Young Minds and Popular Charts

An empirical study on mainstream music consumption of children

Francisco Duque de Morais Amaro[1]

Supervisors: Maria Soledad Pera[1]**, Robin Ungruh**[1]

[1]**EEMCS, Delft University of Technology, The Netherlands**

A Thesis Submitted to EEMCS Faculty Delft University of Technology,
In Partial Fulfilment of the Requirements
For the Bachelor of Computer Science and Engineering
June 22, 2025

Name of the student: Francisco Duque de Morais Amaro
Final project course: CSE3000 Research Project
Thesis committee: Maria Soledad Pera, Robin Ungruh, Masoud Mansoury

Abstract

Music recommender systems have a hidden yet significant influence on children's development, as musical exposure during childhood substantially impacts personality and creative development. Despite this, children remain a neglected and under-represented demographic in research within this domain. This study examines the connection between children's favorite artists and mainstream music charts, given the dynamic nature of their musical tastes, which adult data cannot replicate. Utilizing multi-year listening logs from thousands of children aged 12 to 18, spanning several countries, we investigate the evolution of this relationship as they age, and examine the influence of geography on listening habits compared to age. Our findings suggest that children tend to drift away from the charts as they age, and that in our current globalized world, local trends still remain relevant. With this, we aim to emphasize the importance of incorporating age-related developmental considerations into the design of recommender systems tailored for children.

1 Introduction

As our daily lives move online, *recommender systems* have become the digital guides that shape what we buy, read, watch, and hear [16]. Their promise is simple: *show the right item to the right user at the right moment*. Unfortunately, the reality is notoriously more complex, and not in many domains is that complexity more evident than in music. A music catalog contains millions of tracks that vary along genre, timbre, mood, social context, and era. Furthermore, listeners' tastes are also complex as they evolve, sometimes drastically, and new songs and artists appear every week. This volatility is amplified in certain demographic groups, most notably in **children**, where developmental research shows that listening preferences between the ages of 12 and 18 are especially volatile, whereas adult taste tends to stabilize over time [11; 21]. Commercial recommenders, however, are usually trained on the much larger adult-listener data, so the models they learn can misserve younger users [9]. The research literature mirrors this imbalance [1; 13; 19; 23], and most children studies still focus on genre preferences differences [7], showing a clear deviation in what type of music users from different ages prefer. Yet genre is only one facet of music. In Spear et al. [25], it is proposed that one of the attributes that also shows significance in how children consume music is *mainstreamness*. Since children are highly influenced by popular trends and their peers [10], we decided to explore this topic further, to assess whether there is a clear relationship between children's age and their alignment with popular charts.

To address this gap, we propose answering the following two research questions: **RQ1** - What is the alignment between children's most-played artists and reference mainstream charts?; **RQ2** - How does aging influence children's mainstream music consumption?

In **RQ1**, we aim to analyze and quantify the evolution of children's preferred artists over time, with their presence in various established mainstream music charts, and compare it with adults' alignment.

For **RQ2**, we build on top of **RQ1** and search for a development trend by comparing a child's monthly artists rankings [19], with relevant platform charts. Since mainstreamness, unlike genre or mood, is in constant change with what's "trendy", following the development of young users, by age, reveals how much of their listening aligns with different trends over time.

Additionally, we could not ignore the previous research done by Schedl & Bauer [20; 1] on mainstream music consumption. They showed that some countries mirror the *global* charts while others follow their own *local* favorites, forming a local-to-global mainstreamness axis. This study, however, combined children and adults, which could mask age-related effects. We want to extend the analysis with a second axis: *all-listeners* vs *young-listeners*, and with that, capture how young users are not only influenced by geographical scope but also by peers with a similar age. For this challenge, we propose **RQ3**: Which scope (age vs. geography) has the highest influence when building reference charts that mirror children's mainstream listening behavior?

To answer these questions, we analyze the listening logs of young users, with registered activity, in the widely used LFM-2b dataset [22]. Then, for every calendar month available to us, we construct four reference charts across the axis previously mentioned. To ensure statistical validity and diversity, we focus our study on the five countries with the most significant numbers of young users (the United States, Poland, Russia, Brazil, and the United Kingdom). These countries have also previously shown to align differently on the local-global scope, making them a strong basis for comparison [1]. Next, we derive a personal popularity chart for each child in each month and compare it with the four reference charts utilizing rank-based similarity measures. This setup enables us to examine the developmental trajectory of mainstream alignment **(RQ1, RQ2)** and identify which scope of age or geography has the most significant influence on alignment **(RQ3)**. All code utilized to generate and analyze the charts is publicly available in a *GitHub* repository [4].

After answering these questions, we can understand how children follow or depart from trends over time. This can reveal standardized behavior that could be applied to further improve music recommender algorithms and aid in finding solutions for the field's current challenges [24].

2 Related Work

Current issues in children's recommender research Children remain an under-represented and uniquely challenging population for recommender systems. Ekstrand's Position Paper [5] pinpoints three persistent obstacles: (i) The *lack of available datasets* and legal measures that make it harder to create them; (ii) The *limited literary abilities* and attention span for long and insightful surveys; (iii) How there are *multiple stakeholders*, like parents and policy-makers, that want to influence what media children should (or should not) consume. These obstacles still define the state of the field, and to them we would like to add the *preference for the adult majority* since most of research still concerns this user group. Gomez et al. [8] highlight another flaw in current recommender-system research: evaluations focus almost exclusively on accuracy. While this metric may be adequate for adults, systems designed for children require a broader perspective. Effective child-oriented recommenders should also be assessed on how well they foster developmental outcomes and promote key aspects of childhood, including creativity, curiosity, and exploration. Ungruh et al. [26] note that despite the limited representation in the LFM-2b dataset, children display a large diversity in their listening preferences, diverging notably from adult patterns. This highlights the difficulty of deriving generalizations about children based on adult data, emphasizing the need for focused research on this and other minority groups.

Mainstream music recommender research On the intersection of mainstream music and recommender systems, Schedl & Bauer [19] have conducted an in-depth exploration. Initially, they introduced innovative distance-based and rank-based measures. Later, utilizing them to demonstrate that country-specific mainstreamness scores often outperform global scores, indicating that certain nations follow closely their music charts. In contrast, others are more aligned with a worldwide scope [20; 1]. Although Schedl and Bauer's research serves as a foundational basis for this study, it lacks differentiation between children and adult users. It employs a single-time snapshot approach, which may potentially obscure developmental patterns and trends. Nonetheless, it provides a robust hypothesis for the anticipated findings and constitutes an essential foundation for our research.

Children's music recommender research Spear et al. [25] divided children into educational stages: ground school, middle school, and high school, assessing each group's artists' genre mainstreamness with the metric introduced in [18]. Their month-by-month analysis shows that mainstreamness peaks among ground-school users, declines sharply during middle school, and increases again in high school, showing a close correlation with the peer-alignment phase theory [2]. Even so, the absolute mainstreamness scores remain relatively low across all age groups.

