Children also like music:

Exploring the prominence of specific musical features in music listened by children of different age ranges

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Abstract

Music recommender systems are increasingly present in our lives, and it is important to keep trying to improve recommendations in order to make them match the users preferences as well as possible. To achieve this, a vast amount of song and user data has to be analysed and taken into account. One of the approaches to do this, includes analyzing different audio features in order to find other songs with similar traits. The majority of the research and data in this sector is focused around adults, with little research surrounding children, which can result in worse recommendations for this demographic. In this paper, the focus is shifted towards children with the purpose of filling that gap. This is achieved by examining the prominence of specific song features among children of different age groups, expanding the knowledge on listening habits of a major demographic. More specifically, the research presented in this paper explores the prominence of various song features, aiming to find a connections between these features and the listening habits of children of specific age ranges from 8-18. This paper's conclusions will offer potential enhancements, which can improve existing recommender systems by considering findings for their design. These findings will therefore allow for a more tailored experience for children of different age ranges, increasing overall user experience.

1 Introduction

In the current increasingly digital world, countless apps offer an overwhelming and almost unlimited amount of media content, including music, which makes it progressively harder for users to come by content they actually enjoy. Recommender systems offer a great solution to this overload of information [6], by suggesting to users content they are more likely to engage with, as measured by multiple times streams or by leaving reviews. Although a lot of research has been conducted to improve these systems, most research works in this area keep their main focus on adults, improving recommendations for them. This comes at the cost of less research around recommendation systems around children [8]. The reason this is so important is because the musical preferences of children greatly vary compared to those of adults [7]. Therefore, further research on this topic would greatly improve children's overall pleasure and engagement when interacting with content, by providing them more suitable and age appropriate suggestions.

For the scope of this research, we focus on an important category of recommender systems which is music recommendations. One of the main aspects of music recommender systems is using song features, such as lyrics, genre, beat etc. to suggest songs with similar traits to a user who has been engaging with songs containing them [6]. Additionally, while research on children remains quite limited, works such as Spear et al. [10] have set a strong baseline into analyzing how the prominence of features such as valence, loudness, energy, acousticness, instrumentalness, tempo and liveness vary across different age groups. While the findings of this paper present a significant contribution in the exploration of the prominence of song features among children's listening habits, they also emphasize the need for further research by expanding the current findings through the examination of new features. Analysing audio features which have been overlooked, could potentially improve the overall knowledge of listening habits, resulting in a better understanding of children and their preferences. This is especially important as children are in a developing stage in their lives and music is considered as a crucial part of development [2].

This leads us to the following question: To what extent do some song features influence the listening habits of children of different age groups? Despite the general advancements in knowledge regarding the prominence of certain song features in children's listening habits, a gap in the research persists, hindering a detailed understanding of said habits in the different age groups within this demographic. This research paper attempts to bridge this gap by identifying key song features which have not been examined yet, followed by analyzing their prominence within specific age groups in minors, finally aiming to find a connection between the presence of these features and age. The findings of this research will help improve the understanding of children's listening habits and could potentially be used to better fine tune music recommender systems based on the age of the user.

2 Related Work

Research on children's musical preferences has greatly improved in the past years, with work such as Spear et al. [10] which set a very strong foundation in the analysis of musical features, especially when separating age groups depending on educational level. This research will look to extend these works by finding additional features and analysing their prominence in the different age groups.

3 Methodology

The main goal of this paper is to analyze the prominence of three main song features, those being: Key, time signature, and micro-genre. In this research we aim to find a connection between children's age groups and feature prominence.

