# From Hook to Chorus

**Analyzing the relation between song structure and music listening behavior of children**

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## Abstract

The music listening preferences of children have been the subject of numerous studies, intending to inform the design of music recommender systems to better cater to children's specific needs. Most of these studies are centered around genre, while few explore other traits of songs to capture listening behavior. In this research, we propose song structure, the arrangement of songs into sections, as a novel lens to analyze children's music preferences. We create an extension from the popular LFM2b dataset to the Genius Lyrics dataset. Using this dataset, we group song interactions of users according to the educational level of children aged 12 through 17 and adults, and analyze and compare how song sections play a role in their listening behavior, based on the share of similarly structured songs in their listening data. To identify similar song structures, we cluster songs on their song structure fingerprints, extracted from their lyrics. We find no salient differences in the preferences of the children's age groups, but we do find preliminary indications that adults interact less with songs characterized by the presence of lyrical Hooks (the most catchy parts of songs) than children and more with songs that are focused around Choruses. Although these insights can be used directly by recommender systems, our findings can be used as a springboard for future audio-based research to focus on not only lyrical, but also instrumental Hooks and their relation to children's music preferences.


## 1 Introduction

Recommender systems (RS) are systems designed to find content that users of that system might like. One of the evident challenges of these systems is the heterogeneity of these users, who are diverse in all aspects of life, including their developmental phase. In the context of music RS, children in particular (in this work aged 12 up to and including 17) are a target group often under prioritized by these systems according to Ungruh, Bellogin and Pera [19], due to the relatively small representation of children in the datasets on which RS are typically trained. Meanwhile, children are still a large music consumer base [15]. Additionally, they are in the phase of their lives in which music preferences are shaped [4]. Therefore, it is important that music RS can aptly cater to the specific needs of children.

Studies in which RS are trained specifically on children's listening data show that doing so can sometimes lead to better performance [16], but can also lead to poorer performance [19]. These different and inconclusive results suggest that there is still a gap in knowledge of why children listen to the music that they listen to. This knowledge is highly valuable for RS. If more preferences are known, RS can leverage these preferences in their recommendations, which can possibly lead to better catering towards the music taste of children.

Many previous works examining children's music listening preferences have done so in the context of song genre [3; 16; 19]. In other work, Spear et al. [17] have broadened the scope by including additional simple music traits such as loudness, acousticness or tempo. Still, relations between other, more complex song characteristics and children's music preferences are left unexplored.

Thus, in this research we propose song structure as a new lens of analyzing children's listening behavior. As such, we maintain a common definition of song structure, which can be described as *the composition or arrangement of a song in terms of song sections* (i.e., Intro, Verse, Chorus). We pose the following research question.

**"To what degree does the structure of songs relate to the music listening behavior of children in different age groups?"**

To address this question, we conduct a mixed method empirical data analysis on the song structure of songs listened to by users (from children to adults) of the popular music streaming service Last.fm. From these users, we utilize the history of their interactions with tracks: listening events (LEs).

Akin to Spear et al. [17], we follow the practice of grouping children on ages related to their educational level, as it was shown by LeBlanc et al.[5] that music preferences can be similar within educational levels, while differing across them. We add adults as a reference group.

First, we produce a linkage between the popular LFM2b dataset from Last.fm (as processed by Ungruh, Bellogin and Pera [19]) with the Genius Lyrics (GL) dataset [6]. We then calculate the normalized share of songs with a similar song structure in the LEs of the age groups. The latter is achieved by clustering songs on their calculated song structure fingerprint, extracted from the song's lyrics. With a more qualitative analysis, we inspect song structure and gain insights on what differences exist in the listening behavior from children aged 12-14 and 15-17 and adults (aged $\geq 18$).

This research contributes to the knowledge of the distinctness of children's music preferences from adults through a new perspective of song structure. The insights can be used to further inform recommender systems tailored to serving children. In addition, we provide an extension of the LFM2b dataset to the GL dataset that can be used in further research.

## 2 Related work

Music listening behavior (also referred to as [music] preferences [3; 16; 17] or consumption patterns [19]) over different age groups has been researched through two opposite lenses. On the one hand, works have highlighted the relation between personal characteristics and listening behavior, highlighting the user side of the user-music interaction that is the essence of RSs. For example, Ferweda, Tcalcic and Schedl [3] find that extroverted individuals aged 12-19 favor r&b music, while listening less to classical or punk music. Other factors include the user's country and gender [16] or more latent factors as novelty: how willing users are to try new, unknown music [17]. On the other hand, traits of songs – the music side of user-music interaction – are a different way to analyze listening behavior, with the benefit that this needs no extra personal data from the users. Spear et al. [17]

note that most works consider genre as the indicator for music preference and in response add different music traits such as song tempo, loudness and acousticness to their analysis. Yet, they call for future research to investigate more elements including song composition.

In this work, we build on top of their view by focusing analysis on song structure. Interestingly, song structure is related to genre. For example, there exists research that aims to predict genre based on song structure [9] and the Merriam Webster dictionary [11] defines the term *genre* as

> "a category of artistic, musical, or literary composition characterized by a particular style, form, or content".

It is in this that we argue that song structure, corresponding to the form of the content in the definition, captures a more niche aspect of songs than genre and can thus account for more nuances of music taste. Using the structural information on which sections appear in a song, where they appear and how much they appear, we can for instance identify which sections are most present in songs and how early or scattered they appear. This provides valuable information with respect to repetition in songs, which is understood to be a key factor in music. For instance, repeatedly listening to songs over and over is a way that infants develop multiple auditory skills [10]. In addition, research found that repetition of lyrics in songs increases the likelihood of the song reaching high positions in the charts [12].

# 3 Analysis setup

In this section, we outline the required setup for the qualitative analysis of song structures. This setup covers the data used, data pre-processing and methods for data-analysis such as clustering. The codebase containing all steps for (pre-)processing and analysis is available at https://www.github.com/sbakker6/MusicRSAndChildren.

## 3.1 Datasets & pre-processing

Since no dataset is available that satisfies the need for both listening events with user age information and information on song structure, we use two distinct datasets.

We use the two datasets (LFM2b) as processed by Ungruh, Bellogin and Pera [19] and the Genius Expertise dataset [6] – in this work referred to as Genius Lyrics (GL) to emphasize the main focus on lyrics. The LFM2b dataset originates from the music streaming platform Last.fm[1]. The used processed version contains 1.131.465.529 listening events (LE) of 45.601 users from 193 countries around the world, spanning 20.131.689 tracks. The events date from 2015 to 2020 and provide information on which user has interacted with which track by which artist at what timestamp and at what user age ($\pm 1$ year). The GL dataset contains annotated lyrics of 37.993 song, as provided on the popular website Genius.com[2], as well as some information on the song artists.

Since these two datasets are not directly compatible, we use fuzzy matching of song titles and artist names to link the songs of GL to tracks in LFM2b. In order to do this, we preprocess GL and LFM2b, then apply fuzzy matching as follows. To help distinguish database sources, we use the terms *track* and *song* to describe the musical entries in LFM2b and GL respectively.

**Extract artist and song title from URLs (GL)** GL provides lyrics as the content of the genius website at a specific page, i.e. the data gives a URL and its contents. From inspection of the data, we see that the URL of these pages contains information on artist, song and the type of content. One example from such a URL is *Dr-dre-darkside-gone-lyrics*. We disregard the 545 entries that were genius annotations; we only consider songs with the suffix *lyrics*. By cross-referencing the established URL names of artists (also provided by the GL dataset), we extract the artist as the first matching artist to the prefix of the song URL. The rest of the URL (excluding suffix *lyrics*) is then considered the song name. This method successfully finds 37.351 mappings from song URL to artist.

For the failed 97 URLs, no artist mapping can be found. However, by using a longest-common-prefix matching per song URL on this failed subset of URLs, we can successfully map 58 URLs to their most probable artist and song names. For example, *Cashmere-cat-wild-love-lyrics* and *Cashmere-cat-europa-pools-demo-lyrics* and seven other songs from the artist Cashmere Cat can confidently be mapped to this artist, as their common prefix *Cashmere-cat* appears nine times in the set of failed URLs. In total, we are able to extract an artist and song name for $\sim 97\%$ of the songs.

**Filtering out instrumental songs (LFM2b)** To slightly speed up the process, we reduce the matching search space by crudely filtering out any tracks in LFM2b that contain any form of the literal *instrumental* in their name. We assume that these tracks do not contain lyrics at all, and therefore will not yield a useful match to any song in GL. We are left with 19.990.774 (99.3%) tracks and 1.129.614.290 LEs (99.8%).