3 Experimental Setup

In this section, we formalize the notion of mainstreamness and expose our methodological and experimental approach. We begin with an introduction to the dataset, followed by the construction of platform charts and the monthly popularity rankings of children. In addition, we discuss the rank-similarity measures employed and describe the experiments conducted to answer the proposed research questions.

3.1 Mainstream Definition

The term **mainstream** can have multiple interpretations if not defined correctly beforehand. Throughout this work, we use the term mainstream to refer to all music and artists that are on the top listening charts at a given point in time. So if an artist A was in the top charts in December 2012, we say that they were a mainstream artist at that time. If, by February 2013, they were no longer in the charts, then in this new period, the artist would no longer be considered mainstream. Moreover, **mainstreamness** also has to be defined. This term is used to describe the proportion of each user's music consumption that consists of artists considered mainstream, as defined in the previous statement.

3.2 Dataset

LFM-2b We base our study on the **LastFM-2b** [22] dataset, which logs 2,014,164,872 music-listening events (**LEs**) from 120,322 Last.fm accounts between the years of 2004 and 2020. For consistency reasons with other studies focused on children, we used a pre-preprocessed version by Ungruh et al. [26]. This subset contains 1,337,596,535 LEs from 46,005 users with a valid annotated age on the 31st of October 2013 and activity spanning February 2005 to March 2020. We further isolate young users by considering accounts that registered activity between 12 and 18 years of age. This filter identifies 18,785 accounts that can be included in the study cohort. Since the exact birthday of each user is not given, we assume that in the 31st of October 2013, the user is turning the annotated age, following the convention adopted in previous Last.fm studies with this dataset version.

Since the registration date is given for every user, we can then approximate the sign-up age by backdating the annotated age to the sign-up date. This approximation enables us to mark every listening event with the child's age at the time it occurred, thereby allowing us to follow their developmental trajectory. Finally, we restrict our analysis to the top-5 most populated countries in the dataset: the United States, Poland, Russia, Brazil, and the United Kingdom, as Figure 1 reflects. These five countries have also shown to align differently with the local-global mainstream axis [1], thereby providing a more extensive analytical panorama.

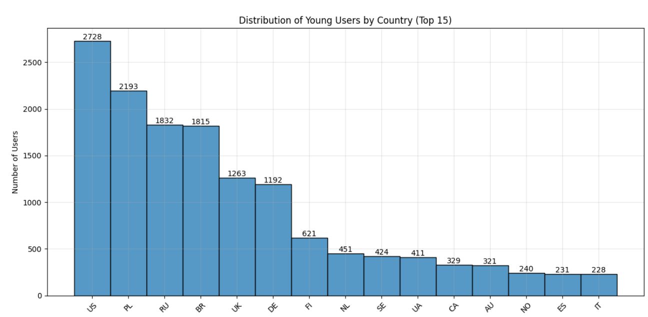

Figure 1: Top-15 young user counts of pre-processed LFM-2b dataset

Handling collaborative tracks The raw LFM-2b dump assigns a new artist ID to every collaborative song, e.g. "Future *featuring* Drake" or "Beyoncé & Jay-Z", so plays of such tracks were not credited to the headline artists' given IDs. To avoid biasing rankings, we resolved these pseudonyms by adding two new columns to the dataset's initial setup: *main_artist_id* and *collaborators_ids*. Matching all found regex patterns for features, we were able to map 20 096

(9.2%), collaborative artist-IDs to the canonical artist-ID and with that give credit to all artists that were part of a featured popular song equally. The script utilized to generate this new dataset is available in the project's repository [4].

3.3 Reference Charts

Platform based charts Measuring mainstreamness in music is not an easy challenge since it can be approached from various angles. To make our results directly comparable with earlier work on local-global specific popularity [20; 1], we construct four artist charts that span the local-global and age dimensions, which can be defined for each calendar month m and each country c, as follows:

Label	Symbol	Population counted
Global–All	$\vec{\mathrm{ALC}}_m^{G}$	all Last.fm users world-wide
Global–Young	$\vec{\mathrm{ALC}}_m^{G_Y}$	world-wide users *age* < 18
Country–All	$\vec{\mathrm{ALC}}_m^{c}$	all country c users
Country–Young	$\vec{\mathrm{ALC}}_m^{c_Y}$	all country c users *age* < 18

Table 1: Monthly reference charts used in this study

Artists are ranked by **Artist Listener Count** (ALC), which represents the number of **distinct** accounts that streamed the artist during the month, So, heavy repeat-listeners do not inflate the score. ALC is therefore directly related to popular platform *Spotify's "monthly listeners"*.

Chart Construction To construct all calendar charts defined in Table 1, we divide the listening events by calendar month and count, for every artist, the number of different users who played at least one of their songs during that period. The users to be taken into consideration should also be part of the age and geographical group that the chart aims to represent, e.g. user should be Brazilian and under 18 for the chart $A\vec{L}C_m^{Brazil_y}$, and have registered some activity in the calendar month m.

Ultimately, by assessing mainstreamness in relation to these four charts, we avoid favoring any individual population and enable the identification of age developmental patterns that may be overlooked if children were assessed solely against a non-age-aware, global baseline.

Individual user popularity chart With the four platform charts in place, we next derive a **per-children** ranking vector for every calendar month m.

For listener u let:

$$n_{u,m} = |\{\text{ artists streamed by } u \text{ in month } m\}|$$

be the number of distinct artists u played in month m. To rank those artists, we use **Artist Play Count (APC)** metric [19] and rank them in descending order. The resulting vector is

$$A\vec{P}C^{u}_{m,m'} \;=\; \left[APC_m(a^{(1)}),\, \ldots,\, APC_m(a^{(n_{u,m})})\right],$$

where $a^{(i)}$ is the i-th most played artist, in calendar month m, by user u. We index each month by the listener's age rather than by calendar date, so m' denotes their development months measured from the listener's 12th birthday ($m' = 0$ at age 12). As an example, a user's 18th birthday would start development month $m' = 72$.

Each user's ranking is then compared against four reference charts, all precomputed for the same calendar month m and user country c, mentioned in table 1.

3.4 Rank-Similarity Metrics

In this section, we present the rank-based metric used to compare the reference charts to the user's artists' preferences.

Rank-Biased Overlap *Rank-Biased Overlap (RBO)*, introduced by Webber et al. [27], is a rank similarity measure that compares lists of different lengths and allows for giving higher importance to their head, through a persistence parameter $p \in [0, 1]$. For a depth d of a ranking, the cumulative weight w assigned to that prefix of the rank is:

$$w(d) \;=\; 1 - p^{\,d-1} \;+\; \frac{1-p}{p}\, d\left(\ln\frac{1}{1-p} - \sum_{i=1}^{d-1}\frac{p^{\,i}}{i}\right)$$

This method helps us understand how similar the highest positions of both the platform and the children ranks are. In the application of this method, we set $p = 0.98$, which concentrates 61% of the total weight for the top-20 artists, 80% for the top-40, and 95% for the top-60, enabling a focus on the artists higher on the charts. Since the cumulative weight is already plateauing by rank 60, extending the list beyond the top-100 artists would only marginally affect the RBO scores. This way, we can align our study with popular reference charts, such as the *Billboard Hot 100*.