3.1 Data Collection

In order to conduct the proposed empirical exploration, we require a very large dataset containing users as well as their ages, listening events and tracks along with their features. For our data, we chose to use the LastFM-2b music data set, as it also contains crucial information on the user's age, which is not included in the Spotify database. Furthermore, we are using the song feature "micro-genre", present in the LFM dataset, which is a list of more fine-grained genres of a track. Finally, in order to improve and develop our analysis with more features, we also expanded the LFM dataset by using the Spotify database, creating a new dataset, containing the age of the users along with their listening counts, as well as additional features on the tracks which were not present in the original LFM database. The chosen features are song key and time signature. By combining the two datasets we manage to get all the features we are looking to explore, which are **key**, **time signature**, and **micro-genre** along with the different age groups. This improved dataset contains a total of

3.2 Age Group Selection

The main focus of this paper is to examine the prominence of musical features for different ages. To conduct this empirical exploration, one of the most important parameters to choose is the different age groups. Various approaches can be taken for this, such as comparing all individual ages or pairing them up. Another approach would be to group children depending on education levels. In fact, works such as Spear et al. [10] and LeBlanc et al. [4], support this approach by splitting children in age groups according to their education level, including Grade School (ages 6 to 11), Middle School (ages 12 to 14), and High School (ages 15 to 17), with a focus on the ages 15, 16, 17. Therefore, we also choose this method to be the most appropriate for this research.

4 Experiment

In order to conduct the experiment, we need additional information on the general listening population as well as more specific information on the users within the chosen age groups. Additionally, we need to get a basic understand of the musical features that we will analyse.

4.1 Setup

Prior to measuring feature prominence, we find the total number of users with valid ages, and to keep only those in the age ranges that are pertinent to this research.

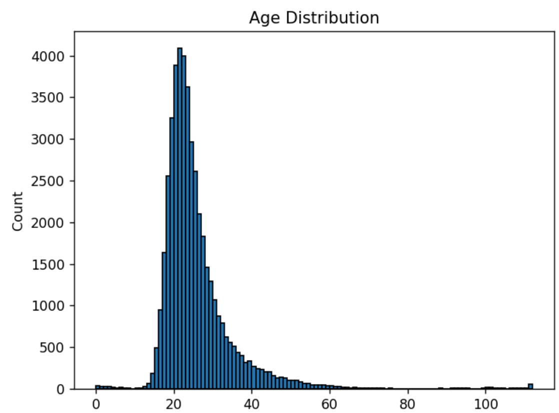

Figure 1: Number of users for each age

From Figure 1 find that from a total number of 120, 322 users, only 46, 120 have valid ages, with the overwhelming majority (82%) of those users being under 30 years old.

Age	6	7	8	9	10	11
Nb of users	17	9	9	4	9	9

Table 1: Number of users for ages 6 to 11

Age	12	13	14	15	16	17
Nb of users	24	69	189	493	946	1638

Table 2: Number of users for ages 12 to 17

Age group	GS	MS	HS
Nb of users	57	282	3077

Table 3: User distribution for different age groups based on education levels

By taking a deeper dive in the users aged from 6 to 17, we can observe that there are 3416 total users in this category. The Tables 1, 2, and 3 show us how the number of users in this demographic is distributed across ages. More specifically, 57 users are in the Grade School category, 282 users are in the Middle School category and 3077 users are in the High school category. Finally, 493 users are 15 years old, 946 users are 16 and 1638 users are 17 years old. While these numbers only present a fraction of the total population of children, they can still be used to obtain information about musical preferences within these groups.

