Baby Shark to Barracuda: Analyzing Children's Music Listening Behavior

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ABSTRACT

Music is an important part of childhood development, with online music listening platforms being a significant channel by which children consume music. Children's offline music listening behavior has been heavily researched, yet relatively few studies explore how their behavior manifests online. In this paper, we use data from LastFM 1 Billion and the Spotify API to explore online music listening behavior of children, ages 6–17, using education levels as lenses for our analysis. Understanding the music listening behavior of children can be used to inform the future design of recommender systems.

CCS CONCEPTS

• **Social and professional topics** → *Children*; User characteristics; • **Human-centered computing** → *User models.*

KEYWORDS

music recommendation, children, preferences, music traits

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1 INTRODUCTION

Music is an essential part of human life, with much of it being consumed through online platforms equipped with recommender systems designed to aid users in discovering new music. However, these platforms largely cater to adult listeners, as does most literature on music recommendation [23]. Research aiming to address the lack of representation for children in music recommendation includes the work by Schedl and Bauer [20], who explored music genre preferences of children in order to generate recommendations specifically for them. They discovered significant distinctions in music preference between child and adult users. Other prior works have mostly considered music genre preferences in children [3, 27]; however, there are many other aspects of music that can influence music preference.

Psychological research has also investigated music listening behavior among children of different age groups based on factors such as gender, location, and education level [4, 6, 7, 16, 18]. Further, the social and cognitive impact of music on children has been heavily examined [10, 24]. Among notable studies we find the work by Holbrook and Schindler [12], who explain that the development of music preference continues to develop until 23 years of age, at which time it is implied that music preferences crystallize; Ter Bogt et al. [26] support the previous claim by inspecting children's music preferences at different age groups while considering the influence of time-related factors and the evolution of music on children's listening behaviors. To examine the impact of different musical

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Table 1: Overview kMusic. GS (Grade School), MS (Middle School), and HS (High School) are the education levels in our analysis.

	Education Level			High School - Ages		
	GS	**MS**	**HS**	**15**	**16**	**17**
Users	57	282	3,077	493	946	1,638
LEs	951,840	2,385,849	33,758,826	4,296,583	9,747,692	19,714,551
LEs w/ Audio Features	490,280	1,395,974	19,693,605	2,524,450	5,729,399	11,439,756
Distinct LEs	237,714	330,315	2,212,716	484,126	892,385	1,588,660
Distinct LEs w/ Audio Features	116,157	159,607	786,301	221,099	368,285	607,248

features on children, LeBlanc [13] considers the open-earedness–defined as an openness to new music [11]–of children by highlighting how this trait fluctuates according to age and pinpointing when these fluctuations occur [8, 9]. Further, LeBlanc et al. [14] claim that children can develop music preferences differing from adults' and therefore seek to prove that maturation influences open-earedness; a claim which serves as a motivation for our work. Although aforementioned studies analyze the music listening behavior of children, many of the insights have not been applied to the field of music recommendation.

Unlike findings from psychological research related to changes in listening behavior at distinct age groups, recommender systems research has primarily focused on children's music genre preferences as a whole. Ferwerda et al. [3] do emphasize the importance of considering age when studying personality-based music preferences by comparing and contrasting taste in users' music preferences as individuals go through different phases of their life. While they offer insights on the effect of age in personalized music recommendations, the authors limit their exploration to adolescence, young adulthood, and middle adulthood. Much like Ferwerda et al. [3], we agree that it is important to consider children in specific age groups, such as developmental or education levels, when examining music tastes as individuals in those groups might share similar preference traits. To expand on the existing knowledge of music listening behavior of children (defined for our work as individuals aged 6 to 17), we investigate preferences of children based on their interactions with music platforms. For this, we create a dataset, i.e., *kMusic*, by leveraging the popular LastFM 1 billion [19, 21] (LastFM-1b), which we augment with other domain-specific information extracted from the Spotify API [25].