Coverage While RBO captures the *rank similarity* between a user's list and reference chart, it falls short of answering a more straightforward question: *"What fraction of a user's favorite artists in a given month were in the top-100 list?"*. To answer this question, we compute a straightforward *Coverage* score. Let:

$$\mathcal{A}_{u,m} = \{\text{artists streamed by listener } u \text{ in month } m\},$$

$$\mathcal{C}_{m,c} = \{\text{top-100 artists in reference chart } c\text{, and month } m\}.$$

$$\text{Coverage}_{u,m}(c) \;=\; \frac{|\mathcal{A}_{u,m} \cap \mathcal{C}_{m,c}|}{|\mathcal{A}_{u,m}|}, 0 \leq \text{Coverage} \leq 1$$

Coverage, in this context, refers to the proportion of a listener's artists that are represented within the chart to which they are being compared. The use of this method will offer a more intuitive reference for users' mainstream scores.

Common Artists Alongside Coverage, we report the count of *Common Artists*. This represents the raw number of chart artists that also appear in a user's monthly top list. Although this count is the numerator for Coverage, it has its value as the user's total artist list does not normalize it, so it exposes *how many mainstream names users engage with*, independent of how broad their streaming habits are.

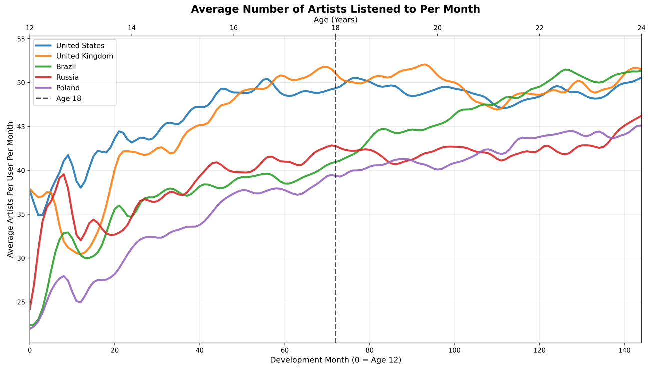

Figure 2: Average number of distinct monthly artists over development

3.5 Setup

Metric Extraction Using the process described in Section 3.3, we generate four monthly reference charts and individual artist popularity rankings for every child. Then, compute for each user-month pair, with registered activity, the *RBO* and *Coverage* scores defined in Section 3.4. Finally, we map the score to their relevant month in the development axis. To manage outliers, we only retain months that contain at least 10 distinct artists and cap the ranks at their top-100. Figure 2 illustrates the evolution of the mean quantity of artists consumed by users across all studied age groups.

Country Data This paper examines data from the five countries most prominently represented by children within the dataset: the United States (US), Poland (PL), Russia (RU), Brazil (BR), and the United Kingdom (UK). Figure 3 provides a detailed overview of the number of unique users who registered listening activity for each age group under study.

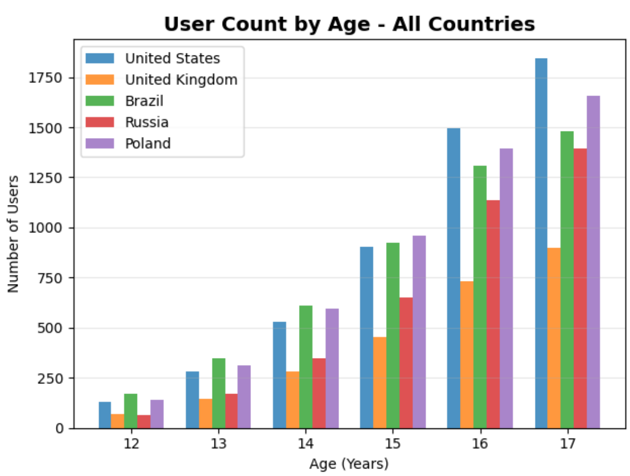

Figure 3: Distinct users active each year by country

The data points considered for constructing the individual user charts are presented in Table 2, where "children" denotes the age range of 12-17, and "adults" refers to the age range of 18-24; each observation corresponds to one development month.

Trend Visualization For each developmental month, we compute the average scores for individual RBO, Coverage, and Common Artists, charting these metrics from age 12 (month 0) to age 18 (month 71). This process is conducted for each country to facilitate a comparative analysis of developmental trends across various user cohorts. To provide additional context, we extend the charts to age 24 (month 144) while maintaining the same user basis. However, the primary focus of our analysis remains on children.

The means and standard deviations regarding the trends are also provided to offer further statistical validation.

Age-related Drift Analysis To analyze children's development comprehensively, we compare the shifts in mainstream alignment as they age. To capture the variations across rank-similarity metrics related to age, we integrate the results from the charts that encompass all users: *Global All* and *Global Young*. This integration disregards individual country separation, emphasizing our primary focus on age-related analysis rather than geographic distinctions to answer **RQ2**. This experiment offers a deeper understanding of the distinction between the distinct stages of childhood and their relationship with mainstream music. The results enable us to investigate additional factors that may contribute to these variations.

Polynomial Fitting To quantify the developmental trend, we fit a polynomial regression model to the mean RBO and Coverage data obtained before.[1] The quality of the found curve is assessed by the *coefficient of determination (R^2)* and the *Mean Absolute Error (MAE)*, which together indicate how good the curve fit is and the average monthly deviation from it. Furthermore, if the coefficient of determination reports values approaching 1, this suggests that the curve accurately represents the data, whereas values near 0 indicate a poor fit. Although it is acknowledged that polynomials of higher degrees are prone to overfitting, it is hypothesized that, given the characteristics of the dataset, such polynomials might yield valuable insights to support our findings.

4 Results

This section combines descriptive statistics with a series of graph-centric visualizations that suit the longitudinal design of the study. We first present and interpret the rank-similarity analyses, then discuss the insights gained from our polynomial fit, and finally compare alternative chart types to assess how each one influences mainstreamness within different countries.

4.1 Overall Metric Extraction and Trend Visualization

Coverage & Common artists Coverage values, as previously mentioned, are intended to provide an intuitive and straightforward representation of the relationship between the user and platform rankings, specifically by identifying how many of the user's most frequented artists are also featured

[1] Implemented with `scikit-learn` [15].