**Apply fuzzy matching between GL and LFM2b** First, we use broad pattern matching in our PostgreSQL database to select tracks and artist from LFM2b similar to the song and artist from GL. Then, using the Levenshtein distance [1], we compute an overlap-ratio for both the artist name (artist confidence) and the song name (track confidence). We rank them on the overlap-ratio (highest ratio gets ranked first). The highest ranked track that also has a 100% artist match is directly assigned and if no such track exists, we take the highest ranking track. In the case that multiple GL songs map to the same track, we use the mapping where the sum of the artist and track confidence is greatest.

These pre-processing steps have eliminated a substantial amount of listening events (see Appendix A for details). Of the initial 1.129.614.290 non-instrumental LEs, we keep 1.482.194 (0.13%) due to the matching. Of these 8.850 are of children in MS, 71.831 of children in HS and 1.401.478 of Adults. Despite the skewed distribution, Figure 1 shows that the drop in the share of children is similar across the ages 12-17, indicating that we retain similar distributions for the focus age groups of this research to the original dataset.

[1]https://www.last.fm

[2]http://www.genius.com

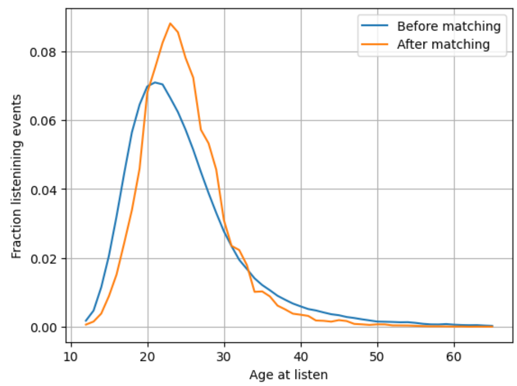
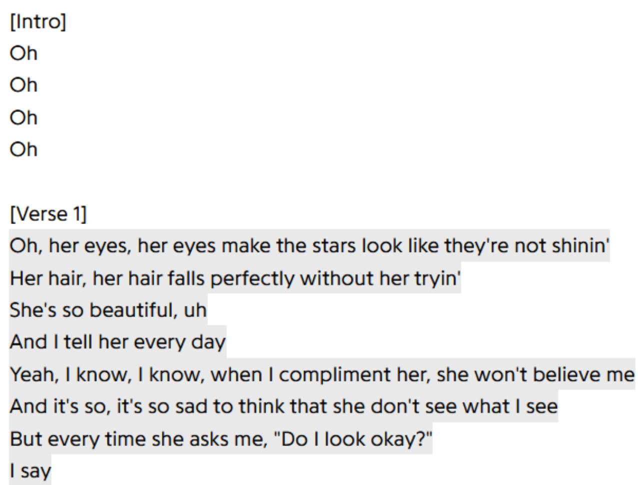



Figure 1: Distribution of LEs over user age, before and after matching the two datasets.


[Intro]
Oh
Oh
Oh
Oh

[Verse 1]
Oh, her eyes, her eyes make the stars look like they're not shinin'
Her hair, her hair falls perfectly without her tryin'
She's so beautiful, uh
And I tell her every day
Yeah, I know, I know, when I compliment her, she won't believe me
And it's so, it's so sad to think that she don't see what I see
But every time she asks me, "Do I look okay?"
I say

Figure 2: Screenshot of Genius' lyrics for Bruno Mars - Just The Way You Are from https://genius.com/Bruno-mars-just-the-way-you-are-lyrics.

### 3.2 Extracting and encoding song structure

GL contains the exact content from the Genius.com website. As such, lyrics contain embedded annotations inside brackets that structure the lyrics textually (Figure 2).

Using this information, we extract all brackets from the lyrics and filter on specific keywords, such as *Intro* or *Chorus*. A full list of all keywords can be found in appendix B.

In order to be able to quantify and standardize song structure, we encode the structure as a 42-dimensional vector: the structure fingerprint. This fingerprint is comprised of three descriptors of a song section for fourteen distinct sections (e.g., *Verse*, *Bridge*, *Hook*). Using (1) the amount of section appearances, (2) the average section position and (3) the standard deviation of the section positions as the three descriptors, we retain some information on the song structure ordering, while being able to standardize the structure for songs of arbitrary length. We define a position of a section in the song as a zero-indexed position it appears in with respect to all sections. For an exemplary song with structure *[Intro, Verse, Chorus, Verse, Chorus, Chorus, Outro]*, the section *Verse* will have positions $1$ and $3$. For sections that do not appear in the song, the average position and standard deviation are $0$.

The following fourteen sections have been selected based on a sample of the annotations in the lyrics and have been used to capture the song structure.

1. Intro
2. Verse
3. Pre-Chorus
4. Chorus
5. Post-Chorus
6. Pre-Hook
7. Hook
8. Post-Hook
9. Bridge
10. Outro
11. Instrumental
12. Vamp
13. Break
14. Solo

More detailed information on the keywords used to extract these sections can be found in appendix B.

### 3.3 Clustering song structure fingerprints

The structure fingerprints of songs can very a lot, as there are 42 dimensions. Analyzing based solely on individual fingerprints will be infeasible as there will likely be almost as many distinct fingerprints as songs. Therefore, it is imperative for a more meaningful analysis that similar song structure fingerprints are grouped together.

Since the clustering serves as a facilitating step towards interpreting similar song structures, rather than being a product of the research itself, there is little weight on which clustering method we use. In our case, we use k-means clustering with Euclidean distance, as it is simple and well-available. The fingerprints are first normalized according to common practice, to prevent scaling bias in certain components of the fingerprint. To assess the number of clusters to use, $k$, we use the elbow method to visually inspect the additional benefit of adding clusters to the overall mean distortion (see Figure 3). This distortion indicates the average distance of individual observations (song structure fingerprints) to their assigned cluster centroid. We take $k = 20$ as a good amount of clusters, as we see the diminishing returns after $20$ clusters on the average distortion. The distortion decreases marginally from this point forwards, visible from the derivative fluctuating around $0.0$.

## 4 Analysis Results

In this section, we analyze how the clustering of songs on their structure fingerprints provides perspectives to differences of listening behavior within age groups as well as across age groups.

### 4.1 Differences of cluster share within age groups

With $k = 20$ clusters, we obtain the share of clusters in LEs of MS, HS and Adults as presented in Figure 4.

Using the Chi-squared statistical test [13] we test for significant differences between the groups. This test is particularly suitable, as it compares observed cross-categorical counts with their expected counts under the assumption that the distributions are the same. In this case, we test whether

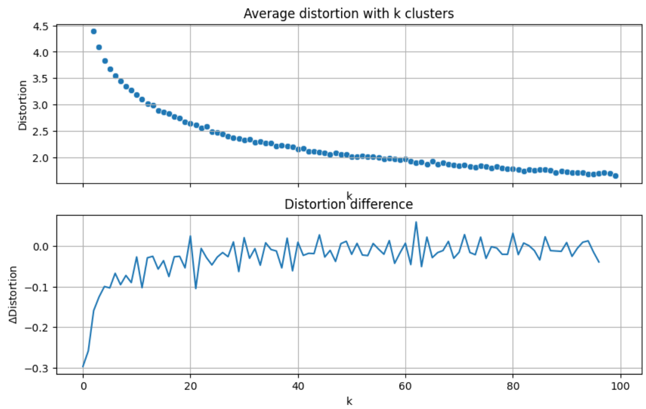



Figure 3: Average distance (distortion) between song structure fingerprints and their assigned cluster centroid (top) and the first derivative of the average distortion (bottom) for $k \in \{2, ..., 100\}$.

the age group has significant impact on the observed counts of listening events per cluster. The Chi-squared test yields a $\chi^2$ value of $23526.5$, with $38$ degrees of freedom and a $p$-value of $0.0$, indicating a significant difference of observed counts across groups MS, HS and Adults in comparison to our $\alpha = 0.05$. The full counts of listening events per cluster and age groups can be found in Appendix C.

If we look at the cluster share of LEs within the different age groups, we note that the children groups MS and HS have a less equal representation of clusters than Adults. For example, clusters 1-4 account for less than a combined $20\%$ of the LEs for both MS and HS, while the 4 largest clusters in both MS and HS $(5, 12, 13, 16)$ account for almost half $(50, 6\%$ for MS and $48, 4\%$ for HS). In contrast, we observe a more equal distribution in Adults, where only half of the clusters each represent less than $5\%$ of LEs and the top 4 song structure clusters $(13, 0, 12, 2)$ together cover only $42, 0\%$ of LEs.

The lack of variance of song structures of songs listened to by children compared to adults corroborates that children can be identified as a distinct group of music consumption with different listening behavior. In this case, it can be a sign that children are still in the process of finding and developing their music taste, while adults have already solidified their preferences [4], resulting in a more diverse set of song structures.