Motivated by findings from LeBlanc et al. [14], who claim that music preferences can vary according to education level, we use educational levels as lenses for our analysis. We divide users in kMusic into Grade School (**GS**) ages 6–11, Middle School (**MS**) ages 12–14, and High School (**HS**) ages 15–17. This segmentation allows us to investigate the differences that can occur based on maturing preference and corroborate the observed shift in preference across education levels. As individuals near adulthood, they show a diversity of preference and an interest in a wide range of music styles [3, 27]. Given that the HS population portion of kMusic is noticeably larger than the GS and MS counterparts, we posit that there might be more distinctions among children in this group. Therefore, we also probe preferences among users in the HS group with more granularity, by analyzing their preferences by age (15–17).

Our primary goal is to analyze online music listening behavior in order to discover emerging trends in children's music preference at different stages of their lives[1]. In particular, we go beyond examining preferences in popular music genres (e.g., rock and pop) by considering a wider range of genres (e.g., alternative rock and soul), *user characteristics*, such as the number of distinct tracks they listen to, and other specific *music traits* they favor, such as tempo. Unlike previous work, we study the fluctuation of these characteristics by educational level and further dig deeper into high-school children by individual age. Outcomes from this exploration are meant to provide insights into the musical preference of children and prompt future avenues of research related to recommender systems for children. Specifically, findings can inform the development of user models that better represent the music preferences of children and can be used to inform design and development of recommender systems targeting this audience.

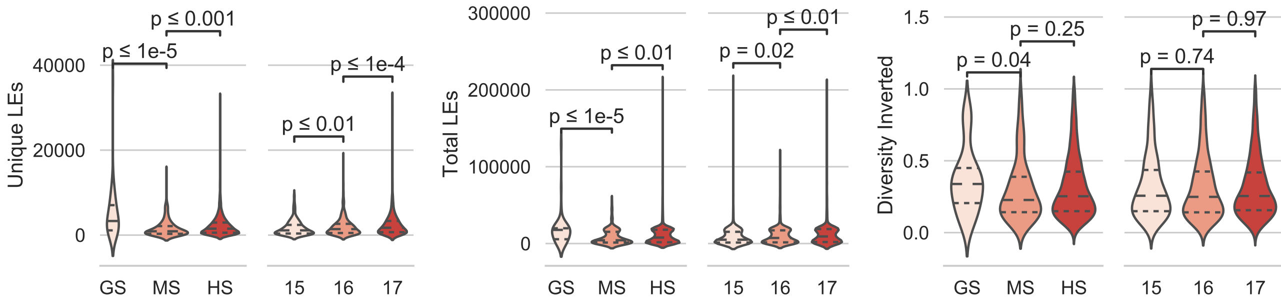
2 KMUSIC DATASET SETUP

We use LastFM-1b as the primary basis for our study. LastFM-1b captures 1,088,161,692 listening events (**LE**) collected from January 2013 to August 2014 [19, 21], each of which contains a user-id, artist name, album name, track name, timestamp, and artist genre-related information. To focus on children, we consider only LE corresponding to the 3,416 users aged 6 to 17. To enable a more in-depth exploration of children's preferences (i.e., going beyond music genre), whenever possible, we augment LastFM-1b with additional domain-specific traits, called audio features, for tracks extracted via the Spotify API [25]: acousticness, danceability, energy, instrumentalness, key, liveness, loudness, mode, speechiness, tempo, and valence. This results in the integrated **kMusic** dataset we use in our exploration (see Table 1).

3 ANALYSIS

We detail our analysis based on user characteristics and music traits. Results reported are averaged per user (in each user segment) in kMusic. Statistically significant results are identified by employing Student's t-test with $p \leq 0.005$.

[1]Notebooks for dataset generation and replication of analysis available at https://www.github.com/PIReTship/kMusic-LBR21



(a) Unique LE (b) Total LE (c) Diversity Inverse

Figure 1: Diversity of LE across users in kMusic, based on education levels and age for HS.

3.1 Do user characteristics influence musical preferences of children?

We start our exploration by analyzing three user characteristics that are commonly used to describe users' preferences in music: diversity, novelty, and mainstreaminess.