Country	Total users	Total observations	Total observations children	Total observations adult
US	2 878	103 503	27 016	76 487
BR	1 885	68 749	24 380	44 370
PL	2 273	82 712	27 252	55 463
RU	1 909	67 133	18 682	48 456
UK	1 335	50 321	13 423	36 900

Table 2: Country-level monthly data retained for the longitudinal analysis (ages 12–24)

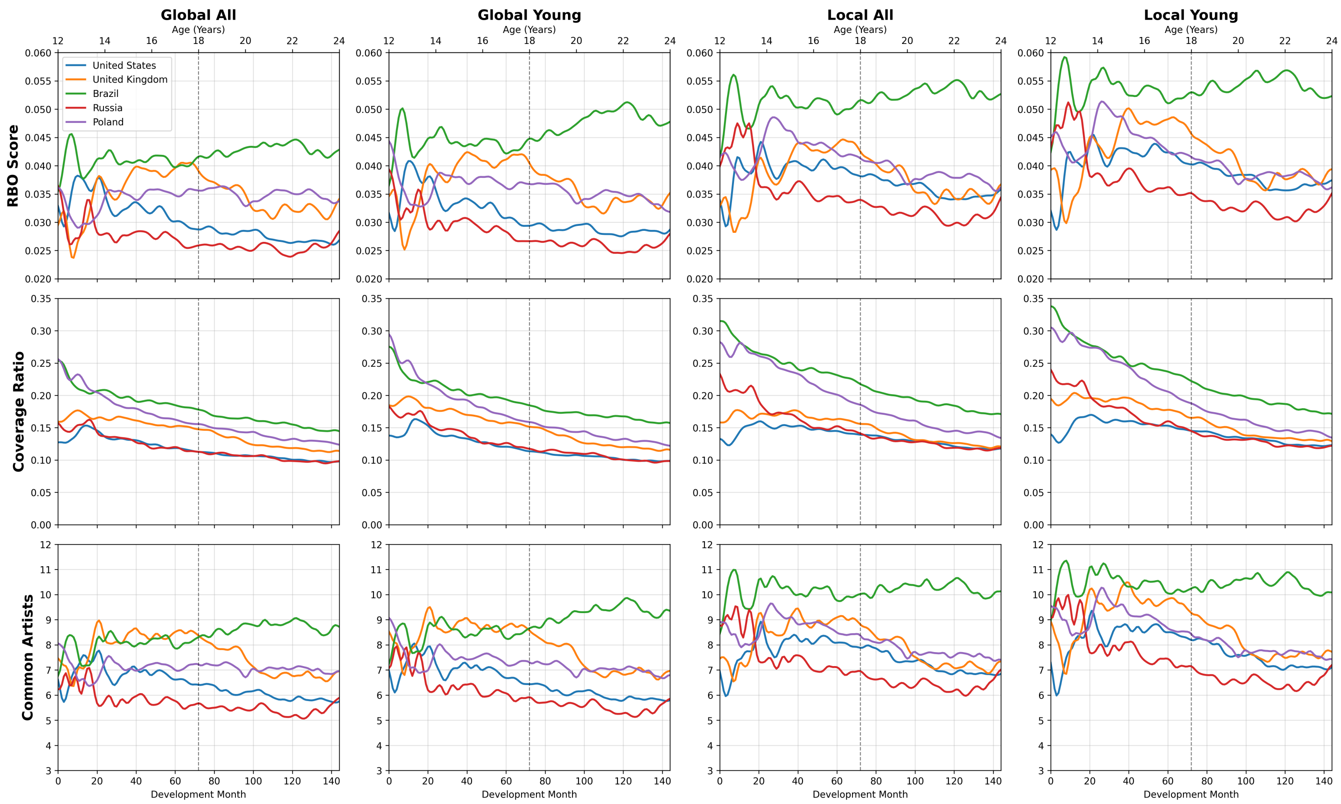

Figure 4: Gaussian Smoothing ($\sigma = 2$), for Average: RBO Scores, Coverage Ratios and Common Artists from 12 to 24 years of age

in the reference charts. This metric produced outcomes characterized by relatively high average scores, while also showing lower standard deviations relative to the mean when compared with RBO. This value indicates that on average, 11.5-31% of a user's most played artists are also in the top-100 of the reference charts. This high overlap is most significant for younger listeners, implying a stronger mainstream preference that gradually fades and stabilizes with age. Moreover, as coverage declines, its standard deviation also decreases, suggesting that, over time, personal music tastes tend to stabilize and become less influenced by popular charts.

The raw count of *Common Artists* also offers a direct view of how mainstream alignment drifts with age. Figure 4 shows that this count stays more flat, while Figure 2 reveals a steady rise in the *total number of artists* a user streams each month. Together, the two plots suggest that younger listeners tend to listen to fewer artists, while preferring more mainstream music. In contrast, older listeners exhibit the opposite trend, engaging with a greater number of artists and increasingly less mainstream music, indicating a progressive consolidation of musical preferences.

Rank-Biased Overlap The RBO analysis indicates a small alignment between users' top-ranked artists and the top of the mainstream charts, as most RBO scores, on average, remain low and stable across all countries and metrics. This is evident in Table 7, where each metric is characterized by considerable standard deviations alongside consistently low means, underscoring the *small average **ranking alignment** between individual user preferences and mainstream charts*, and thus artists that appear in both rankings are distributed across arbitrary positions, as illustrated by Table 7. This finding complements the understanding previously deduced, through the coverage metric, and strengthens our response to **RQ1** by showing that, despite users maintaining a substantial proportion of mainstream artists in their list of favorites. This does not necessarily imply that these artists are prominent on the top charts. We can go deeper into the results with an example. For instance, Brazil's *Local Young* chart, and its user average at 14 years of age share 11 artists, yet the RBO score is 0.056. If those same artists occupied the top-11 slots in both charts, the score would approach 0.45, illustrating the lack of head alignment.

Age-related drifts To address **RQ2**, we refer to Tables 3 and 4, where age-related variances are illustrated. This examination contributes to our understanding of chart preference dynamics, as observed changes on RBO over time are marginal, suggesting a strong correlation with the findings stated before. On the other hand, a noticeable decline is observed in the coverage measurement. This decline reflects the trend of misalignment with popular charts and temporary trends, also linked to the reduction in standard deviation, which is representative of the increasing refinement in musical preferences.

Age	RBO μ	RBO σ	Cov μ	Cov σ	Com μ	N_{total}
12	0.0334	0.0396	0.1927	0.1328	7.2	3 484
13	0.0353	0.0410	0.1828	0.1246	7.4	9 436
14	0.0355	0.0407	0.1695	0.1181	7.4	21 234
15	0.0362	0.0410	0.1608	0.1123	7.4	38 720
16	0.0357	0.0403	0.1527	0.1066	7.4	60 856
17	0.0350	0.0401	0.1470	0.1035	7.3	87 776

Table 3: Overall average statistics across all countries and metrics (RBO, Coverage, Common Artists and Total Monthly Observations)

Age Range	ΔRBO μ	ΔCoverage μ	ΔCommon μ
12→13	+0.0019	−0.0099	+0.22
13→14	+0.0002	−0.0133	−0.02
14→15	+0.0007	−0.0087	+0.04
15→16	−0.0005	−0.0081	−0.03
16→17	−0.0007	−0.0057	−0.15
17→18	−0.0003	−0.0071	−0.06

Table 4: Development trends: change from one age to the next

Deeper age statistical data can be found for consultation in the Appendix A.