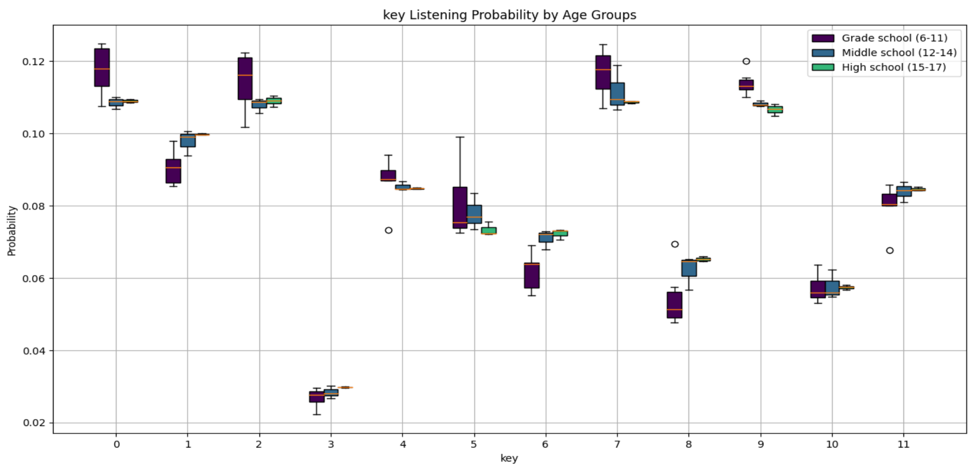

Figure 2: Key prominence within education levels

4.2 Musical features

Key and Time signature. The first features of our experiment are key and time signature, which have been extracted using the Spotify API. Before getting to the results, we must first understand what these features are, as well as the notation used to describe the key and time signature of a song.

Key in music is a group of related chords, which is based around a central note called the tonic note of the key. There are 12 keys in total, which can be major or minor, and when an entire song is composed around a single key, it is called the key of the song [3]. For scope of this research, and since Spotify's documentation maps keys to integers ranging from -1 to 11, without providing an indication on minors or majors, we are limited to these 12 keys ranging from 0 to 11. These numbers represent keys using Pitch Class notation, with 0 being the C key, 1 being C#/D♭ etc. and -1 meaning that no key has been detected for that song [12].

As for time signature, it is a musical notation which indicates the metre of the composition. It is generally of the form of two vertically aligned numbers, also commonly represented by a fraction (i.e. 3/4) where the top number represents the number of beats in each measure and the bottom number represents the value of the note that receives the beat (i.e. half notes/quarter notes etc.) [11]. Unfortunately, the Spotify API does not offer both the number of beats and the value of the note, but instead provides a singular number representing the time signature of each track. The Spotify documentation specifies that this number represents the numbers of beats per measure, ranging from 3 to 7, indicating time signatures from "3/4" to "7/4" [12].

The Figures 2 and 3 represent the density functions of the different keys based on the listening counts of different age ranges. The Figures 4 and 5 represent the density functions of the different time signatures based on the listening counts of different age ranges. The Figures 6 and 7 represent the density functions for the top 15 most listened to micro-genres for the each different age group.