## 4.2 Differences of cluster share between age groups

To further investigate the relation of song structure and listening behavior across age groups, we identify that the most salient differences in the LEs of children and adults are apparent for song structure clusters $2, 3, 5, 11, 12$ and $16$ (see appendix C for details), and that these differences are almost exclusively present in the comparison between HS and Adults, as differences between children in MS and HS are small.

For children, we see a $3.4\%$ decrease in songs listened to by children in MS versus HS in cluster 12. Other differences are minute, ranging only from $-1.5\%$ to $+1.8\%$. In contrast, results show a high increase from children in HS to Adults in clusters 2 $(+6.4\%)$ and 3 $(+5.2\%)$, while a starker decrease is present in clusters 5 $(-5.4\%)$, 11 $(-4.4\%)$, 12 $(-6.8\%)$ and 16 $(-4.4\%)$.

We leave the remaining $14$ clusters out of further analysis as they do not account for large differences.

### Interpreting clusters

From the cluster centroids (see Appendix C for details) we have identified the most relevant sections for comparing the clusters as being the Verse, Hook, Pre-Chorus, Chorus, Post-Chorus, Bridge and Outro. We use these sections to describe and distinguish the clusters.

***Cluster 2: Pre-Choruses and no Bridges*** Of all 20 clusters, cluster 2 contains songs that have on average the most amount of Pre-Choruses (Figure 5.3a), together with cluster 13, although the latter distinguishes itself from cluster 2 by the presence of Bridges in its songs.

***Cluster 3: Post-Choruses*** Cluster 3 is characterized by songs with Post-Choruses. Figure 5.5a shows that songs in this cluster typically have 2 or 3, while almost all songs in the other clusters do not contain Post-Choruses at all.

***Clusters 5, 11 and 16: Verses and Hooks*** Clusters 5, 11, and 16 are special from the other clusters due to the prevalence of Verses and Hooks (Figure 5.2a) in combination with an overall lack of Choruses (Figure 5.4a). Cluster 11 differentiates itself by the presence of Outros in songs, which are not present in clusters 5 and 16 (Figure 5.7a). The difference between 5 and 16 lies in the number of sections present in the songs. Table 1 shows that songs of cluster 5 consist of around 7 sections on average, versus 4 to 5 sections in cluster 16. This can explain the overall lower amount of Hooks in cluster 16 versus cluster 5.

***Cluster 12: Short and free*** Songs in cluster 12 lack evident structures. We see a clear absence of sections in this cluster apart from verses (Figure 5.1a). Table 1 shows that there are indeed only 1.16 sections on average for the songs in cluster 12.

From these cluster descriptions, we see that most of the noteworthy differences can be explained by whether different sections are present in clusters. The average position of sections in the song structure, nor the standard deviation thereof, has little added value to the identification of similar songs.

### Contextualizing differences using cluster insights

Since cluster 12 is characterized by songs lacking song sections, we are cautious in reasoning about the observed overall decrease for both MS to HS $(-3.4\%)$ and HS to Adults $(-6.8\%)$. It could mean that the data is inconclusive or that songs indeed have no structure. As an example, the song *We are the dead* by David Bowie is present in this cluster, and its lyrics contain no sections. Upon inspection of the song lyrics on the Genius website[3], we find a version of the lyrics where labels including *[Verse 1]* and *[Chorus 1]* are provided. A total of $754$ out of the 2.031 (37.1$\%$) songs in cluster 12 contain zero sections. For this fraction, we cannot be sure whether these songs lack section annotations in the

[3]https://genius.com/David-bowie-we-are-the-dead-lyrics, accessed on 13/06/2025

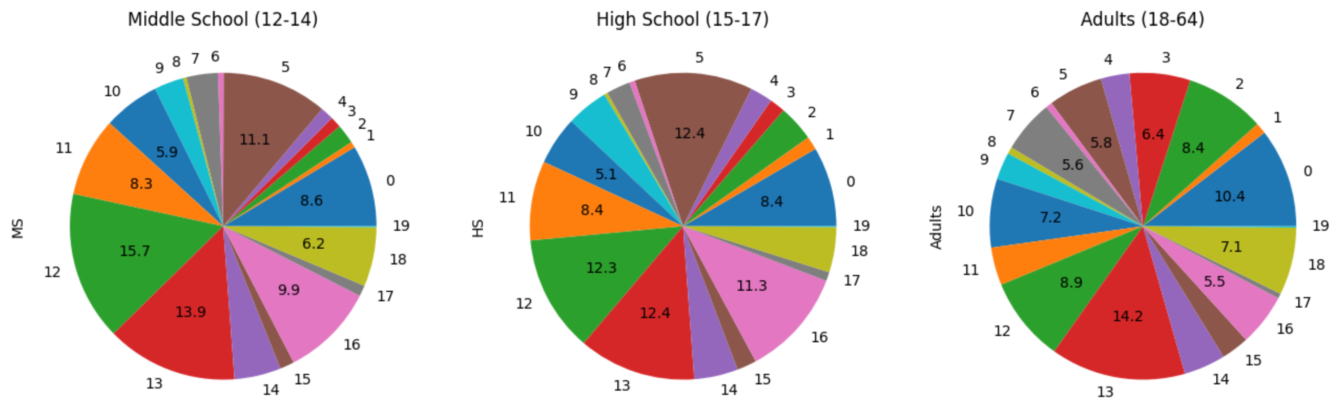



Figure 4: Distribution of song structure clusters 0 through 19 in the LEs per age group. Percentages ($> 5\%$, rounded to one decimal) are displayed inside the pie slices.

Table 1: Descriptive data of clusters $2, 3, 5, 11, 12$ and $16$.

| **Cluster** | **#Songs** | **#Artists** | **#Song Sections (avg)** | **Artist genres in 75th-percentile** *alt. = alternative* *elec. = electronic* |
|---|---|---|---|---|
| 2 | 900 | 287 | 7.96 | pop, alt., elec., rap,rnb, rock |
| 3 | 534 | 208 | 9.75 | elec., pop, alt., rnb, rock, rap |
| 5 | 2754 | 573 | 7.12 | rap, pop, rnb, alt., rock |
| 11 | 1476 | 390 | 6.60 | rap, pop, rnb, alt., rock |
| 12 | 2031 | 444 | 1.16 | rap, pop, alt., elec., rnb |
| 16 | 1908 | 432 | 4.64 | rap, pop, rnb, alt., elec. |

dataset or the songs are indeed lacking structure. Taking this into consideration, we highlight another song in this cluster, namely *Flow* by Bones[4]. This song consists of only one long Verse and is only 1:15 minutes in duration. In the context of structural preferences, it makes sense that free-flowing or freestyle-like songs are not generally preferred by children. They can be hard to follow and difficult to actively participate in, for example, singing along to.

The overall decline of the share of clusters 5, 11 and 16 from the songs listened to by HS compared to Adults is most notable, as we have identified that these clusters mainly represent the Hook section. We can interpret these clusters as functionally the same, with all revolving around Hooks. This means that the overall decrease in the share of Hook-heavy songs is $-14.2\%$. In contrast, we find a shared focus around the Chorus in clusters 2 and 3, which have a combined increased share of $+11.8\%$ in the LEs of Adults with respect to children in HS.

This Hook-Chorus contrast suggests that songs can have either Hooks or Choruses, but typically not both, which is supported by Figure 6.

## 5 Discussion and limitations

The results of our study show that children aged 12-14 consume similar music to children aged 15-17 when viewed through the lens of song structure. Similar sectional properties of songs are represented fairly equally in the songs that they listen to, according to our data. This could mean that there are fewer differences in listening preferences, but we attribute this to the complexity of capturing music preference nuances. One distinct difference between these two age groups was identified in our results, showing a downward trend of short songs, lacking sectional structures and characterized by free-flowing speech, such as improvisation.

One of the limitations in this regard is that the data used from the Genius Lyrics dataset for the song lyrics was incomplete for a particular subset of the songs. This is because lyrical annotations on the Genius website, such as the section annotations used as a basis for extracting song structure, can be updated over time. We identified that $37.1\%$ of the songs lacking structure were not annotated at all. In the worst case, all of these songs are incomplete, meaning that they influence the interpretation of the songs placed in the same cluster. Therefore, we refrain from generalizing these results.