We consider whether children are interested in a variety of music by looking at the **diversity** of their listening behavior. Diversity is defined as the total number of LEs over distinct LEs [22], meaning diversity increases as children listen to mostly the same songs repeatedly. We invert this score to represent the same concept but bounded in the range $[0, 1]$ with higher numbers representing greater diversity. There are no significant differences between the groups, as shown in Figure 1(c). To understand why the lack of significance occurs, we explore the components of diversity. In Figure 1(a), we see GS is inconsistently listening to various music, exhibited by the large range of unique LEs, when compared with individuals in MS and HS. With MS, we note that children in this segment start to separate into a mainstream group: children who listen to similar music and another smaller group who listen to a much larger variety of music. In HS this separation further expands. In Figure 1(b), a similar separation pattern occurs with GS, MS, and HS for the total LEs of children's listening habits. We further explore the HS ages and see in Figure 1 a slight trend down of their diversity preference. However, regarding unique LEs, we can see as children mature the separation between the majority group of children, that prefer less variety of music, and those that prefer a large variety of music increases. The same holds true with total LEs.

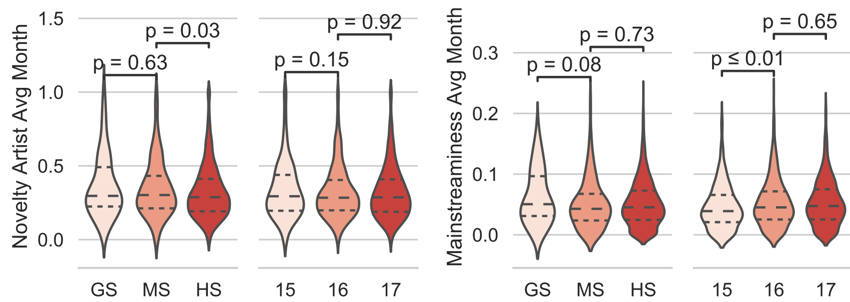
Next, we explore whether children are open to novel music, or if they instead adopt a more conservative approach to music selection. **Novelty** is defined as a user's "inclination to listen to unknown music" [22]. In our analysis, we use the *Novelty Artist Avg Month* score (novelty for short) introduced by Schedl [19], which averages each user's monthly novelty scores. As shown in Figure 2(a), GS has the largest range of novelty scores with MS being smaller and HS being the smallest. Also, a similar separation as diversity is seen, with a group of children preferring a lower novelty and another demanding it, with the gap in those groups increasing from MS to HS. Within this latter group, we see in Figure 2(a) that when considering the age of children in this group, novelty decreases as children age and separation widening between the groups, but the difference is less pronounced than what we saw in diversity. However, like diversity, none of the novelty scores across GS, MS, HS, or HS ages are significant between the groups.

Lastly, we consider if children listen to more mainstream music or if they instead avoid "trendy" music. **Mainstreaminess** is defined by Schedl and Hauger [22] as user's preference of music that is currently trendy. In our analysis, we use the *Mainstreaminess Avg Month* score (mainstreaminess for short) introduced in [19], which averages each user's monthly mainstreaminess scores. From Figure 2(b) we see that GS has the largest range of mainstreaminess with a sharp decline in MS and a slight increase to HS, but overall the amount of mainstream music is low. Again, as with diversity and novelty, we see a separation of groups with MS and HS. Within this latter group, we see in Figure 2(b) that mainstreaminess slightly increases as children age. However, like novelty and diversity, none of the mainstreaminess scores across GS, MS, HS, or HS ages are significant between groups.

