the user, because the actual few year time-frame could be misleading.

In this paper, we primarily focused on methodological problems: validity issues and operationalization questions. However, our combined data source could be used also to better understand some important sociological phenomenon. Social desirability and self-representation in social media are one of these areas. "Mulatós" genre is a good choice for this. As there are negative stereotypes toward the genre, we might assume that middle-high class users will not express their preference toward this music style by Facebook page likes. Of course, they can also give biased answers in a survey, but in a self-reported questionnaire (without an interviewer), we might expect a weaker effect. Our sample is not big enough to conduct such analysis, but the combination of these data sources gives the theoretical opportunity to detect answers biased by social desirability.

Digital data - like social media data or search engine data - opens the possibility to examine topics we could not examine earlier or re-examine topics with new approaches. However, all the data sources have their own validity problems. In the case of big data, social scientists often raise the problem of generalizability even if we have data from millions of users. We did not deal with generalizability, rather with a less studied topic, the validity of this data. Our paper adds a new contribution to this topic. Platform affordance, algorithmical classification, and different types of platform usage all influence the expressed (observable) interest of users. We need to consider all these effects when we are relying on social media data.
References

Astudillo, Ignacio, Carolina Fuentes, and Valeria Herskovic. 2018. Analízate: Towards a Platform to Analyze Activities and Emotional States of Informal Caregivers. *Proceedings*, 2, no. 19: 1205. https://doi.org/10.3390/proceedings2191205

Beer, David, and Mark Taylor. 2013. The hidden dimensions of the musical field and the potential of the new social data. *Sociological Research Online*, 18, no. 2: 11-21. https://doi.org/10.5153/sro.2943

Berkers, Pauwke. 2012. Gendered scrobbling: Listening behaviour of young adults on Last.fm. *Interactions: Studies in Communication & Culture*, 2, no. 3: 279-296. https://doi.org/10.1386/iscc.2.3.279_1

Bourdieu, Pierre. 1984. *Distinction: A Social Critique of the Judgement of Taste*, translated by Richard Nice, Richard. London: Harvard University Press.

Caton, Sinom, Margeret Hall, and Cristoph Weinhardt. 2015. How do politicians use Facebook? An applied social observatory. *Big Data & Society*, 2, no. 2. doi: 10.1177/2053951715612822

DeVito, Michael A. (2017). From editors to algorithms. *Digital Journalism*, 5, no. 6: 753–773. doi: 10.1080/21670811.2016.1178592

DiMaggio, Paul. 1982. Cultural Capital and School Success: The Impact of Status Culture Participation on the Grades of U.S. High School Students. *American Sociological Review*, 47, no. 2: 189–201. http://dx.doi.org/10.2307/2094962.

Eslami, Motahhare, Sneha R. Krishna Kumaran, Christian Sandvig, and Karrie Karahalios 2018. *Communicating algorithmic process in online behavioral advertising*. Montreal, Canada: ACM.
Ferrer, Rafael, Tuomas Eerola, and Joanna K. Vuoskoski. 2013. Enhancing genre-based measures of music preference by user-defined liking and social tags. *Psychology of Music*, 41, no. 4: 499-518. doi: 10.1177/0305735612440611

Freelon, Deen. 2018. Computational research in the post-API age. *Political Communication*, 35, no. 4: 665-668. https://doi.org/10.1080/10584609.2018.1477506

Gil-Or Oren, Yossi Levi-Belz, and Ofir Turel. 2018. Corrigendum: The “Facebook-self”: characteristics and psychological predictors of false self-presentation on Facebook. *Frontiers in Psychology* 9:652. doi: 10.3389/fpsyg.2018.00652

Greenberg, David M., and Peter J. Rentfrow (2017). Music and big data: a new frontier. *Current opinion in behavioral sciences*, 18: 50-56. https://doi.org/10.1016/j.cobeha.2017.07.007

Groves, Robert. 2018. Faculty research collectives. Post of *The Provost's Blog*, Georgetown University. https://blog.provost.georgetown.edu/faculty-research-collectives/ assessed 27 January 2020.

Haim, Mario, and Angela Nienierza. 2019. Computational observation: Challenges and opportunities of automated observation within algorithmically curated media environments using a browser plug-in. *Computational Communication Research*, 1, no. 1: 79–102. https://doi.org/10.5117/CCR2019.1.004.HAIM

Halavais, Alexander. 2019. Overcoming terms of service: a proposal for ethical distributed research. *Information, Communication & Society*, 22: no. 11, 1567-1581.

Kovácsik, Katalin. 2010. The Romani musicians on the stage of pluri-culturalism: the case of the Kalyi Jag group in Hungary. In *Multi-disciplinary approaches to Romany studies*, edited by Michael Stewart and Márton Rövid, 55-70. Budapest: Central European University Press.
Kristóf, Luca and Zoltán Kmetty. 2019. Szereti ön Vivaldit?: Zenei ízlés és társadalmi státusz. [Do you like Vivaldi? Music preference and social status] Szociológiai Szemle, no. 2: 49-67.