Other results show that a notable shift in listening behavior emerges when comparing children aged 15-17 to the reference group of adults. This shift can be characterized by the presence of lyrical Hooks in the songs listened to by children and the presence of Pre-Choruses, Choruses and Post-Choruses in the songs listened to by adults. Both Choruses and Hooks fulfill similar roles in music, as they tend to capture the audience, although Hooks are considered to be the most catchy elements of a song, and shorter than a chorus [18; 14; 2]. They can be anything from instrumental riffs, rhythms, or phrases. Choruses convey the main ideas of a song, both musically and lyrically [8]. We think that this Hook-Chorus contrast is indicative that children in particular value the appeal of short and catchy elements of songs – reflecting the notion of fast content [7] in modern media consumption. On the other hand, adults might be more open to more complicated structures, having found their music preferences.

This observed result also raises the question of whether more nuanced preference differences can be uncovered when

[4]https://genius.com/Bones-flow-lyrics, accessed on 22/06/2025

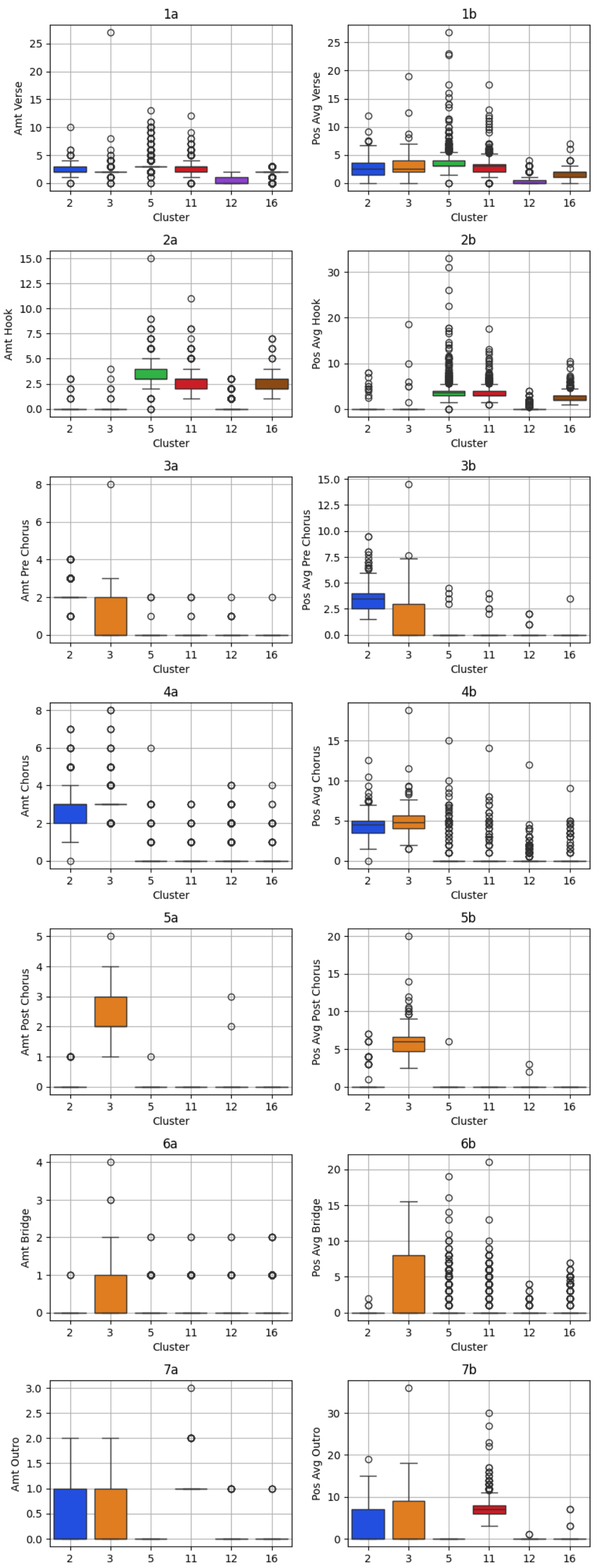



Figure 5: Distribution of the amount (left) and average position (right) of the 7 most discriminative song sections for clusters 2, 3, 5, 11, 12, 16.

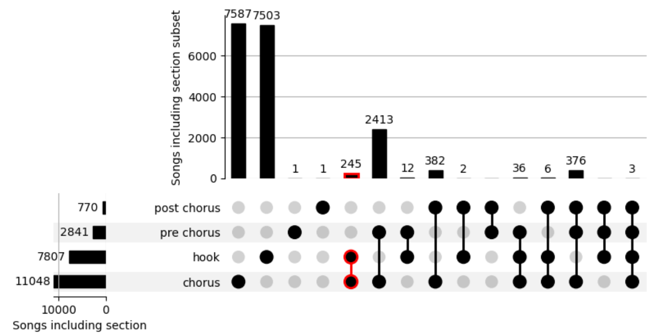



Figure 6: Presence of Hooks, Pre-Choruses, Choruses or Post-Choruses in the dataset songs. The shown subsets are exclusive. For example, there are 245 songs with at least one Hook and Chorus and no Pre-Chorus nor Post-Chorus.

considering also instrumental Hooks. It could be feasible that including a broader definition of Hooks identifies more differences between age groups of children. This was not possible within the limitations of this study, as instrumental hooks are not present within the lyrical annotations. However, it proposes an interesting take for future research.

These findings are additionally influenced by the setup of the analysis. Firstly, the amount of listening data of children has been reduced drastically in the combination process of the LFM2b and GL datasets. This limits the generalizability of the results, as more song structure preferences could have been identified from more available data and certain song structure preferences could have been inflated. Nonetheless, we identified that the representations of LEs in our combined dataset of children aged both 12-14 and 15-17 were subject to similar reductions. Moreover, due to the broad nature of our results, we believe that the reduction of LEs does not pose an integral threat to the validity of this study.

Secondly, the combination of LFM2b and GL posed challenges, as fuzzy matching is inherently imprecise. In our matching process, we combated the risks of wrong matches with a two-step process of filtering (using PostgreSQLs ilike) and then ranking results based on both track name as well as artist.

Finally, we have to take note of the general limitations related to working with the LFM2b dataset and identifying preferences. For instance, we do not know to what extent the LEs in the LFM2b dataset represent conscious plays by the users in contrast with the automatic playing of songs, for example in the background, as also argued by Spear et al. [18]. We have to assume that a user interacting with a song is proportional to the user's liking to that particular song. Another general consideration is that although we can be confident that LEs belong to a certain LastFm user, we are unsure whether it is actually the same individual represented by that user, that is responsible for all LEs on the user's LastFm account. Multiple people of different ages might have listened on the same account (think of a parent and their child), mixing their preferences and obscuring the real relationship between age and music listening behavior.

Despite the limitations of this study, this research corroborates the well-established narrative that children are a distinct consumer group of music [19; 17; 16]. Even through the lens of song structure, we can observe that children exhibit overall different music listening behavior from adults.

## 6 Responsible Research

In this section, we reflect on the data used in this research and the usage of generative Artificial Intelligence (AI).

### 6.1 Datasets

**Accessibility** The popular LFM2b dataset is **not** publicly available online anymore since April of 2024, due to licensing issues[5]. The version of the dataset used in this research was provided by the supervisor, who already obtained it when the dataset was still hosted. Even though it is not available online anymore, the dataset is still widely used in research within the RecSys community.

To respect not distributing the dataset while the original is not available, this work distributes only the link between the LFM2b dataset and GL dataset in the form of LFM2b track IDs to GL song IDs. Those who already poses the LFM2b dataset or who will in the future if licensing permits, can use this data to reproduce the experiment in this research.

The Genius Lyrics dataset is still available at [6] and the processed version produced by this research is available at full at the public repository[6].

**Privacy** The LFM2b dataset contains personal information, such as the notion of users from a country for which extensive data on their music listening behavior in the form of listening events is known. Despite this, the data is anonymous through the abstraction of users to IDs and therefore not traceable to individuals.

**Reproducibility and integrity** The large amount of data pre-processing and the data analysis itself have been recorded and published in a publicly visible GitHub repository[6] to ensure transparency and reproducibility of the steps taken. In addition, the appendices contain relevant, detailed information to ensure that readers can verify that claims made in the main text have a solid basis.

### 6.2 Usage of Generative Artificial Intelligence (AI)

During this research, the unpaid version of ChatGPT [7] has been used to:

- Find academic resources
- Optimize SQL queries
- Optimize or bugfix Python code

Relevant prompts are disclosed in appendix D.
Grammarly[8] was used to check grammar and spelling. Otherwise, no AI was used to generate the textual content of this work.