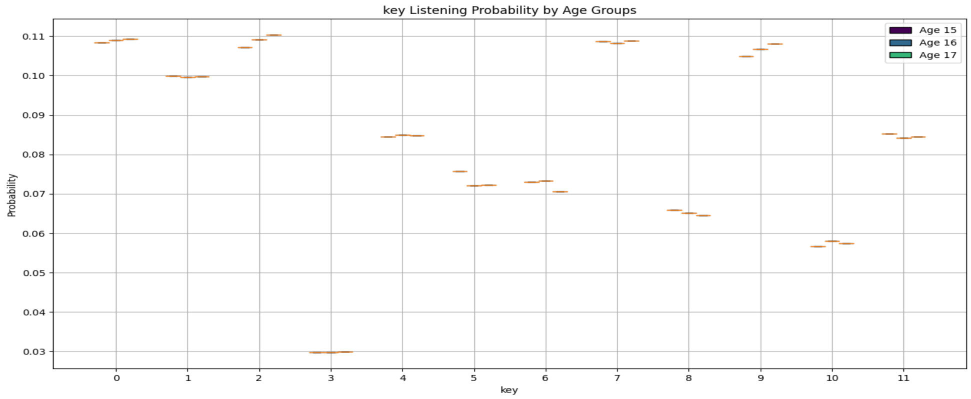

Figure 3: Key prominence ages 15, 16 and 17

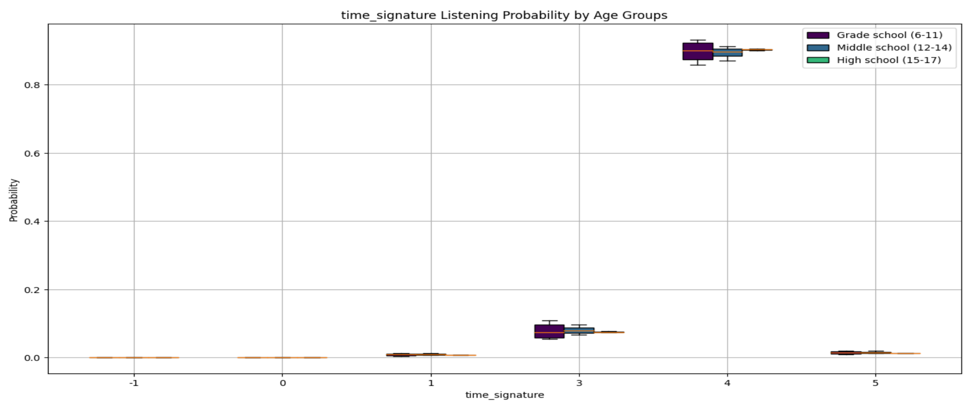

Figure 4: Time signature prominence within education levels

Micro-genre. The last feature of our analysis is micro-genres. As opposed to keys and time signatures, we did not extract this feature using the Spotify API, as it is directly available in the LFM dataset. As a matter of fact, the LFM dataset contains a category of records called tags, which are labels generated and given to tracks by users. Tags also have weights, with the value of the weight being proportional to the number of times that tag was assigned to the specific track. There are $1,041,819$ unique tags and micro-genres are a subset of tags can be defined as "fine-grained indications of musical genres or styles" [9]. In the LFM-2b Dataset, micro-genre records are present under the form of {track_id, (micro-genre, weight)+}. For our exploration, we aggregate all micro-genres regardless of the weight, as the most common ones show up more often either ways, thus the distribution not be skewed. For simplicity's sake, since there are more than 2000 different micro- genres, in order to get additional information this paper will only analyze the top 15 most listened to micro-genres per age groups compared to the top 10 general micro-genres.

Micro-genre	**Rel. frequency**
rock	19,46%
pop	12.02%
metal	7.61%
alternative rock	6.20%
jazz	5.98%
ambient	5.56%
folk	5.00%
experimental	4.92%
singer-songwriter	4.68%
electronic	4.66%

Table 4: Relative frequency of the top 10 micro-genres [9]