3.2 Do music traits influence music preferences of children?

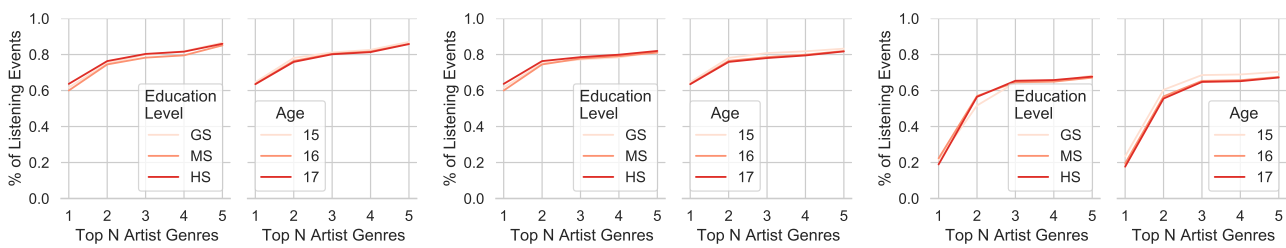
We switch the perspective of our analysis towards music specific traits that manifest in children's music listening behavior: artist genres, along with acousticness, danceability, energy, instrumentalness, key, liveness, loudness, mode, speechiness, tempo, and valence, as defined in the Spotify API Spotify [25].

To investigate **artist genres**, we use the 20 artist genres defined in AllMusic [1]. It emerges from Figure 3(a) that a majority of the LEs have the top artist genre of Rock across all children regardless of education levels. The top 5 artist genres cover over 80% of the LEs. We attribute this to be the result of AllMusic's artist genre list being too generic, so we extend our genre exploration by instead considering Freebase's taxonomy of nearly 2,000 artist genres. In Figure 3(b), we still see that the majority of LEs have the top artist genre of Rock for all education levels, and the top 5 artist genres also cover over 80% of the LEs. Freebase's artist genres are a superset of AllMusic's artist genres, so Freebase would have the same generic artist genres. This prompts us to exclude the AllMusic artist genres from the Freebase artist genres, with the aim of bypassing genres that are overly generic, and re-examine genre preferences



(a) Artist Genre Novelty Average Over a Month (b) Mainstreaminess Average Over a Month

Figure 2: Novelty and mainstreaminess analysis for children in kMusic, based on education levels and age for HS.



(a) AllMusic Artist Genres (b) Freebase Artist Genre (c) Freebase Excluding AllMusic Artist Genre

Figure 3: Artist genre preferences across children in kMusic.

for children in kMusic. As shown in Figure 3(c), instead of only needing the top genre to get the majority of LEs, we need the top 2 artist genres regardless of the educational group. The same trend emerges when analyzing in-depth the HS group.

Energy measures the intensity and loudness of music, with high energy suggesting more intense and louder music. As shown in Figure 4(b), GS has the lowest overall energy level and MS has a significant increase over GS. HS stays about the same as MS. When looking at music energy levels of HS ages, we see that the energy levels slightly but significantly decrease as the children get older. We see a similar trend in Figure 4(a) with **Loudness**, a logarithmic measurement (Spotify API [25]) that captures music's average loudness across the song measured in decibels.

Valence, measures music's positiveness, where high valence suggests happier and more upbeat music and low valence represents more depressing and angry music. As evidenced in Figure 4(c), valence slightly but significantly decreases from GS to MS to HS. When we explore HS by ages for a more detailed look into this decrease, we find the trend does continue down in a significant manner from 15 towards 17.