[5] https://www.cp.jku.at/datasets/LFM-2b/
[6] https://github.com/sbakker6/MusicRSAndChildren
[7] https://www.chatgpt.com
[8] https://www.grammarly.com

## 7 Conclusion and future work

In this work, we analyzed the differences in music listening behavior of children aged 12-14 (MS) and 15-17 (HS) and adults (aged $> 18$) through the lens of song structures, to better understand children as a unique user group of music recommender systems (RS). By combining two datasets, we gained insight into the song interactions of individuals in these age groups and the structure of these songs. We then grouped songs with similar structure to inform further analysis, resulting in 20 clusters of songs with similar song structures. Our combined dataset showed no notable differences between song structures in the songs listened to by children in MS versus children in HS. The most informative differences are that, compared to children in the HS age group, adults seemed to drop interactions with songs that are characterized by the presence of (lyrical) Hooks, widely considered the most catchy sections of songs, while increasing interaction with songs characterized by Pre-Choruses, Choruses and Post-Choruses. Although these findings show some signs that children in general prefer Hook-heavy songs more than adults, more nuanced relations could be present in song structures that could not be uncovered due to the limitations of the study setup.

It is left for future work to investigate whether favoring songs that contain more Hooks in music RS leads to a better performance for children. In addition, we propose a more comprehensive study in which song structure is extracted from song audio instead of the lyrics. This allows for a more flexible setup, with potentially more preserved data, where a broader definition of song Hooks can be investigated. This might yield additional insights into preferences across children age groups, related to structural elements of songs.

## A Pre-processing

Table 2: Number of tracks, LEs and distinct users retained in the dataset during phases in pre-processing.

| **Processing step** | **#Track** | **#LE** *(#distinct user)* | | | |
|---|---|---|---|---|---|
| | | **Total** | **MS** | **HS** | **Adults** |
| Before processing | 20.131.689 | 1.131.465.529 (*45.601*) | 20.323.076 (*3.745*) | 110.085.965 (*13.454*) | 1.001.056.488 (*42.566*) |
| Removing instrumental songs | 19.990.774 | 1.129.614.290 (*45.601*) | 20.302.471 (*3.745*) | 109.942.865 (*13.454*) | 999.368.954 (*42.566*) |
| Fuzzy matching | 22.009 | 1.482.194 (*20.500*) | 8.885 (*487*) | 71.831 (*2.901*) | 1.401.478 (*19.225*) |

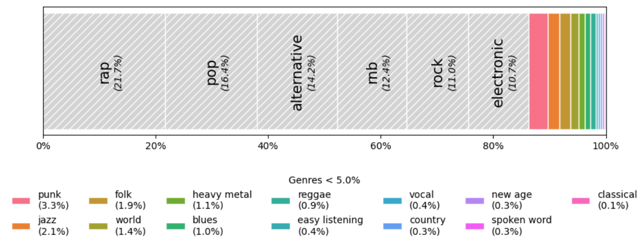



Figure 7: Distribution of artist genres (from LFM2b) over all songs in the matched LFM2b-GL dataset.

# B Acquiring Song Structure

Table 3: Sections and the keywords used in the mapping of labels to sections. The term Refrain is also used in the Genius Lyrics dataset, however as it is synonymous with Chorus [8], we map it to Chorus.

| Section | Keywords in labels |
|---|---|
| Intro | Intro |
| Verse | Verse, Couplet, Verso, Zwrotka, Strofa, |
| Pre-Chorus | Pre-Chorus, Pre-Coro |
| Chorus | Chorus, Refrain, Refren |
| Post-Chorus | Post-Chorus |
| Pre-Hook | Pre-Hook |
| Hook | Hook |
| Post-Hook | Post-Hook, Post Hook |
| Bridge | Bridge, Pont |
| Outro | Outro |
| Instrumental | Instrumental, Interlude |
| Vamp | Vamp |
| Break | Break |
| Solo | Piano Solo, Guitar Solo |

# C Cluster data

## Cluster observations

Figure 8: Centroids of the 20 identified clusters. Data bars are added per column to highlight differences between clusters.

| Cluster | INTRO | | | VERSE | | | PRE-CHORUS | | | CHORUS | | | POST-CHORUS | | | PRE-HOOK | | | HOOK | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos | amt | pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos |
| 0 | 0.00 | 0.00 | 0.00 | 2.17 | 1.26 | 1.65 | 0.02 | 0.02 | 0.00 | 1.86 | 1.31 | 1.57 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.01 |
| 1 | 0.96 | 0.15 | 0.18 | 2.21 | 1.84 | 2.07 | 0.79 | 0.75 | 0.76 | 1.28 | 1.47 | 1.43 | 0.22 | 0.28 | 0.14 | 0.02 | 0.02 | 0.00 | 0.43 | 0.50 | 0.44 |
| 2 | 0.77 | 0.06 | 0.06 | 2.10 | 1.95 | 2.31 | 3.05 | 2.91 | 2.87 | 1.79 | 2.15 | 1.98 | 0.06 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.03 | 0.02 |
| 3 | 0.84 | 0.10 | 0.09 | 2.01 | 2.03 | 2.36 | 1.38 | 1.50 | 1.57 | 1.92 | 2.25 | 2.42 | 6.00 | 5.57 | 5.91 | 0.00 | 0.00 | 0.00 | 0.02 | 0.05 | 0.03 |
| 4 | 1.01 | 0.13 | 0.13 | 2.44 | 2.42 | 2.46 | 0.06 | 0.10 | 0.06 | 0.84 | 0.95 | 0.96 | 0.01 | 0.01 | 0.00 | 0.02 | 0.02 | 0.00 | 0.98 | 1.17 | 1.15 |
| 5 | 1.12 | 0.09 | 0.10 | 2.71 | 2.25 | 2.18 | 0.00 | 0.00 | 0.00 | 0.02 | 0.04 | 0.02 | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.00 | 2.28 | 2.09 | 2.13 |
| 6 | 0.81 | 0.03 | 0.00 | 2.14 | 2.15 | 2.41 | 0.05 | 0.07 | 0.06 | 0.09 | 0.14 | 0.12 | 0.00 | 0.00 | 0.00 | 9.53 | 9.16 | 9.17 | 1.92 | 2.58 | 2.36 |
| 7 | 0.87 | 0.05 | 0.02 | 2.14 | 1.58 | 1.76 | 0.06 | 0.07 | 0.00 | 1.89 | 1.67 | 1.71 | 0.10 | 0.16 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.03 | 0.03 |
| 8 | 0.38 | 0.07 | 0.00 | 2.33 | 1.56 | 2.25 | 0.78 | 0.76 | 0.81 | 1.73 | 1.77 | 1.83 | 0.40 | 0.46 | 0.28 | 0.00 | 0.00 | 0.00 | 0.07 | 0.07 | 0.07 |
| 9 | 0.78 | 0.06 | 0.00 | 2.62 | 1.34 | 1.42 | 0.00 | 0.00 | 0.00 | 0.05 | 0.06 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.10 | 0.12 | 0.00 |
| 10 | 1.91 | 0.06 | 0.03 | 2.36 | 2.22 | 1.82 | 0.02 | 0.03 | 0.00 | 1.95 | 1.80 | 1.69 | 0.01 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.03 | 0.01 |
| 11 | 1.37 | 0.09 | 0.10 | 2.40 | 2.02 | 1.88 | 0.01 | 0.01 | 0.00 | 0.02 | 0.05 | 0.02 | 0.00 | 0.00 | 0.00 | 0.02 | 0.03 | 0.00 | 2.01 | 1.94 | 1.83 |
| 12 | 0.39 | 0.01 | 0.00 | 0.51 | 0.22 | 0.05 | 0.01 | 0.00 | 0.00 | 0.11 | 0.07 | 0.06 | 0.01 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.10 | 0.07 | 0.02 |
| 13 | 0.59 | 0.04 | 0.03 | 1.92 | 1.50 | 2.10 | 2.97 | 2.76 | 2.81 | 1.94 | 2.41 | 2.15 | 0.11 | 0.19 | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.07 | 0.04 |
| 14 | 0.00 | 0.00 | 0.00 | 1.60 | 0.60 | 0.88 | 0.02 | 0.02 | 0.00 | 0.47 | 0.34 | 0.33 | 0.03 | 0.03 | 0.00 | 0.01 | 0.01 | 0.00 | 0.35 | 0.27 | 0.24 |
| 15 | 2.01 | 0.08 | 0.10 | 1.40 | 1.10 | 0.54 | 0.01 | 0.01 | 0.00 | 0.13 | 0.15 | 0.05 | 0.02 | 0.03 | 0.00 | 0.03 | 0.03 | 0.00 | 0.15 | 0.19 | 0.06 |
| 16 | 0.42 | 0.00 | 0.00 | 1.56 | 1.05 | 1.07 | 0.00 | 0.00 | 0.00 | 0.02 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.00 | 1.74 | 1.31 | 1.46 |
| 17 | 1.42 | 0.77 | 0.26 | 2.49 | 2.39 | 2.42 | 0.21 | 0.32 | 0.24 | 0.74 | 1.00 | 0.92 | 0.10 | 0.13 | 0.13 | 0.00 | 0.00 | 0.00 | 0.45 | 0.60 | 0.55 |
| 18 | 1.33 | 0.09 | 0.08 | 2.49 | 2.03 | 1.87 | 0.02 | 0.02 | 0.00 | 1.82 | 1.58 | 1.55 | 0.04 | 0.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.02 | 0.00 |
| 19 | 1.13 | 0.09 | 0.05 | 2.10 | 2.46 | 2.18 | 0.17 | 0.14 | 0.15 | 0.17 | 0.20 | 0.23 | 0.08 | 0.13 | 0.00 | 2.14 | 2.32 | 2.34 | 1.75 | 2.06 | 2.16 |