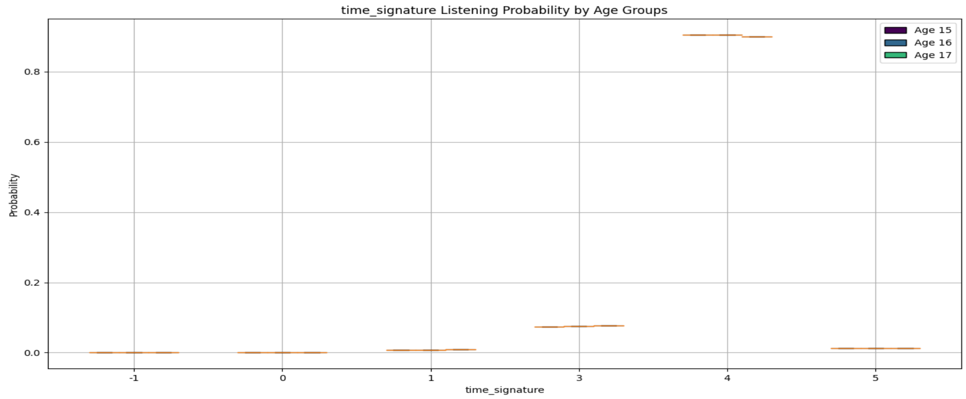

Figure 5: Time signature prominence ages 15, 16 and 17

5 Results

We begin our analysis by exploring keys. Starting with children within grade school, on Figure 2 we observe a very high frequency of keys 0, 2 , 7 and 9, which correspond to C, D, G, and A. A lower frequency is observed for keys 1, 4, 5, 6, 8, 10, and 11. Finally, a very low frequency is seen for key 3, which corresponds to E♭. This is actually due to the fact that all notes in this key are either sharps or double sharps, making it harder to play on certain instruments such a s the guitar, which explains why it is such an unpopular key. For children in middle school, the same pattern seems to emerge, with the highest frequency of songs listened to in the keys C, D, G, and A. An observation that can be made is that songs in C#, F# and G#, are slightly more listened to in middle school than in grade school and songs written in F have a slightly lower listening count in middle school users, compared to grade school users. Finally, for children in high school, the listening counts remain almost the exact same than in middle school, with a very slight variability across the board and a slight decrease in the listening counts of songs in F. By taking a closer look on Figure 3, for ages 15, 16 and 17, we can see a trend appearing for F, where its frequency lowers as the user gets older. For the other keys, the frequencies remain approximately the same. Overall, a pattern emerges across all age ranges, with a very high prominence for keys C, D, G, and A. While this pattern might seem arbitrary, we posit there is a very good reason for that. In fact, about a third of pop songs nowadays are written in these four keys which explains their very high frequency [5].

We now switch our analysis to time signature. From the results we have obtained on Figure 4, we can observe that time signature distribution greatly differs from key prominence. In fact, in Grade School has the higher variability among the education levels, with its probability varying by 0.04 for the time signatures 3 and 4. For the other time signatures the variability is negligible. Taking into account the other education levels, we see that this variability becomes even small and finally negligible for users in High school, within all education levels. Additionally, one of the most important observations that we can make is the presence of a very significant prominence of time signature 4, which makes up for over 90% of all listening events across age groups. The second most prominent time signature is 3, representing about 10% of listening events. By using Spotify's documentation, we can deduce that these values represents the time signatures 4/4 and 3/4 respectively. It is important to note that the probability of all the other time signatures, -1, 0, 1, and 5 can be considered null. Finally, when looking at time signature for ages 15, 16, and 17 on Figure 5 the results are as expected, a negligible variability between these three ages with the frequencies for all time signatures.

We finally move on to the last feature of our exploration, which is micro-genres. As seen on Figure 6 the top 15 most listened to micro-genres within the ages 6-17 are the following: Rock, pop, alternative rock, metal, indie rock, hard rock, punk, experimental, indie pop, pop rock, hardcore, singer-songwriter, emo, classic rock, and progressive rock. Once again we observe the highest variability within the Grade School age group. Looking into the most popular, rock makes up for 19% of all listening events. Rock is then followed by pop ranging from 5% to 15% depending on the age within Grade School. Moreover, sub-types of rock such as alternative rock, indie rock, and hard rock closely follow with their prominence varying between 0.09-0.1, 0.04-0.12, and 0.03-0.075 respectively. An interesting observation to make is that metal has the highest variability withing Grade School, with its listening percentage ranging from 2% to 14%, hinting towards a more individual preference within each age in this age group. The rest of the micro-genres do not have very significant findings, all around the ranges of 2%-5% of listening events. Middle School users follow the same pattern of Grade School users, with rock being the most common micro-genre, accounting for 18% of all listening events. Pop follows closely as well, ranging from 12% to 16%. Moreover, once again alternative rock and metal come in third and fourth places, both ranging from 7.5% to 10%. The rest of the micro-genres do not seem to have a very noticeable difference, all ranging between the 2.5% and 5% mark. Lastly, it is important to note that the variability within these age groups decreases, with a maximum variability within one micro-genre being equal to 5%. Similarly, rock is also the top listened to micro-genre for users in High School, with a probability of 0.18. Pop and alternative rock follow with 0.11-0.125 and 0.11 respectively. The third most listened to genre is metal accounting for 8%-9.5% of listening events. The rest of the micro-genres slowly and steadily decrease from 6.5% with hard rock, down to 3% with progressive rock. Looking more specifically at ages 15, 16, and 17 on Figure 7 we notice a very small variability between these ages, with the maximum variability being for pop, where the listening probability decreases as age increases, with percentages being equal to 13%, 11.9% and 11% respectively. Another observation worth mentioning is that metal listening events increase as age increases, with listening percentages of 7.98%, 9% and 9.4% for the ages 15, 16, and 17 respectively. For the rest of the micro-genres, variability remains under 1% hinting at more uniform listening habits for users in High School.

