The Economics of App Success: How Revenue Streams Influence Downloads and User Ratings

Group Assignment - Strategy and Business Models

Group 5

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Contents

1 Introduction

With the every-growing popularity of cellphones (Richter 2023), the popularity of mobile applications is also steadily increasing. In 2024, mobile applications are estimated to generate over $900 billion in revenue (“Mobile App Revenue Worldwide by Segment (2019-2027)” 2023). Generally, mobile applications (‘*apps*’ from here on) tend to be categorized in three different categories (Roma and Ragaglia 2016). Paid apps are the most transparent; they revenue is based on an up-front purchase by the user. Free apps, on the other hand, require no purchase by the user at any stage. According to Roma and Ragaglia (2016), these apps make their revenue from deals with third-parties, either through advertisement or other purposes such as market information.

Finally, freemium apps are, as the name suggests, a middle-ground between free and premium. Users get access to a basic version of the application first and can unlock more features through an in-app payment (Kumar 2014). Of these three revenue models, freemium is the most commonly used and the most (Salehudin and Alpert 2021) and leads to more downloads as well as revenue (Liu, Au, and Choi 2014).

1.1 Academic Background

Most research uses these three established categories—paid, freemium, and free—when discussing revenue models for apps. However, by limiting the discussion to these three terms, nuances within these categories might be missed.

In a review paper from 2023 (Djaruma et al. 2023), different levels of monetization are suggested based on previous literature. These levels provide a clear framework for the revenue models of mobile apps.

Strategy	Description
Level 5: Premium	Pay to use the application. This either happens up-front, or after a trial period.
Level 4: Semi-premium	Use a limited number of features for free. Unlock the app with all features through an in-app purchase.
Level 3: In-app advertisement and in-app purchases	Free application with ads, encouraging users to remove ads or to make in-app purchases.
Level 2: Sample and premium	Two different versions of the same app. One is a version with limit features and/or ads. The other version is a premium version.
Level 1: In-app advertisement	Only one version of the app, with only ads and no in-app purchases.
Level 0: Free	The app has no monetization. However, money can still be made through selling user information.

Strategy	Description

Table 1: Six levels of monetization for apps

1.2 Societal Background

Currently, most apps utilize the freemium revenue model (Salehudin and Alpert 2021). However, as discussed in Djaruma et al. (2023), there are many revenue models between completely premium and completely free. A more fine-grained classification of app revenue models beyond the traditional "paid-freemium-free" framework holds significant societal and business implications.

For society, such distinctions enhance transparency. Some monetization models, such as free or ad-filled apps, may rely on selling user information as a source of revenue (Bamberger et al. 2020). Therefore, clearer distinctions regarding the revenue model will empower consumers to make informed choices. It may also enable policymakers to identify and regulate exploitative practices, such as manipulative microtransactions or intrusive ad models, ensuring all applications align with ethical and legal standards (Mileros and Forchheimer 2024).

For businesses, this paper should unlock more insight into the effectiveness of different revenue streams. This will allow developers to tailor monetization strategies to specific audiences. Furthermore, both consumers and regulatory bodies are growing more concerned with the privacy concerns of apps, especially ones that rely on market information (Mileros and Forchheimer 2024). A granular understanding helps businesses adapt, aligning profitability with sustainability and ethical considerations.

1.3 Research Gap

In short, apps play an increasingly important role in our techno-centric society. To improve the user experience and increase profits, consideration of revenue models is key. Despite the great depth of research on this topic, literature tends to be focussed on the three big categories of paid, freemium, and free. This lack of nuance prevents us from understanding the fine-grained details that may help improve future apps.