| Cluster | POST_HOOK | | | BRIDGE | | | OUTRO | | | INSTRUMENTAL | | | VAMP | | | BREAK | | | SOLO | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos | amt | avg pos | std pos |
| 0 | 0.00 | 0.00 | 0.00 | 0.50 | 0.50 | 0.01 | 0.00 | 0.00 | 0.00 | 0.14 | 0.16 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 1 | 0.00 | 0.00 | 0.00 | 0.81 | 0.98 | 0.26 | 1.10 | 1.26 | 0.13 | 0.36 | 0.42 | 0.12 | 0.00 | 0.00 | 0.00 | 6.66 | 6.81 | 2.91 | 0.05 | 0.06 | 0.00 |
| 2 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.89 | 0.97 | 0.03 | 0.26 | 0.45 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.00 | 0.00 | 0.00 | 0.86 | 1.44 | 0.14 | 0.90 | 1.20 | 0.01 | 0.15 | 0.26 | 0.04 | 0.00 | 0.00 | 0.00 | 0.13 | 0.24 | 0.00 | 0.00 | 0.00 | 0.00 |
| 4 | 0.01 | 0.01 | 0.00 | 3.87 | 1.82 | 4.66 | 0.79 | 0.93 | 0.02 | 0.18 | 0.30 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| 5 | 0.01 | 0.01 | 0.00 | 0.18 | 0.23 | 0.00 | 0.00 | 0.00 | 0.00 | 0.10 | 0.13 | 0.00 | 0.02 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 6 | 0.22 | 0.31 | 0.06 | 0.67 | 0.89 | 0.31 | 0.64 | 0.78 | 0.06 | 0.16 | 0.28 | 0.18 | 0.00 | 0.00 | 0.00 | 0.13 | 0.13 | 0.09 | 0.00 | 0.00 | 0.00 |
| 7 | 0.00 | 0.00 | 0.00 | 1.74 | 1.96 | 0.15 | 1.99 | 1.96 | 0.07 | 0.19 | 0.31 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 |
| 8 | 0.00 | 0.00 | 0.00 | 0.77 | 0.88 | 0.22 | 1.03 | 1.16 | 0.03 | 0.24 | 0.31 | 0.04 | 0.00 | 0.00 | 0.00 | 0.09 | 0.12 | 0.00 | 9.24 | 8.93 | 2.26 |
| 9 | 0.00 | 0.00 | 0.00 | 0.19 | 0.10 | 0.02 | 0.04 | 0.03 | 0.00 | 0.40 | 0.28 | 0.00 | 0.00 | 0.00 | 0.00 | 0.09 | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 |
| 10 | 0.00 | 0.00 | 0.00 | 0.30 | 0.37 | 0.00 | 0.00 | 0.00 | 0.00 | 0.15 | 0.19 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 |
| 11 | 0.04 | 0.05 | 0.00 | 0.29 | 0.34 | 0.00 | 2.06 | 1.96 | 0.10 | 0.18 | 0.24 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 12 | 0.00 | 0.00 | 0.00 | 0.03 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 | 0.11 | 0.02 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 13 | 0.00 | 0.00 | 0.00 | 1.71 | 2.63 | 0.17 | 0.99 | 1.21 | 0.03 | 0.12 | 0.23 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 14 | 0.02 | 0.02 | 0.00 | 0.20 | 0.11 | 0.02 | 2.05 | 0.98 | 0.03 | 0.18 | 0.09 | 0.00 | 0.00 | 0.00 | 0.00 | 0.05 | 0.01 | 0.00 | 0.01 | 0.00 | 0.00 |
| 15 | 0.00 | 0.00 | 0.00 | 0.22 | 0.14 | 0.01 | 2.07 | 1.00 | 0.16 | 0.35 | 0.24 | 0.00 | 0.06 | 0.01 | 0.00 | 0.08 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 |
| 16 | 0.01 | 0.01 | 0.00 | 0.15 | 0.14 | 0.01 | 0.00 | 0.00 | 0.00 | 0.07 | 0.07 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 17 | 0.00 | 0.00 | 0.00 | 0.47 | 0.62 | 0.30 | 1.22 | 1.37 | 0.62 | 6.48 | 3.57 | 7.63 | 0.00 | 0.00 | 0.00 | 0.16 | 0.23 | 0.00 | 0.06 | 0.07 | 0.00 |
| 18 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 2.06 | 1.89 | 0.14 | 0.21 | 0.28 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 19 | 16.14 | 15.45 | 15.81 | 0.69 | 0.82 | 0.39 | 1.02 | 1.35 | 0.00 | 0.25 | 0.41 | 0.27 | 4.74 | 5.27 | 2.25 | 0.17 | 0.36 | 0.00 | 0.00 | 0.00 | 0.00 |

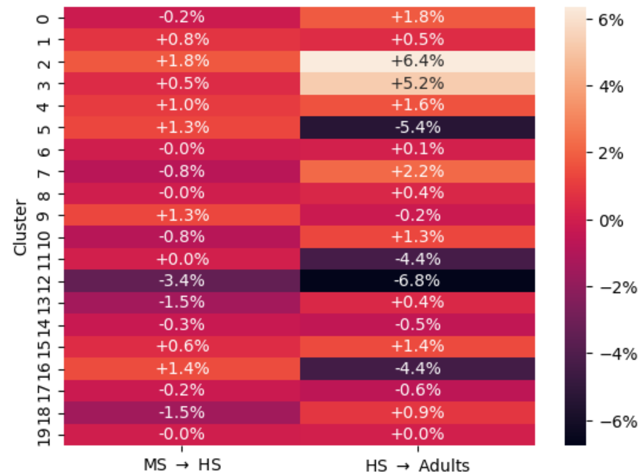



Figure 9: Percentage point differences of share of clusters in the listening events across the age groups. Notable differences between age groups are visible for cluster 12 for MS $\rightarrow$ HS and clusters 2, 3, 5, 11, 12, 16 for HS $\rightarrow$ Adults.

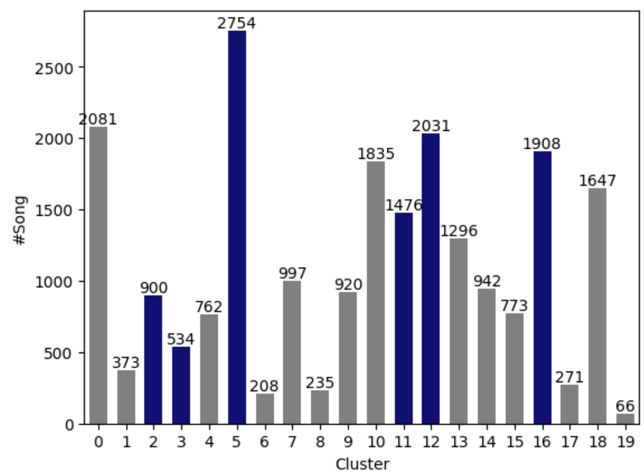



Figure 10: Amount of songs per cluster. Clusters of interest in the analysis are highlighted blue.