4.2 Trend Analysis

To complete our answer to **RQ2**, we modeled the metric curves with polynomial regression.

Tests with fourth and fifth-degree polynomials produced only marginal, not statistically relevant, R^2 gains while inflating standard errors, showing over-fitting. We therefore keep the cubic model ($degree = 3$) for both metrics. The resulting coefficients and R^2 scores are listed in Tables 6 and 5.

None of the fitted polynomial trends provided an adequate explanation of the data, as not only are the R^2 values low, but the average errors are also significant. This suggests that age accounts for only a small portion of the distance to mainstream charts. That doesn't mean age is irrelevant, as previous results show significant behavioral patterns, but it hints that other factors could also have a strong influence on how children consume mainstream music.

	$\mathrm{A}\vec{\mathrm{LC}}^{G}$		$\mathrm{A}\vec{\mathrm{LC}}^{Gy}$		$\mathrm{A}\vec{\mathrm{LC}}^{c}$		$\mathrm{A}\vec{\mathrm{LC}}^{cy}$	
Country	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE
US	0.0130	0.0664	0.0159	0.0670	0.0114	0.0787	0.0134	0.0814
UK	0.0288	0.0742	0.0359	0.0767	0.0285	0.0784	0.0370	0.0835
BR	0.0252	0.0863	0.0231	0.0906	0.0426	0.1036	0.0460	0.1084
RU	0.0116	0.0692	0.0185	0.0710	0.0213	0.0798	0.0255	0.0822
PL	0.0311	0.0830	0.0445	0.0851	0.0664	0.0946	0.0765	0.0973

Table 5: Polynomial-fit regression metrics for *Coverage* (degree 3): R^2 and MAE by country and metric.

	$\mathrm{A}\vec{\mathrm{LC}}^{G}$		$\mathrm{A}\vec{\mathrm{LC}}^{Gy}$		$\mathrm{A}\vec{\mathrm{LC}}^{c}$		$\mathrm{A}\vec{\mathrm{LC}}^{cy}$	
Country	R^2	MAE	R^2	MAE	R^2	MAE	R^2	MAE
US	0.0029	0.0262	0.0022	0.0271	0.0020	0.0329	0.0025	0.0344
PL	0.0002	0.0313	0.0013	0.0317	0.0030	0.0352	0.0043	0.0357
RU	0.0008	0.0251	0.0014	0.0257	0.0020	0.0297	0.0027	0.0306
BR	0.0006	0.0344	0.0022	0.0376	0.0004	0.0424	0.0004	0.0453
UK	0.0054	0.0309	0.0055	0.0319	0.0064	0.0331	0.0076	0.0354

Table 6: Polynomial-fit regression metrics for *RBO* (degree 3): R^2 and MAE by country and metric.

4.3 Chart Comparison

To address **RQ3**, we compare four chart variants (Global–All, Global–Young, Local–All, and Local–Young). Each chart narrows the comparison group, so one might expect *RBO* and *Coverage* to rise as the reference becomes more similar to the user. It is noticeable that different countries are more aligned with mainstream by looking at the absolute values in Tables 7 and 8. Additionally, gains from more specific metrics also vary depending on whether the country is more or less influenced by age and geography. Switching from global to local charts, for example, boosts coverage most in Brazil (≈ 0.05) but only marginally in the United States (≈ 0.025). Conversely, changing the age-scope of users in reference charts varies United States scores (≈ 0.008) yet moves less in Brazil (≈ 0.006). Consequently, considering that the United States exhibits greater variation concerning age compared to Brazil, it can be inferred that the alignment of its population with mainstream music is more *age-sensitive* than that of Brazil, which, in contrast, demonstrates higher *geographical-sensitivity* on a proportional basis. Moreover, the geographical scope has a greater influence on proximity to mainstream charts compared to age, as demonstrated by the larger variation in *Coverage*. Specifically, the range of variance in age is from 0.003 to 0.016, with an average change of 0.011, whereas the range for geography extends from 0.010 to 0.050, with an average change of 0.033.

5 Discussion and Limitations

In this section, we build on our findings, aiming to address the proposed research questions and understand the implications these answers have on music recommender systems research.

	$\vec{\text{ALC}}^{G}$		$\vec{\text{ALC}}^{G_y}$		$\vec{\text{ALC}}^{c}$		$\vec{\text{ALC}}^{c_y}$	
Country	(12–17)	(18–24)	(12–17)	(18–24)	(12–17)	(18–24)	(12–17)	(18–24)
US	0.031±0.038	0.028±0.034	0.032±0.038	0.029±0.035	0.040±0.047	0.036±0.041	0.042±0.049	0.038±0.049
PL	0.035±0.041	0.035±0.041	0.037±0.042	0.035±0.041	0.043±0.049	0.039±0.044	0.044±0.050	0.039±0.044
RU	0.027±0.035	0.026±0.034	0.028±0.036	0.026±0.034	0.035±0.041	0.032±0.039	0.036±0.042	0.033±0.040
BR	0.041±0.043	0.043±0.044	0.044±0.045	0.048±0.049	0.051±0.052	0.053±0.055	0.053±0.054	0.054±0.060
UK	0.039±0.043	0.034±0.040	0.041±0.044	0.035±0.041	0.043±0.047	0.037±0.042	0.047±0.049	0.040±0.044

Table 7: RBO Score Summary (Mean ± SD) by country and metric.

	$\vec{\text{ALC}}^{G}$		$\vec{\text{ALC}}^{G_y}$		$\vec{\text{ALC}}^{c}$		$\vec{\text{ALC}}^{c_y}$	
Country	(12–17)	(18–24)	(12–17)	(18–24)	(12–17)	(18–24)	(12–17)	(18–24)
US	0.122±0.097	0.104±0.081	0.125±0.097	0.104±0.082	0.146±0.114	0.127±0.095	0.154±0.117	0.132±0.099
PL	0.170±0.119	0.139±0.100	0.179±0.125	0.139±0.102	0.214±0.142	0.156±0.112	0.221±0.147	0.157±0.114
RU	0.121±0.098	0.104±0.087	0.129±0.102	0.107±0.088	0.154±0.116	0.126±0.098	0.161±0.121	0.129±0.100
BR	0.190±0.120	0.159±0.104	0.200±0.124	0.169±0.110	0.240±0.141	0.190±0.125	0.246±0.146	0.193±0.132
UK	0.155±0.104	0.126±0.091	0.163±0.108	0.128±0.094	0.165±0.112	0.133±0.096	0.181±0.120	0.141±0.101

Table 8: Coverage Score Summary (Mean ± SD) by country and metric.