The levels of monetization as proposed by Djaruma et al. (2023) would allow for this nuance. However, their framework has never been used in an empirical setting, as the paper by Djaruma et al. (2023) was published only last year. Applying this framework to see how different revenue streams impact the popularity of an app may yield valuable insights into the preferences of consumers. Therefore, the question to answer within this paper will be: *How are the 5 different revenue models as proposed by Djaruma et al. (2023) correlated to the success of an app?*

2 Theory and Hypotheses

In this section, prior research into the topic of revenue streams and its correlation to success in apps will be discussed. As mentioned in the Introduction section, this paper will apply the 5 levels of revenue as proposed by Djaruma et al. (2023) to app data. The following section will contain a holistic overview of the existing research, as well as hypotheses that arise from this theoretical framework.

2.1 Literature Review

To answer the question "*How are the 5 different revenue models as proposed by Djaruma et al. (2023) correlate to the success of an app?*", we must first define what constitutes to success. In this paper, success will be defined by a couple of factors: popularity, rating, and estimated revenue.

2.1.1 Popularity

The popularity of an app can be measured by the number of downloads. It is important to note the popularity of an app is complex, and is not solely dependent on the chosen revenue model. Other features, such as whether an app is featured on charts, whether it has frequent updates, and word-of-mouth awareness, will also impact the popularity of an app (Aydin Gokgoz, Ataman, and Bruggen 2021). However, despite these other variables, to versions of the same app will still have drastically different performances with different revenue streams (Liu, Au, and Choi 2014).

H1a: Apps that allow the user to have free access to all features (level 0 and 1) will have the highest amount of downloads overall. However, the ratings may fluctuate, as quality can vary for free-to-access apps.

H1b: The apps with the most downloads will be level 1. Most social media platforms, which dominate our culture, tend to have this revenue stream (Djaruma et al. 2023).

H1c: For apps that utilize a sample and a premium version of the same app (level 2), the free versions of an app will have more downloads than their paid-for counterpart. Most, if not all, users will download the free version first, and then might upgrade. This means there should be a disparity between the number of downloads between the apps, as is also demonstrated by Liu, Au, and Choi (2012).

H1d: The most downloaded apps in the gaming category will likely fall under level 4. Many popular games use this type of "pay-to-win" mechanism (Nieborg 2016). Therefore, it would be expected this same pattern would arise from our data.

2.1.2 Rating

The downloads of an app are not everything. An app can be downloaded often, but may not be highly rated.

H2a: Apps that require the user to pay to unlock features (level 2, 3, and 4) will tend to have lower ratings than the version that requires payment upfront (level 5). The main draw of a freemium model is to attract users, and have them update to a paid version (Kumar 2014). However, as Kumar (2014) points out, this can be a double-edged sword. Too few features, and it may not be attractive to users. Too many features, and the users will not update.

H2b: Fully premium apps (level 5) will have less variance in their ratings, while all other levels will have more. In the same vein as H2a, users have more realistic expectations of paid apps compared to apps that require you to unlock features (Kumar 2014). Therefore, more users downloading premium apps will be satisfied with their purchase, leading to less variance.

H3: For apps that utilize a sample and a premium version of the same app (level 2), the rating of the paid-for version is positively associated with the rating of the free version of the same app. This was true for the study on the most popular apps in the Google Play Store by Liu, Au, and Choi (2012), so it is expected a similar pattern should arise for this dataset.

2.1.3 Revenue Estimation

It is important to point out downloads and ratings likely do not directly correlate to the actual revenue of an app. The revenue of apps "premium" apps that require an upfront payment, the revenue is relatively simple to track and compare. However, for apps that rely on advertisement, in-app purchases and/or selling market information, this is harder to track.

For apps that solely on advertisement, time retention can be a good measure of revenue (Ross 2018). However, this only works if the app solely relies on ads. An example of this given by Djaruma et al. (2023) is TikTok: this app relies not only on advertisement, but also on users purchasing products through its shop. Therefore, using solely the time retention would not accurately capture the revenue of an app with both revenue streams. Furthermore, the selling of user data is usually not publicized, meaning it is not possible to know the revenue from this.

Unfortunately, our data only contains the price of "premium" app versions. The data does not include any details regarding in-app purchases nor time-retention. Because of this lack of sufficient data, solely downloads and ratings will be taken into account as indicators of success.