Lavrakas, Paul J. 2008. Encyclopedia of survey research methods (Vols. 1-0). Thousand Oaks, CA: Sage Publications, Inc. doi: 10.4135/9781412963947

Kosinski, Michal, Sandra Matz, Samuel G Gosling, Vesselin Popov and David Stillwell. 2015. Facebook as a research tool for the social sciences: Opportunities, challenges, ethical considerations, and practical guidelines. American Psychologist, 70, no. 6: 543-556. doi: 10.1037/a0039210

Marino, Claudia, Livio Finos, Alessio Vieno, Michela Lenzi, and Marcantonio M. Spada. 2017. Objective Facebook behaviour: Differences between problematic and non-problematic users. Computers in Human Behavior, 73: 541–546. doi: 10.1016/j.chb.2017.04.015

McPherson, Miller; Smith-Lovin Lynn; Cook, James M. 2001. Birds of a feather: Homophily in social networks. Annual review of sociology, 27.1: 415-444.

Nave, Gideon, Juri Minxha, David M. Greenberg, Michal Kosinski, David Stillwell, and Jason Rentfrow. 2018. Musical preferences predict personality: evidence from active listening and facebook likes. Psychological science, 29, no. 7: 1145-1158.

https://doi.org/10.1177/0956797618761659

Park, Minsu, Ingmar Weber, Mor Naaman, and Sarah Vieweg. 2015. Understanding musical diversity via online social media. In Ninth International AAAI Conference on Web and Social Media. arXiv:1604.02522 [cs.CY]
Perrin, Andrew. 2018. Americans are changing their relationship with Facebook. Pew Research Center, at https://www.pewresearch.org/fact-tank/2018/09/05/americans-changing-their-relationship-with-facebook/, assessed 25 January 2020.

Peterson, Richard. A. 1992. Understanding audience segmentation: From elite and mass to omnivore and univore. Poetics, 21, no. 4: 243–258. http://dx.doi.org/10.1016/0304-422X(92)90008-Q.

Peterson, Richard. A. and Roger M. Kern. 1996. Changing Highbrow Taste: From Snob to Omnivore. American Sociological Review, 61, no. 5: 900–907. http://dx.doi.org/10.2307/2096460.

Potter, Jonathan, and Chloe Shaw 2018. The virtues of naturalistic data. In The sage handbook of qualitative data collection, edited by Uwe Flick, 182-199. London: SAGE

Thorson, Kjerstin, Kelley Cotter, Mel Medeiros, and Chankyung Pak. 2019. Algorithmic inference, political interest, and exposure to news and politics on Facebook. Information, Communication & Society, 1-18. https://doi.org/10.1080/1369118X.2019.1642934

Vitak, Jessica. 2017. “Facebook as a Research Tool in the Social and Computer Sciences”. In The SAGE Handbook of Social Media Research Methods, edited by Luke Sloan, and Anabel Quan-Haase. London: Sage Publications. doi: 10.4135/9781473983847

Way, Samuel. F., Santiago Gil, Ian Anderson, and Aaron Clauset. 2019. Environmental Changes and the Dynamics of Musical Identity. Proceedings of the International AAAI Conference on Web and Social Media, 13, no. 1: 527-536.

Zhan, Yongcheng, Jean-François Etter, Scott James Leischow, and Daniel Dajun Zeng. 2019. Electronic cigarette usage patterns: a case study combining survey and social media data. Journal of the American Medical Informatics Association, 26, no. 1:9-18. doi: 10.1093/jamia/ocy140.
Table A1. Basic socio-demographic characteristic of the survey

|                | Frequency | Percent |
|----------------|-----------|---------|
| **Gender**     |           |         |
| Male           | 37        | 24.7%   |
| Female         | 113       | 75.3%   |
| **Age category** |         |         |
| 18-28          | 95        | 63.3%   |
| 29-48          | 36        | 24.0%   |
| 49+            | 19        | 12.7%   |
| **Education**  |           |         |
| Less than secondary | 14  | 9.3%   |
| Secondary      | 96        | 64.0%   |
| University     | 40        | 26.7%   |
Table A2. Used ads interest categories

| Music genre | Ads interest groups                                      |
|-------------|----------------------------------------------------------|
| Pop         | Pop music                                                |
| Rock        | Blues music, Blues-rock, Heavy metal music, Rock music, Rhythm and blues music |
| Electronic  | Electro music, Electronic dance music, Electronic music, House music, Psychedelic music, Trance music |
| Hip-hop/rap | Hip-hop music, Rap                                       |
| Classical   | Classical music                                          |
| Jazz        | Jazz music                                               |
| World music | Country music, Hungarian folk music, Folk music, World music |