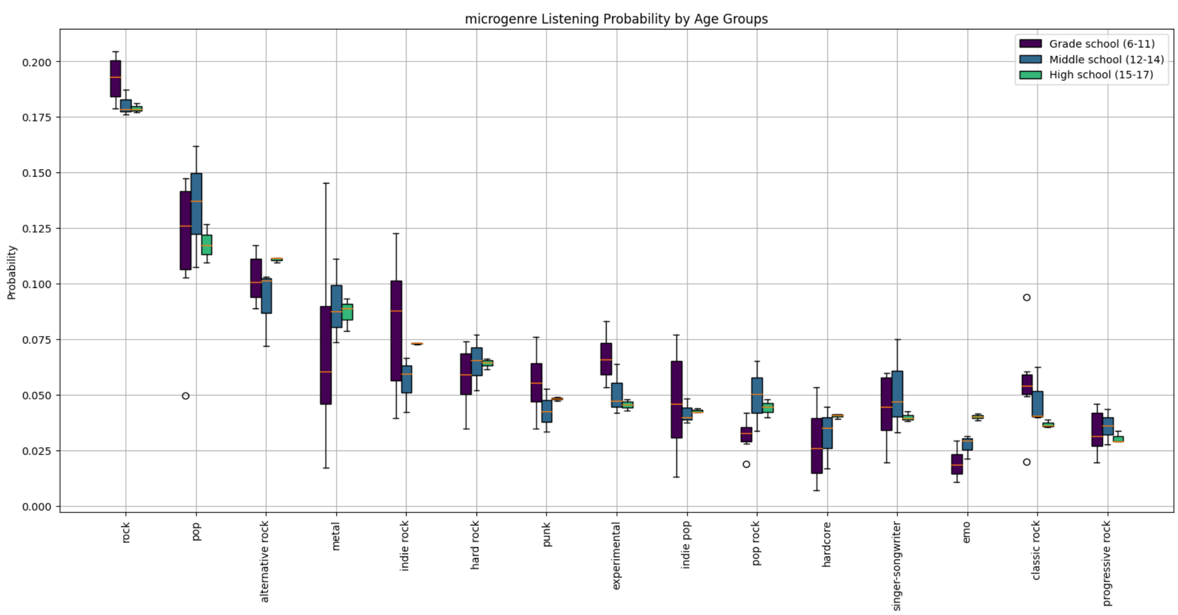

Figure 6: Micro-genre prominence within education levels

6 Discussion and Limitations

In our research we have seen that the prominence of song varies across age groups, this implies that listening habits vary as well, depending on the age of the user. To better understand these listening habits, we need to first understand if all the results we obtain purely depend on user preference.

As seen in Figures 2,6, and 4 some features are clearly more prominent among all age groups. For example the keys C, D, G, and A clearly overpower the rest of the keys. This is actually in due to the fact that a third of popular music is written in those 4 keys [3]. This indicates that the high percentage of listening events in those keys is most likely due to the high likelihood that the songs are written in those keys, rather than a preference of children.

This also applies to micro-genres, where the popularity matches well with the overall prominence of these micro-genres in tracks 4. However,