Table 4: LE count per cluster per age. Age groups MS, HS and Adults are separated via horizontal bars.

| Cluster<br>Age at listen | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 12 | 170 | 11 | 20 | 22 | 2 | 80 | 1 | 13 | 1 | 47 | 92 | 27 | 108 | 80 | 13 | 0 | 64 | 5 | 116 | 0 |
| 13 | 149 | 24 | 40 | 34 | 25 | 232 | 24 | 74 | 16 | 84 | 120 | 198 | 321 | 302 | 124 | 36 | 234 | 17 | 189 | 4 |
| 14 | 423 | 20 | 116 | 44 | 93 | 646 | 26 | 199 | 14 | 137 | 300 | 494 | 925 | 812 | 287 | 94 | 555 | 77 | 233 | 5 |
| 15 | 1080 | 162 | 296 | 219 | 412 | 1767 | 93 | 254 | 73 | 526 | 668 | 976 | 1665 | 2000 | 577 | 219 | 1362 | 99 | 675 | 5 |
| 16 | 1561 | 236 | 984 | 292 | 449 | 3175 | 105 | 581 | 65 | 707 | 1063 | 2425 | 2817 | 2462 | 1024 | 511 | 2872 | 224 | 913 | 9 |
| 17 | 3380 | 616 | 1445 | 663 | 850 | 3971 | 220 | 982 | 117 | 1929 | 1930 | 2595 | 4322 | 4403 | 1714 | 746 | 3890 | 353 | 1817 | 52 |
| 18 | 4788 | 677 | 2340 | 1018 | 1426 | 5750 | 497 | 1651 | 97 | 2001 | 2408 | 3514 | 5687 | 6076 | 2565 | 1188 | 5277 | 376 | 2644 | 112 |
| 19 | 7434 | 823 | 4425 | 2228 | 2259 | 6312 | 763 | 2204 | 282 | 2548 | 3880 | 3382 | 7583 | 7882 | 3746 | 1659 | 6116 | 448 | 3779 | 127 |
| 20 | 11430 | 1274 | 5692 | 3975 | 2781 | 8103 | 890 | 4259 | 269 | 3101 | 6078 | 5894 | 9706 | 16484 | 4822 | 2531 | 7763 | 468 | 4821 | 110 |
| 21 | 12046 | 1442 | 7319 | 4199 | 3417 | 8886 | 1051 | 4723 | 368 | 3642 | 7354 | 5651 | 11506 | 15799 | 4901 | 2960 | 8454 | 642 | 6533 | 127 |
| 22 | 14157 | 1532 | 9320 | 6318 | 4165 | 7829 | 789 | 7093 | 539 | 3574 | 8715 | 5009 | 10386 | 17951 | 5412 | 3367 | 7318 | 587 | 7698 | 249 |
| 23 | 12936 | 1947 | 10363 | 7202 | 4672 | 7742 | 1063 | 7718 | 608 | 4351 | 9585 | 5970 | 11840 | 16974 | 5569 | 3636 | 8169 | 494 | 9302 | 155 |
| 24 | 13050 | 1392 | 11518 | 8225 | 4367 | 6895 | 721 | 6296 | 678 | 3167 | 9029 | 5010 | 11392 | 17809 | 5267 | 4007 | 6959 | 724 | 9918 | 154 |
| 25 | 12448 | 1252 | 10323 | 8444 | 3446 | 5255 | 761 | 6824 | 928 | 3018 | 8826 | 4457 | 9839 | 17196 | 4819 | 3375 | 5205 | 907 | 8025 | 174 |
| 26 | 10500 | 1203 | 9248 | 10800 | 3094 | 4782 | 544 | 6832 | 766 | 2583 | 8004 | 3888 | 9456 | 14459 | 4798 | 3024 | 4461 | 543 | 7728 | 233 |
| 27 | 8762 | 1056 | 7424 | 6180 | 2359 | 3543 | 490 | 4883 | 626 | 2190 | 7135 | 2857 | 7589 | 11065 | 4287 | 3093 | 3249 | 412 | 7354 | 85 |
| 28 | 8307 | 759 | 7637 | 6053 | 2536 | 2933 | 612 | 5282 | 782 | 1861 | 6742 | 2243 | 6289 | 10554 | 3452 | 2532 | 2896 | 319 | 6959 | 101 |
| 29 | 6312 | 510 | 9361 | 6023 | 1623 | 2396 | 351 | 3981 | 1095 | 1540 | 6347 | 1656 | 4860 | 7976 | 2658 | 2375 | 2178 | 235 | 6022 | 45 |
| 30 | 4358 | 410 | 3782 | 4335 | 964 | 1796 | 204 | 2790 | 507 | 1095 | 3032 | 1158 | 3523 | 9229 | 1723 | 1252 | 1793 | 127 | 3637 | 120 |
| 31 | 3663 | 578 | 2920 | 3120 | 877 | 1698 | 95 | 2251 | 337 | 756 | 2460 | 1093 | 2719 | 5779 | 1152 | 1064 | 1301 | 166 | 2638 | 58 |
| 32 | 2916 | 332 | 3390 | 2515 | 992 | 1281 | 143 | 2506 | 255 | 716 | 2188 | 747 | 2265 | 7238 | 1074 | 810 | 1101 | 130 | 2347 | 41 |
| 33 | 2413 | 265 | 2300 | 2217 | 918 | 976 | 130 | 2634 | 299 | 868 | 1567 | 467 | 2068 | 5045 | 1157 | 639 | 795 | 71 | 1664 | 24 |
| 34 | 1689 | 107 | 1358 | 937 | 399 | 711 | 63 | 940 | 253 | 496 | 1197 | 510 | 1460 | 1533 | 758 | 497 | 660 | 93 | 1305 | 17 |
| 35 | 1259 | 78 | 2276 | 1013 | 320 | 577 | 69 | 626 | 156 | 436 | 1225 | 405 | 1209 | 2390 | 584 | 613 | 574 | 100 | 1213 | 25 |
| 36 | 1416 | 151 | 1531 | 1182 | 228 | 518 | 53 | 663 | 159 | 362 | 1088 | 309 | 986 | 1562 | 607 | 442 | 445 | 80 | 1196 | 8 |
| 37 | 966 | 110 | 878 | 692 | 211 | 460 | 32 | 637 | 208 | 302 | 686 | 283 | 826 | 769 | 437 | 301 | 371 | 60 | 855 | 11 |
| 38 | 723 | 95 | 635 | 471 | 290 | 392 | 33 | 671 | 149 | 237 | 510 | 299 | 729 | 805 | 297 | 235 | 325 | 62 | 514 | 4 |
| 39 | 693 | 73 | 432 | 385 | 142 | 242 | 13 | 433 | 122 | 165 | 439 | 180 | 477 | 703 | 246 | 228 | 175 | 21 | 460 | 10 |
| 40 | 495 | 85 | 359 | 336 | 168 | 231 | 33 | 263 | 37 | 141 | 466 | 209 | 510 | 856 | 137 | 140 | 153 | 38 | 505 | 8 |
| 41 | 713 | 17 | 361 | 273 | 165 | 253 | 12 | 144 | 67 | 105 | 362 | 164 | 330 | 516 | 147 | 176 | 277 | 22 | 553 | 16 |
| 42 | 315 | 26 | 300 | 190 | 69 | 137 | 13 | 104 | 78 | 78 | 188 | 68 | 305 | 283 | 119 | 76 | 129 | 4 | 230 | 1 |
| 43 | 252 | 13 | 206 | 94 | 57 | 136 | 8 | 191 | 62 | 128 | 287 | 36 | 248 | 266 | 104 | 72 | 138 | 22 | 252 | 1 |
| 44 | 290 | 20 | 219 | 131 | 59 | 78 | 6 | 132 | 43 | 63 | 191 | 50 | 226 | 259 | 153 | 60 | 53 | 9 | 169 | 1 |
| 45 | 268 | 38 | 354 | 187 | 52 | 140 | 8 | 156 | 70 | 27 | 431 | 80 | 223 | 262 | 102 | 84 | 72 | 2 | 292 | 14 |
| 46 | 228 | 15 | 315 | 268 | 26 | 79 | 12 | 261 | 46 | 33 | 181 | 41 | 110 | 446 | 59 | 90 | 66 | 3 | 192 | 1 |
| 47 | 113 | 9 | 109 | 127 | 27 | 60 | 2 | 90 | 17 | 43 | 134 | 26 | 72 | 182 | 59 | 19 | 31 | 0 | 124 | 0 |
| 48 | 91 | 9 | 146 | 79 | 22 | 24 | 5 | 89 | 18 | 143 | 73 | 10 | 70 | 92 | 30 | 25 | 29 | 1 | 95 | 0 |
| 49 | 103 | 4 | 103 | 54 | 26 | 14 | 4 | 94 | 15 | 50 | 55 | 9 | 56 | 118 | 12 | 21 | 13 | 2 | 57 | 1 |
| 50 | 106 | 4 | 112 | 82 | 33 | 36 | 5 | 79 | 10 | 30 | 63 | 53 | 99 | 137 | 57 | 35 | 14 | 2 | 86 | 0 |
| 51 | 164 | 4 | 91 | 99 | 15 | 21 | 0 | 83 | 14 | 78 | 46 | 17 | 71 | 106 | 28 | 75 | 10 | 4 | 92 | 0 |
| 52 | 84 | 0 | 71 | 31 | 10 | 17 | 0 | 46 | 14 | 15 | 46 | 13 | 76 | 68 | 24 | 29 | 12 | 4 | 37 | 0 |
| 53 | 85 | 2 | 60 | 27 | 8 | 11 | 1 | 62 | 10 | 8 | 54 | 12 | 55 | 62 | 20 | 26 | 21 | 3 | 52 | 0 |
| 54 | 84 | 9 | 35 | 18 | 2 | 8 | 0 | 56 | 6 | 11 | 9 | 7 | 87 | 78 | 13 | 42 | 53 | 2 | 27 | 0 |
| 55 | 54 | 5 | 33 | 17 | 8 | 13 | 0 | 35 | 0 | 18 | 23 | 5 | 55 | 62 | 5 | 23 | 27 | 0 | 29 | 0 |
| 56 | 44 | 0 | 27 | 16 | 0 | 9 | 0 | 24 | 4 | 5 | 11 | 1 | 39 | 26 | 23 | 17 | 21 | 0 | 14 | 0 |
| 57 | 20 | 2 | 9 | 2 | 0 | 24 | 0 | 13 | 20 | 2 | 13 | 4 | 19 | 29 | 5 | 0 | 12 | 1 | 15 | 0 |
| 58 | 25 | 2 | 18 | 16 | 0 | 8 | 0 | 14 | 17 | 3 | 10 | 2 | 12 | 51 | 2 | 2 | 5 | 1 | 13 | 0 |
| 59 | 33 | 0 | 23 | 13 | 1 | 14 | 0 | 7 | 6 | 3 | 10 | 0 | 9 | 5 | 3 | 4 | 5 | 0 | 16 | 0 |
| 60 | 14 | 1 | 12 | 1 | 1 | 13 | 0 | 0 | 1 | 7 | 4 | 0 | 11 | 3 | 7 | 8 | 1 | 1 | 2 | 0 |
| 61 | 20 | 5 | 7 | 1 | 1 | 34 | 0 | 3 | 1 | 1 | 3 | 13 | 15 | 2 | 2 | 1 | 9 | 0 | 5 | 0 |
| 62 | 9 | 0 | 2 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 2 | 0 | 2 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| 63 | 18 | 5 | 10 | 1 | 0 | 1 | 0 | 3 | 1 | 3 | 1 | 14 | 3 | 4 | 1 | 0 | 2 | 0 | 1 | 0 |
| 64 | 1 | 0 | 0 | 0 | 1 | 9 | 0 | 8 | 1 | 1 | 0 | 3 | 2 | 5 | 2 | 0 | 2 | 0 | 2 | 0 |
| 65 | 6 | 1 | 7 | 0 | 1 | 1 | 0 | 3 | 0 | 0 | 1 | 2 | 1 | 3 | 5 | 9 | 5 | 0 | 1 | 0 |