RQ1 - What is the alignment between children's most-played artists and reference mainstream charts? It has been observed that, over time, *children exhibit a greater alignment with mainstream music charts compared to adults*. On average, **15.2 %** of the artists in a child's monthly top list also appear in the global top-100, whereas the share drops to **12.6 %** once those listeners reach adulthood. It should also be noted that switching from global to local charts increases the absolute numbers, as the comparison pool is smaller. However, the gap between children and adults persists in every country. The rank-similarity results paint a complementary picture: the scores appear to be near zero, indicating that artists shared within charts are arbitrarily distributed along the user rankings rather than concentrated at the very top. Finally, to provide a clearer perspective on the numbers, considering that the platform hosts 218 626 distinct artists, the findings suggest that with the top-100 artists (a mere 0.0045 % of the catalogue), it is possible to capture one-sixth of children's favourites. This significant asymmetry illustrates well the long-tail consumption patterns described by Celma [3], where a tiny slice of the available musical content constitutes a disproportionate representation of the total consumption.

RQ2 - How does aging influence children's mainstream music consumption? Given the longitudinal nature of our study, it is essential to dive deeper into the differences noticed between periods of development.

As demonstrated in our results, there is a decrease in overall coverage from 12 to 18 years of age of 23.7%, which is highly substantial, indicating how, over time, children become less influenced by trends. This contributes to the identification of specific age groups based on their mainstream consumption behavior. To start, we can align early adolescence (12-14) [12] with the period of more intense change. This is a time when children start to hit puberty, developing a deeper relationship with social image and trying to "fit in". For this purpose, children will listen to the most trendy songs, to be more aligned with their peers and face less social exclusion. Furthermore, since their exposure to the broader music landscape is still limited, they are naturally steered toward the most familiar and widely promoted artists. By mid to late adolescence (15–18 years), musical preferences usually shape into a relatively stable component of personal identity, so the impact of whatever is topping the charts weakens at this stage [14]. This consolidation is reflected in our findings: the steep early drop in rank alignment with mainstream artists slows down at this stage, indicating that once children solidify their tastes, trends have a significantly less pronounced impact. Furthermore, our findings are consistent with the study on genre mainstreamness preferences among children conducted by Spear et al. [25]. Although our analysis does not explicitly focus on grade school student data or genres, it does reveal that individuals in middle school (ages 12-14) show a preference for more popular artists, indicating a higher relative consumption of mainstream music compared to their high school peers.

Additionally, we attempt to identify a polynomial trend in the age-mainstreamness scores to gain a deeper understanding of this shift. Our polynomial fits yield low R^2 values, indicating that age alone does not fully explain mainstream listening. Peer dynamics, parental preferences, platform algorithms, or other factors are likely to have a significant influence as well. It is also expected that, since our data is very sparse, higher-order models will risk overfitting, and it is challenging to find a one-size-fits-all solution. For future work, replicating this trend for smaller groupings of similar children would likely yield insightful results.

RQ3 - Which scope (age vs. geography) has the highest influence when building reference charts that mirror children's mainstream listening behavior? In this question, we intend to direct attention towards the reference charts themselves. It can be inferred that *geographical factors show a greater influence on chart construction than age-related factors*. Specifically, there is a more pronounced absolute difference in mainstream alignment when the geographical scope is varied (as indicated by *Global to Local*) compared to variations in age group (as referenced in *All to Young*). The data reveal that the average variation resulting from alterations in geographical scope is 0.033. In contrast, the variation due to age differences is merely 0.011, suggesting that geographical scope is three times more influential than age in our dataset.

In contexts where age variation is more pronounced, it is possible to see that the musical preferences of children significantly diverge from those of adults. Alternatively, for geographical variations, it is evident that countries previously identified as closely aligned with their mainstream charts [1] maintain this characteristic. For instance, Brazil shows the highest geographic variance. In contrast, countries like the United States, which either follow or establish global trends, demonstrate a significantly lower impact when the geographical scope is altered.

5.1 Broader Implications and Limitations

Broader implications Collectively, the results of this study reveal pertinent practical implications. First, the clear age–related drift away from popularity charts highlights the importance of *age-aware recommendation systems*. Platforms that fail to consider age and serve young users with mainstream music may not only be misaligned with their developmental trajectories but also have a detrimental impact on their creative development and self-discovery.

Second, the stronger role of geography over age in chart alignment suggests that regional charts remain highly relevant in our era. Music streaming platforms can then explore country-specific local charts and gain an accurate representation of what current trends children are aligning with.

We can also conclude that age is one of many features that impact mainstream consumption. Since we couldn't confidently fit our scores on an age trend, we are confident that more factors influence the alignment of these charts. Another factor contributing to this is the scope of the project. Since we aimed to cater to all young users of a country, it is still too broad a group to track a developmental trend accurately.

Ultimately, our findings reveal that a mere 0.0045% of the entire artist catalog accounts for one-sixth of the most frequently played artists among children. This phenomenon should raise concerns about a cultural debate regarding diversity and pluralism in media exposure, as well as encourage policymakers to conduct a more thorough examination of recommendation algorithms to reduce the significant concentration observed at the top of media consumption.

Limitations Despite the longitudinal nature of the study, some limitations may affect the generalization of our findings. Since our analysis was conducted using a single dataset, it is challenging to claim with certainty that the observed behavior would be replicated on other platforms. Additionally, the dataset shows that artists such as *The Beatles* and *Pink Floyd*, associated with a previous era of mainstream popularity, continue to dominate the charts [1; 3]. This suggests that Last.fm users could represent a niche audience that does not fully align with the broader mainstream landscape. Consequently, as further datasets become accessible, we strongly recommend replicating this study to confirm the generalization of our findings.

6 Conclusion

In this study, we aim to understand the alignment of children with popularity charts and how it changes over time. Utilizing the well-known LastFM-2b dataset, we generate various monthly popularity charts and use rank-similarity measures to compare these with children's preferences. Our research demonstrated that children are more inclined to listen to mainstream music than adults. In particular, we observed that early adolescence is closely tied to increased consumption of mainstream music and susceptibility to trends. Conversely, during middle to late adolescence, there is a gradual shift towards a more sophisticated music taste, moving slightly away from the most popular artists. Lastly, we highlight how the geographical scope for creating popularity charts is a key factor in understanding children's musical tastes, while age shows a smaller influence. Given these findings, it is crucial to develop age-aware and dynamic recommender systems that can adapt to children's evolving musical interests and developmental needs. These systems should take into account the changes in preferences that occur as children progress through different stages of adolescence, ensuring that recommendations remain relevant, engaging and constructive.