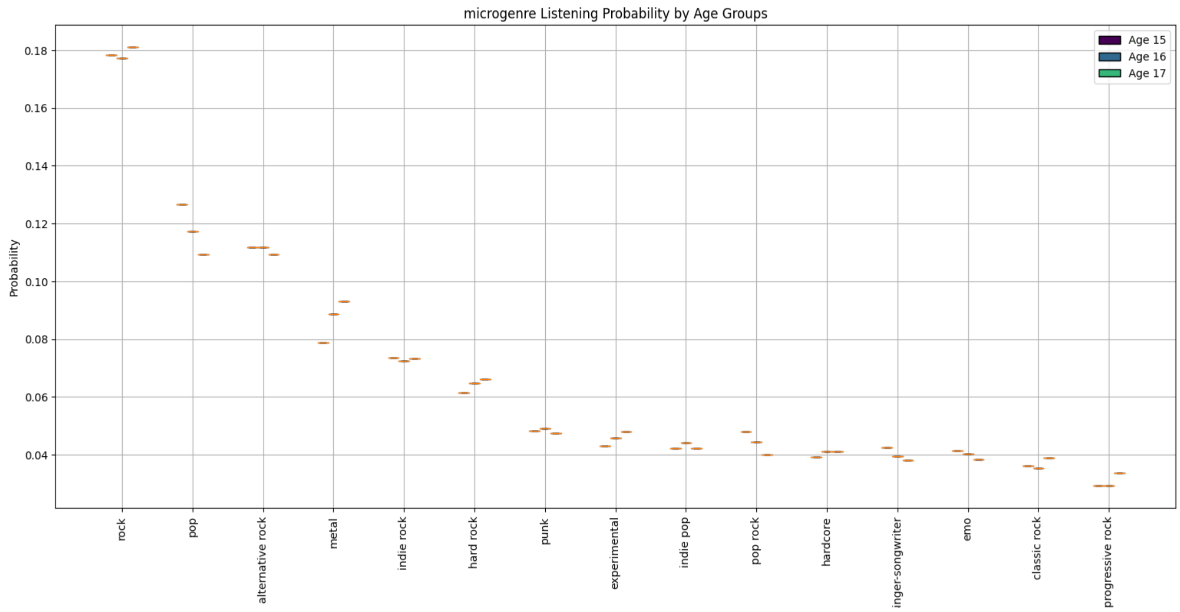

Figure 7: Micro-genre prominence ages 15, 16 and 17

the analysis for this feature differs from the previous ones. In actuality, besides from the fact that micro-genres are complicated to define, they are also composed of labels generated and given to tracks by users, making it a very subjective metric. In fact, users do not always understand the slight differences between genres and can thus mislabel tracks. This makes tags and subsequently micro-genres a less reliable metric as to what category of music they actually belong to. This would also explain the illogical prominence of rock, metal, and other "more aggressive" micro-genres which seem ill-fitting for young children within Grade School.

Another important observation to discuss is the high variability observed for Grade School users, regardless of the feature analysed. We suppose this can be due to a combination of two things. Firstly, the amount of users within this demographic represents a mere 1.67% of the total population of users aged 6 to 17 years old. This makes observations on this demographic less accurate. Secondly, the Grade School educational level contains more ages in comparison to the other groups (i.e. 6 different ages for Grade School but only 3 for Middle school and High School). Moreover, this variability can also be an indication that younger children have more individual preferences, in contrast to High School users, who seem to have more uniform preferences. Analysing this even further, can give us a suspicion that users in High School gravitate towards more similar tastes in order to fit in more with their peers. This is further explained by the fact that music plays an important role in shaping the cultural lives of contemporary teenagers [1].

An additional limitation worth taking into consideration is the technical limits of Spotify's algorithms. More specifically the algorithms responsible for detecting the key and the time signature of a song. In the Spotify documentation, there is an accuracy metric used for key and time signature, which ranges from 0 to 1 with 1 being a very accurate recognition of the feature and 0 being an inaccurate one. For the scope of this research and in order to have as many data points as possible, this metric was ignored. Moreover, an inaccuracy was observed in the Spotify documentation, as it was said that time signature ranged between 3 and 7, while the results showed that it ranged between -1 and 5, excluding the number 2. However, since time signatures 4 and 3 made up more than 95% of listening events, which aligned with time signatures 4/4 and 3/4 being the most popular ones, we decided to ignore the rest of the results.

7 Responsible Research

While conducting this research, we respected several principals in order to ensure the responsible use of data. All data used from Spotify and the LFM data base was anonymous, ensuring that individual users couldn't be identified. Furthermore we recognise and potential biases due to the small number of people within the Grade School level as well as the subjectivity of micro-genres.