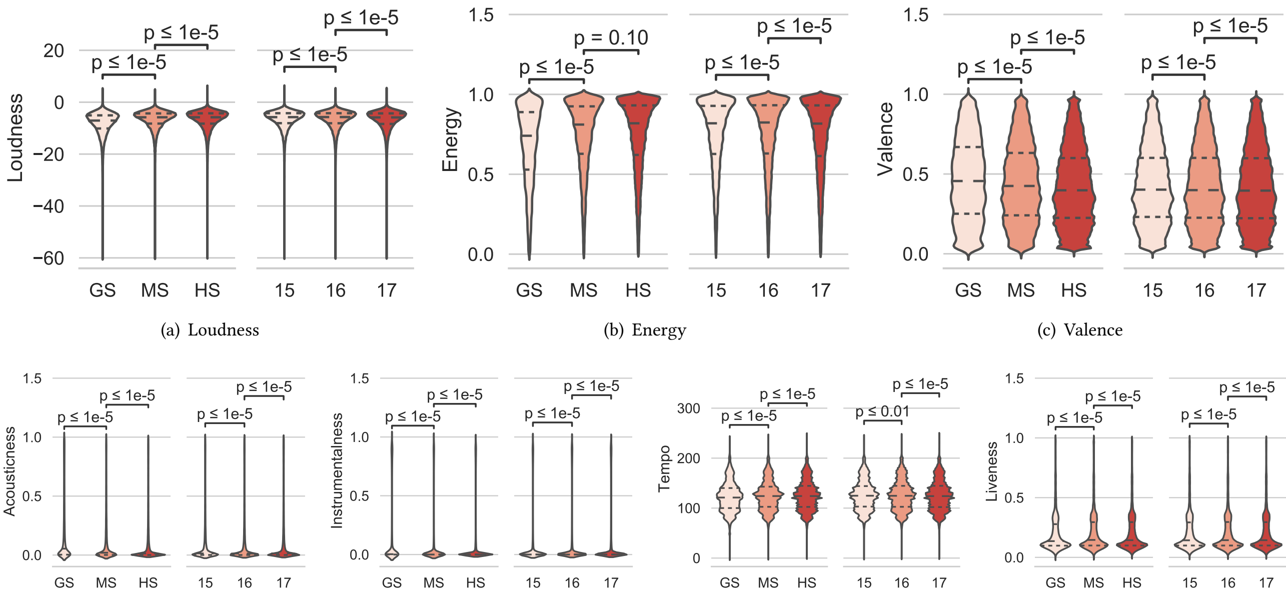
Acousticness (range $[0, 1]$) captures whether a song is acoustic; the higher the score, the more acoustic the song. Again, GS exhibit the largest range in preference for acoustic music (Figure 4(d)). Acousticness preference is instead more uniform in MS and HS. We also see noticeable clusters of MS and HS users who deviate from the stereotypical trends in acousticness. We see similar trends in Figure 4(e) for **instrumentalness** (range $[0, 1]$) captures whether a song contains no vocals; the higher the score, the lower the vocal content.

We also examined preferences for tempo, danceability, speechiness, liveness, and song duration and saw fluctuations across education levels were significant (see Figures 4(f), 4(g)). As most of the differences were in fact negligible, and would therefore not impact recommender system design, we omitted detailed analyses from our discussion.

3.3 Discussion and Implications

Music can benefit children emotionally, socially, and cognitively; with music recommender systems potentially serving as an excellent vehicle for their interaction with music. However, making sure that children are provided with music they would like is difficult. Unfortunately, most music recommender systems are geared towards adults, which differ from children in their music preference [20], and do not account for the tastes and preferences of children.

With this work, we established that children's tastes can vary across age; making the recommendation process more complex when targeting children. We have examined the listening behavior of children in kMusic to better understand trends in tastes and preferences at different stages of their lives–specifically educational levels. To look deeper into some trends, we probed at age for HS groups as well. Previous work explores children's music preferences for online music recommendation [20], primarily focusing on artist genre. Our analysis begins to investigate how other aspects of children's music listening behavior can inform their preferences.



(a) Loudness (b) Energy (c) Valence (d) Acousticness (e) Instrumentalness (f) Tempo (g) Liveness

Figure 4: Audio features preferences across children in kMusic, based on education levels and age for HS.

The trends seen in this preliminary analysis support some of the stereotypes we've come to expect in children's music listening behaviors. The idea that a majority of teenagers listen to the same dark music on repeat is supported by our analysis, however, there is a minority group that diverges from that stereotype. Similarly, GS gravitate to music that is more "happy" or "upbeat" than MS and HS, leaning into the idea of this age group being energetic and mirroring the trend seen with children's books preferences in Milton et al. [15], who found that darker themes and more negative feelings become more prominent as children get older. These insights provide us with a fuller image of the online music consumption behavior and musical preference of children, which can be used by recommender systems to better support music discovery for children.