## D Overview of ChatGPT usage

The following are examples of ChatGPT queries used (verbatim) during this research process.

**Finding academic resources**

- Find me articles that go into anything related to song structure w.r.t listening behavior. I.e., is there evidence or suggestion that children listen more to songs with more repeating sections w.r.t adults?

There were no further instances of using ChatGPT to gather academic resources.

ChatGPT was used extensively to assist in the analysis process by enhancing the performance of slow SQL queries or improving code snippets. The responses have always been carefully interpreted and tweaked to fit the need. Examples include, but are for brevity not limited to:

**Optimizing SQL queries**

- can you optimize this query?

```
WITH distinct_track_ids AS (SELECT DISTINCT
track_id FROM le_children)
SELECT
 t.track_id,
 t.track_name,
 a.artist_id,
 a.artist_name
FROM track t
JOIN artist a USING(artist_id)
WHERE t.track_id IN (SELECT
track_id FROM distinct_track_ids);
```

**Optimizing or bugfixing Python code**

- fix this code snippet

```
'''
sections = ["hook", "pre_chorus",
"chorus", "post_chorus"]
combinations = []
for r in range(2, len(sections) + 1):
    combinations.extend(
    itertools.combinations(sections, r)
    )

base = "(select count(song_id) from
lfm2b_genius join song_fingerprint sf
using(song_id) where {})"
query = "select " + ", ".join(
    base.format(" and ".join("sf.amt_" +
    section + " > 0"
    for section in combination))
    + " as "
    + "_".join(combination)
    for combination in combinations
) + ", " + ', '.join(
    base.format(
        "sf.amt_" + section + " > 0 " + ("
        and ".join("sf.amt_" + other_section
        + " = 0")
        for other_section in [s for s in
        section if s != section]))
        for section in sections
)
'''
```

## References


[1] Paul E. Black. Levenshtein distance. https://www.nist.gov/dads/HTML/Levenshtein.html, 2019. In *Dictionary of Algorithms and Data Structures* [online], CRC Press LLC. Accessed: 2025-06-10.

[2] Gary Burns. A typology of 'hooks' in popular records. *Popular Music*, 6(1):1–20, 1987.

[3] Bruce Ferwerda, Marko Tkalcic, and Markus Schedl. Personality traits and music genre preferences : How music taste varies over age groups. In *Proceedings of the 1st Workshop on Temporal Reasoning in Recommender Systems (RecTemp) at the 11th ACM Conference on Recommender Systems (RecSys)*, volume 1922 of *CEUR Workshop Proceedings*, pages 16–20. CEUR-WS, 2017.

[4] Morris B. Holbrook and Robert M. Schindler. Some Exploratory Findings on the Development of Musical Tastes. *Journal of Consumer Research*, 16(1):119–124, June 1989.

[5] Albert LeBlanc, Wendy L. Sims, Carolyn Siivola, and Mary Obert. Music style preferences of different age listeners. *Journal of Research in Music Education*, 44(1):49–59, 1996.

[6] Derek Lim and Austin R Benson. Expertise and Dynamics within Crowdsourced Musical Knowledge Curation: A Case Study of the Genius Platform. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 15, pages 373–384, 2021. Dataset available at https://www.cs.cornell.edu/~arb/data/genius-expertise/.

[7] Julia Markiewicz. Fast content: what it is and how to use it. https://contentwriter.us/fast-content/, 07 2023. Accessed on 22-06-2025.

[8] MasterClass. Music 101: What is a chorus? https://www.masterclass.com/articles/music-101-what-is-a-chorus, 06 2025. Accessed on 18-06-2025.

[9] Maximilian Mayerl, Stefan Brandl, Günther Specht, Markus Schedl, and Eva Zangerle. Verse versus chorus: Structure-aware feature extraction for lyrics-based genre recognition. In *ISMIR*, pages 884–890, 2022.

[10] Jennifer K. Mendoza and Caitlin M. Fausey. Everyday music in infancy. *Developmental Science*, 24(6):e13122, November 2021.

[11] Merriam-Webster. Definition of genre. https://www.merriam-webster.com/dictionary/genre. Accessed on 22-06-2025.

[12] Joseph C. Nunes, Andrea Ordanini, and Francesca Valsesia. The power of repetition: repetitive lyrics in a song increase processing fluency and drive market success. *Journal of Consumer Psychology*, 25(2):187–199, April 2015.

[13] University of Utah. The chi-square test for independence. https://soc.utah.edu/sociology3112/chi-square.php, 2019. Accessed on 06-11-2025.

[14] Patria. What is a "hook" in rap music? a complete overview. https://www.ourmusicworld.com/archives/10258, 06 2024. Accessed on 18-06-2025.

[15] Musical Pursuits. Music streaming statistics in 2022 (us global data), 01 2024.

[16] Markus Schedl and Christine Bauer. Online music listening culture of kids and adolescents: Listening analysis and music recommendation tailored to the young. *CoRR*, abs/1912.11564, 2017.

[17] Lawrence Spear, Ashlee Milton, Garrett Allen, Amifa Raj, Michael Green, Michael D Ekstrand, and Maria Soledad Pera. Baby shark to barracuda: Analyzing children's music listening behavior. In *Proceedings of the 15th ACM Conference on Recommender Systems*, RecSys '21, pages 639–644, New York, NY, USA, 2021. Association for Computing Machinery.

[18] Daniel Thrasher. Here's the difference between hook and chorus in a song (with 5 examples!). https://improvesongwriting.com/difference-between-hook-and-chorus/, 09 2020. Accessed on 18-06-2025.

[19] Robin Ungruh, Alejandro Bellogín, and Maria Soledad Pera. The impact of mainstream-driven algorithms on recommendations for children. In Claudia Hauff, Craig Macdonald, Dietmar Jannach, Gabriella Kazai, Franco Maria Nardini, Fabio Pinelli, Fabrizio Silvestri, and Nicola Tonellotto, editors, *Advances in Information Retrieval*, pages 67–84, Cham, 2025. Springer Nature Switzerland.