8 Conclusions, Implications and Future Work

Our research aimed to explore the prominence of three specific song features, which are key, time signature and micro-genre among children of different age groups in order to improve existing knowledge about the listening habits of this demographic. For the first feature, our research showed that certain keys are more prominent than others. In fact, over 30% of the listening events for children aged 6 to 17 are in the keys C, D, G, and A. Small differences were noted across age education levels but with minor statistical significance. However, the lower variability within high school students, paired up with key prominence being less extreme (i.e. keys that were extremely popular among Grade School users are slightly less popular and keys that were extremely unpopular are among Grade school users are slightly more popular) shows us that while High School users listen to music with more varied keys compared to younger users, that variance does not change a lot during the ages 15 to 17. While this trend persists across the different age groups it is important to note that the variability within age groups decreases as the age increases. This shows us that listening habits tend to become more uniform as children grow up. When it comes to time signature, we have observed an overwhelming majority (about 90%) of listening events are in the time signature 4 which is the time signature most songs are written in. For this feature, differences between age ranges were negligible. Lastly, micro-genre prominence remains quite similar within the different education levels, and while this metric is by far the more subjective one, rock and pop make up about 30% of listening events, with sub-genres of rock following in popularity.

Finally, the results of this research expand our current knowledge on the musical preferences of children within these educational levels. Additionally, this research helps increase the understanding and the importance of the music features key, time signature and micro-genre. In fact, using the results on feature prominence from this paper, in order to fine tune existing recommender systems has the potential to improve them, offering an improved experience for users under the age of 18.

For further research, a focus could be put on the relation between current song popularity and age, to establish if whether or not users of different ages listen to songs because they like them, or simply because they are popular. In case of a correlation, this could clarify any incoherence found with trending music compared to the average listening tendencies of a particular age group. Another aspect this paper briefly touches upon that could deserve further research is how young is too young for predictive algorithms. As we saw, the 6 to 11 age category constitutes a tiny fraction (1.76%) of the total number of children, distinguish itself from the other two categories. Adding in notions of child psychology would also be useful for future works, as it would allow us to understand why certain keys or rhythms are popular, and could help establish a clearer picture.

References

[1] Tia DeNora. *Music in everyday life*. Cambridge university press, 2000.

[2] Susan Hallam. "The power of music: Its impact on the intellectual, social and personal development of children and young people". In: *International journal of music education* 28.3 (2010), pp. 269–289.

[3] *Key — Music, Major, Minor, & Chromatic Scales*. URL: https://www.britannica.com/art/key-music.

[4] Albert LeBlanc et al. "Music style preferences of different age listeners". In: *Journal of Research in Music Education* 44.1 (1996), pp. 49–59.

[5] *Music Xray's Blog - The Most Popular Keys of All Music on Spotify*. URL: https://blog.musicxray.com/the-most-popular-keys-of-all-music-on-spotify/.

[6] Francesco Ricci, Lior Rokach, and Bracha Shapira. "Recommender systems: Techniques, applications, and challenges". In: *Recommender systems handbook* (2021), pp. 1–35.

[7] Markus Schedl and Christine Bauer. "Online music listening culture of kids and adolescents: Listening analysis and music recommendation tailored to the young". In: *arXiv preprint arXiv:1912.11564* (2019).

[8] Markus Schedl et al. "Current challenges and visions in music recommender systems research". In: *International Journal of Multimedia Information Retrieval* 7 (2018), pp. 95–116.

[9] Markus Schedl et al. "LFM-2b: A Dataset of Enriched Music Listening Events for Recommender Systems Research and Fairness Analysis". In: *Proceedings of the 2022 Conference on Human Information Interaction and Retrieval*. CHIIR '22. Regens-

burg, Germany: Association for Computing Machinery, 2022, pp. 337–341. ISBN: 9781450391863. DOI: 10.1145/3498366.3505791. URL: https://doi.org/10.1145/3498366.3505791.

[10] Lawrence Spear et al. “Baby Shark to Barracuda: Analyzing Children’s Music Listening Behavior”. In: *Proceedings of the 15th ACM Conference on Recommender Systems*. RecSys ’21. Amsterdam, Netherlands: Association for Computing Machinery, 2021, pp. 639–644. ISBN: 9781450384582. DOI: 10.1145/3460231.3478856. URL: https://doi.org/10.1145/3460231.3478856.

[11] *Time signature — Definition & Examples — Britannica*. URL: https://www.britannica.com/art/time-signature.

[12] *Web API Reference — Spotify for Developers*. June 2024. URL: https://developer.spotify.com/documentation/web-api/reference/get-audio-features.