Recommender system design could leverage insights gleaned from analysis regarding user characteristics. For example, increasing serendipity [5] for GS children as they are still listening to a large variety of music, then for MS and HS focus on more "expected" (mainstream) music. However, recommender systems should also look for preferences of children who do not adhere to the patterns for their user group and adjust the level of serendipity or trending music accordingly. From our observations, we also surmise that novelty might be too generic of a grouping to derive significant differences between children. We attribute this finding to artist genre, which is used in novelty's calculation, being too broad a category for useful understanding of listening behavior. Consequently, recommender systems would not be able to rely solely on artist genre for personalization when it comes to recommending music to children, which is anticipated. Yet, artist genre could be a facet to consider for popularity-based recommender algorithms targeting users in the varied educational groups under study. Some trends emerging from domain-specific traits were indeed significant across education levels, but in practice, they were so small that a recommender system may not be able to leverage them. Consider for instance **Tempo**–music's overall beats per minute (BPM). In Figure 4(f), children in GS prefer music around 122 BPM with a significant shift in MS towards 124 BPM, and another shift in HS to 125 BPM. This slight preference change may be hard to leverage in recommender system even though it is significant in our analysis.

Overall, we see a trend where users in GS display non-uniform characteristics (at the user and music level), i.e., there is a broad range of scores among users in the group regardless of the trait considered. On the other hand, users in MS seem to exhibit more uniform preferences on user and music traits, but with a notable cluster of users within the group who do not fit the stereotypical preference trends observed among the majority of users in this group. The same is true in HS, the majority of the users gravitate towards the observed stereotypical preference trends. Nevertheless, as HS users mature (15 towards 17) we see that the cluster of users who deviate from main trends becomes more prominent.

4 CONCLUSIONS, LIMITATIONS, AND FUTURE WORK

In this paper, we present our initial steps towards better understanding children's music preferences. We discuss our preliminary exploration of music listened to by children, extracted from the popular LastFM-1b dataset, and augmented with the Spotify API. We also summarize the main findings emerging from our analysis and bring to attention the potential implications these findings may have on the design of music recommender systems for children.

Our analysis spotlights the music listening behavior of children ages 6 to 17 in our dataset. Even within the younger ages we examine, we may not be capturing the full preferences from logged listening behavior, as younger children tend to be exposed to music the adults in their lives listen to. Similarly, we cannot guarantee that LE are manually triggered as auto-play exists and would log events without interaction of the user, nor can we ensure a user liked a song since LastFM-1b has no user ratings for the LE. From a data perspective, certain ages are sparse in the number of LE and LastFM-1b is an older dataset (2014). Researchers would need to expand the current dataset with more recent listening data for users specifically within the GS and MS education levels, which would also allow for deeper investigation into an age by age comparison. Such an augmented dataset would enable us empirically determine the degree to which existing music recommender systems support children and would provide insights as to what aspects of adult-centric recommender strategies work for children. We also plan on conducting a longitudinal study on how children's music tastes change as they age, which could inform the design of adaptive recommender systems, particularly when children make the transition into adulthood since many recommender systems use historical data to build models of their users. Further, by comparing children to adults, trends can be highlighted for recommender systems to leverage.

We focus on education, yet, there are other demographic data points, e.g., region and culture, of children that could inform preferences. Further, our analysis looks beyond artist genre to investigate trends in children's preferences, yet we only study a subset of the basic music elements that make up music analysis. In the future, we could include more elements of music composition, vocal aspects, lyrical information, and vocabulary. Although children are visual in nature, we deemed visual aspects out of scope. However, we aim to consider visual aspects in future iterations of our work, as they have been shown to influence preference [2, 17]. While we considered artist genre, artists can release tracks or albums for a variety of genres, therefore future work can be expanded to account for these varieties.

Preliminary findings bring clarity to the fact that while there is a "stereotypical" audience within children, there is enough distinction–visible across different groups–to corroborate that "one size fits all" recommendation strategies will not work for children.

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