7 Future Work

Regarding future work, we strongly suggest replicating the study when new datasets become accessible. The existing dataset may represent a niche, so it would be highly valuable to analyze how closely related the dataset's popular artists are to broader mainstream measurements, such as the *Billboard Hot-100* or *Spotify Charts*. A further study on a tighter scope of users would be the next step in this experiment, e.g., studying only American users and dividing them by state or clustering children by genre alignment. Nevertheless, a new dataset with more specific country allocations would be necessary. To integrate with earlier research on genre mainstreamness, it is worthwhile to explore how the concept applies within genres and understand how children align with top artists in each category. This could provide a clearer understanding of the niche changes younger users pursue as they mature.

8 Responsible Research

All research followed the practices from the *TUDelft Code of Conduct* [17]

The anonymity of users is fully preserved, as the dataset excludes any personally identifiable information, such as names, email addresses, physical addresses, or any other data elements that could reveal individual identities. In addition, to mitigate any risk of personal identification, the analysis focuses on aggregate user groups rather than individual user patterns. Furthermore, the Last.FM dataset is acknowledged as a derivative work [22], and their Terms of Service grant a license for its utilization. Unfortunately, the LFM-2b dataset is no longer publicly accessible due to licensing restrictions, thereby compromising the reproducibility and accessibility of this study. Having had the privilege of accessing this dataset, and acknowledging its status as the most widely utilized dataset in the domain of music recommender system research, we express the hope that it will become publicly available again shortly.

The ages reported by users were accepted as trustworthy; however, we acknowledge that there may be inaccuracies, as some platform users have registered with an age below 13, which is the minimum legal age for creating a social media account. Despite this, we find the data for 12-year-old users to be valuable and sizable enough to be included in our analysis. To ensure the reproducibility of our findings, all code utilized to derive these results is available in the following repository [4].

The methodology and experimental setup section provides a comprehensive description of the procedures undertaken. We aimed to ensure that each user's impact on the overall study was equitable. Hence, the option of employing Average Play Count (APC) for the platform charts was dismissed. Instead, we implemented Average Listening Count (ALC) to mitigate bias towards users who extensively listen to specific artists. When examining a vulnerable user group heavily influenced by the media they consume, designers of recommender systems need to exercise caution when tailoring systems for this demographic.

Recommender systems should refrain from propagating political, promotional, or sensitive biased content that could affect children's development. They should also avoid assessing quality based solely on accuracy metrics, as children have more complex developmental needs. The system should facilitate exploration of diverse and less conventional genres to further contribute to their creative development [6], and should not restrict itself to measuring quality based on accuracy.

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A Expanded Age statistics

Detailed statistical information related to each age category used to create Tables 8 and 7 is presented in this appendix. With comprehensive tables including all *RBO scores, Coverage ratios, Number of observations* and *Common artists per year*. Apart from the count of observations, the values presented are mean calculations derived from all users falling within each specified age group.

A.1 Global All

Age	RBO	Coverage	N	Common
12	0.034 ± 0.040	0.136 ± 0.108	345	6.5
13	0.037 ± 0.045	0.148 ± 0.110	1 033	7.5
14	0.032 ± 0.040	0.132 ± 0.107	2 358	6.6
15	0.033 ± 0.040	0.128 ± 0.104	4 359	6.9
16	0.032 ± 0.038	0.121 ± 0.096	7 193	6.8
17	0.030 ± 0.036	0.116 ± 0.089	11 728	6.5

Table 9: United States - Global All metric

Age	RBO	Coverage	N	Common
12	0.030 ± 0.036	0.234 ± 0.157	431	7.1
13	0.031 ± 0.038	0.209 ± 0.149	1 200	6.7
14	0.035 ± 0.041	0.187 ± 0.123	2 774	7.2
15	0.035 ± 0.041	0.176 ± 0.124	5 159	7.1
16	0.035 ± 0.041	0.166 ± 0.117	7 708	7.2
17	0.035 ± 0.041	0.158 ± 0.109	9 980	7.1

Table 10: Poland - Global All metric

Age	RBO	Coverage	N	Common
12	0.027 ± 0.037	0.150 ± 0.127	184	6.2
13	0.030 ± 0.040	0.150 ± 0.120	567	6.1
14	0.027 ± 0.035	0.135 ± 0.112	1 513	5.8
15	0.028 ± 0.036	0.126 ± 0.098	2 967	5.9
16	0.028 ± 0.036	0.119 ± 0.095	5 254	5.8
17	0.026 ± 0.034	0.115 ± 0.095	8 197	5.6

Table 11: Russia - Global All metric

Age	RBO	Coverage	N	Common
12	0.041 ± 0.045	0.225 ± 0.131	572	7.7
13	0.039 ± 0.040	0.207 ± 0.128	1 396	7.6
14	0.042 ± 0.044	0.201 ± 0.132	2 864	8.3
15	0.041 ± 0.042	0.193 ± 0.122	4 617	8.0
16	0.041 ± 0.043	0.188 ± 0.116	6 570	8.2
17	0.040 ± 0.043	0.182 ± 0.116	8 361	8.0

Table 12: Brazil - Global All metric

Age	RBO	Coverage	N	Common
12	0.026 ± 0.033	0.170 ± 0.118	210	6.8
13	0.034 ± 0.039	0.166 ± 0.105	522	8.1
14	0.035 ± 0.040	0.164 ± 0.107	1 108	8.0
15	0.039 ± 0.042	0.160 ± 0.105	2 258	8.4
16	0.039 ± 0.041	0.153 ± 0.102	3 703	8.4
17	0.040 ± 0.045	0.151 ± 0.103	5 622	8.5

Table 13: United Kingdom

A.2 Global Young

Age	RBO	Coverage	N	Common
12	0.036 ± 0.041	0.146 ± 0.113	345	7.0
13	0.038 ± 0.045	0.156 ± 0.114	1 033	7.8
14	0.033 ± 0.040	0.137 ± 0.109	2 358	6.9
15	0.033 ± 0.040	0.131 ± 0.103	4 359	7.1
16	0.032 ± 0.038	0.124 ± 0.096	7 193	7.0
17	0.030 ± 0.036	0.118 ± 0.089	11 728	6.9

Table 14: United States - Global Young metric

Age	RBO	Coverage	N	Common
12	0.036 ± 0.041	0.262 ± 0.174	431	7.8
13	0.034 ± 0.040	0.223 ± 0.149	1 200	7.1
14	0.038 ± 0.043	0.200 ± 0.131	2 774	7.7
15	0.038 ± 0.042	0.188 ± 0.130	5 159	7.5
16	0.038 ± 0.043	0.175 ± 0.122	7 708	7.5
17	0.036 ± 0.042	0.163 ± 0.112	9 980	7.3

Table 15: Poland - Global Young metric

Age	RBO	Coverage	N	Common
12	0.031 ± 0.037	0.170 ± 0.129	184	7.2
13	0.031 ± 0.041	0.164 ± 0.124	567	6.1
14	0.030 ± 0.037	0.148 ± 0.116	1 513	6.2
15	0.030 ± 0.037	0.135 ± 0.104	2 967	6.3
16	0.028 ± 0.037	0.125 ± 0.098	5 254	6.1
17	0.027 ± 0.034	0.122 ± 0.097	8 197	5.9

Table 16: Russia - Global Young metric

Age	RBO	Coverage	N	Common
12	0.044 ± 0.046	0.242 ± 0.136	572	8.2
13	0.043 ± 0.043	0.222 ± 0.131	1 396	8.1
14	0.046 ± 0.046	0.214 ± 0.134	2 864	8.8
15	0.044 ± 0.045	0.203 ± 0.124	4 617	8.4
16	0.044 ± 0.045	0.196 ± 0.119	6 570	8.6
17	0.043 ± 0.046	0.189 ± 0.120	8 361	8.4

Table 17: Brazil - Global Young metric

Age	RBO	Coverage	N	Common
12	0.029 ± 0.034	0.192 ± 0.136	210	7.6
13	0.037 ± 0.039	0.184 ± 0.110	522	8.8
14	0.038 ± 0.042	0.177 ± 0.112	1 108	8.5
15	0.042 ± 0.045	0.169 ± 0.109	2 258	8.9
16	0.041 ± 0.042	0.160 ± 0.105	3 703	8.7
17	0.042 ± 0.045	0.156 ± 0.105	5 622	8.8

Table 18: United Kingdom - Global Young metric

A.3 Local All

Age	RBO	Coverage	N	Common
12	0.035 ± 0.050	0.136 ± 0.117	345	6.8
13	0.041 ± 0.054	0.156 ± 0.120	1 033	8.1
14	0.039 ± 0.049	0.151 ± 0.120	2 358	7.8
15	0.040 ± 0.047	0.150 ± 0.121	4 359	8.2
16	0.040 ± 0.046	0.147 ± 0.115	7 193	8.2
17	0.039 ± 0.046	0.142 ± 0.109	11 728	8.0

Table 19: United States - Local All

Age	RBO	Coverage	N	Common
12	0.039 ± 0.044	0.274 ± 0.161	431	8.3
13	0.041 ± 0.047	0.266 ± 0.172	1 200	8.4
14	0.047 ± 0.052	0.245 ± 0.153	2 774	9.3
15	0.045 ± 0.050	0.230 ± 0.150	5 159	8.9
16	0.044 ± 0.049	0.208 ± 0.139	7 708	8.8
17	0.042 ± 0.047	0.193 ± 0.127	9 980	8.4

Table 20: Poland - Local All

Age	RBO	Coverage	N	Common
12	0.042 ± 0.049	0.210 ± 0.134	184	8.6
13	0.040 ± 0.046	0.200 ± 0.137	567	7.9
14	0.035 ± 0.041	0.172 ± 0.126	1 513	7.3
15	0.036 ± 0.042	0.160 ± 0.119	2 967	7.4
16	0.034 ± 0.041	0.150 ± 0.112	5 254	7.0
17	0.034 ± 0.039	0.147 ± 0.111	8 197	6.9

Table 21: Russia - Local All

Age	RBO	Coverage	N	Common
12	0.05 ± 0.051	0.293 ± 0.153	572	10.0
13	0.048 ± 0.047	0.270 ± 0.149	1 396	9.8
14	0.053 ± 0.053	0.255 ± 0.145	2 864	10.5
15	0.050 ± 0.050	0.243 ± 0.141	4 617	10.0
16	0.051 ± 0.052	0.236 ± 0.137	6 570	10.2
17	0.050 ± 0.053	0.227 ± 0.138	8 361	9.9

Table 22: Brazil - Local All

Age	RBO	Coverage	N	Common
12	0.030 ± 0.040	0.171 ± 0.127	210	7.0
13	0.037 ± 0.044	0.168 ± 0.106	522	8.3
14	0.038 ± 0.043	0.171 ± 0.114	1 108	8.4
15	0.043 ± 0.047	0.172 ± 0.116	2 258	9.0
16	0.043 ± 0.045	0.163 ± 0.110	3 703	8.9
17	0.044 ± 0.048	0.161 ± 0.111	5 622	9.1

Table 23: United Kingdom

A.4 Local Young

Age	RBO	Coverage	N	Common
12	0.036 ± 0.051	0.143 ± 0.122	345	7.1
13	0.042 ± 0.054	0.167 ± 0.127	1 033	8.7
14	0.041 ± 0.051	0.161 ± 0.125	2 358	8.3
15	0.042 ± 0.049	0.158 ± 0.124	4 359	8.6
16	0.043 ± 0.049	0.155 ± 0.118	7 193	8.7
17	0.041 ± 0.048	0.149 ± 0.112	11 728	8.4

Table 24: United States - Local Young

Age	RBO	Coverage	N	Common
12	0.042 ± 0.048	0.294 ± 0.173	431	8.8
13	0.044 ± 0.049	0.280 ± 0.178	1 200	8.9
14	0.050 ± 0.054	0.260 ± 0.161	2 774	9.9
15	0.047 ± 0.051	0.238 ± 0.155	5 159	9.3
16	0.044 ± 0.050	0.214 ± 0.142	7 708	9.0
17	0.042 ± 0.048	0.197 ± 0.130	9 980	8.6

Table 25: Poland - Local Young

Age	RBO	Coverage	N	Common
12	0.045 ± 0.053	0.222 ± 0.141	184	9.2
13	0.042 ± 0.048	0.206 ± 0.134	567	8.3
14	0.037 ± 0.042	0.183 ± 0.131	1 513	7.8
15	0.038 ± 0.045	0.170 ± 0.127	2 967	7.9
16	0.036 ± 0.043	0.156 ± 0.116	5 254	7.4
17	0.035 ± 0.041	0.153 ± 0.116	8 197	7.2

Table 26: Russia - Local Young

Age	RBO	Coverage	N	Common
12	0.053 ± 0.052	0.310 ± 0.160	572	10.5
13	0.051 ± 0.049	0.283 ± 0.155	1 396	10.3
14	0.056 ± 0.054	0.265 ± 0.150	2 864	10.9
15	0.053 ± 0.053	0.25 ± 0.145	4 617	10.4
16	0.053 ± 0.054	0.24 ± 0.141	6 5670	10.4
17	0.052 ± 0.056	0.23 ± 0.144	8 361	10.1

Table 27: Brazil

Age	RBO	Coverage	N	Common
12	0.037 ± 0.038	0.194 ± 0.137	210	7.7
13	0.041 ± 0.044	0.197 ± 0.115	522	9.4
14	0.043 ± 0.046	0.193 ± 0.123	1 108	9.5
15	0.049 ± 0.052	0.193 ± 0.126	2 258	10.1
16	0.048 ± 0.050	0.179 ± 0.120	3 703	9.7
17	0.048 ± 0.050	0.173 ± 0.116	5 622	9.7

Table 28: United Kingdom - Local Young