3 Methods and Data

In this section, we will discuss the dataset and methods used to test the hypotheses outlined in the previous section. The focus lies on providing a comprehensive description of the dataset, including its structure and the variables it contains, followed by an explanation of the variable selection process. Additionally, we outline the statistical methods applied and discuss how assumptions, such as missing values and potential biases, were addressed to ensure the robustness of our analysis.

3.1 Dataset Description

The dataset used for this research consists of 1,016,666 instances and 27 variables, representing a detailed overview of mobile applications across various revenue models. Each instance corresponds to an app, and the variables capture key attributes such as app downloads, user ratings, and monetization strategies. Below is an overview of some of variables:

Variable	Description
my_app_id (object)	Unique identifier for each app.
date_published (object)	The publication date of the app. Only three missing values (0.000295% null).
privacy_policy (object)	Information about the app's privacy policy, missing in 28.57% of cases.
rating_app (float64)	The average rating of the app, with 8.76% missing values.
nb_rating (object)	Number of ratings received by the app, missing in 8.76% of cases.
num_downloads (object)	The number of downloads for the app, nearly complete with only 15 missing values (0.001475% null).
price_gplay (object)	The price of the app as listed on Google Play, missing in 0.43% of cases.
in_app (bool)	Indicates whether the app has in-app purchases (no missing values).
has_ads (bool)	Indicates whether the app contains advertisements (no missing values).
content_rating_app (object)	The app's content rating, with three missing values (0.000295% null).
developer_name (object)	The name of the app developer, missing in only 16 instances (0.001574% null).

The dataset includes several additional variables related to app features, developer information, and user engagement metrics such as visit_website, more_from_developer, and family_library. However, some variables, such as whats_new (100% null) and in_app_product (89.57% null), were deemed unsuitable for analysis due to their high proportion of missing data.

The primary purpose of this dataset in this study, is to analyze app monetization strategies by categorizing apps into distinct revenue levels and evaluating their performance based on key metrics like downloads and user ratings.

3.2 Variable Selection

The dataset utilized in this study consists of 1,016,666 entries, encompassing a broad range of attributes related to mobile applications. For the purpose of our analysis, 13 variables were selected, capturing critical information about app characteristics, user engagement, monetization strategies, and developer details. These variables include the app's unique identifier (my_app_id), the total number of downloads (num_downloads), average user ratings (rating_app), and the number of ratings (nb_rating). Additionally, the dataset provides information on app pricing (price_gplay), the presence of in-app purchases (in_app), and whether the app includes advertisements (has_ads). Other variables, such as content ratings (content_rating_app), app categories (categ_app), and developer information (developer_name and developer_info), further enhance the richness of the dataset. This subset of variables allows us to comprehensively examine the interplay between monetization strategies and app success.

To systematically explore monetization strategies, we classified the apps into six distinct levels based on their monetization models. These levels reflect varying approaches to generating revenue, ranging from completely free apps to fully premium paid apps.

Level 0 represents apps with no monetization, offering free services without ads or in-app purchases. At the opposite end, Level 5 includes premium apps requiring upfront payment, free from ads or in-app purchases, delivering a premium experience.

In between, Level 1 consists of free apps monetized solely through ads, while Level 3 combines ads and in-app purchases, offering additional features for users willing to pay. Level 4 refines the freemium model by removing ads and relying entirely on in-app purchases to monetize.

Level 2 employs a dual-version strategy, featuring both free sample apps with limited functionality (and potentially ads) and paid premium apps with comprehensive features and no ads or in-app purchases.

This classification is grounded in theoretical frameworks, such as the monetization levels proposed by Djaruma et al. (2023) and the App business models of (CITE), and allows for a nuanced analysis of how different revenue models impact app success metrics like user ratings and downloads. Our systematic categorization facilitates a deeper understanding of the relationship between monetization strategies and app performance.

3.3 Statistical Methods

To test our hypotheses, we employed a combination of descriptive statistics, text processing, and machine learning techniques. Descriptive statistics were utilized to analyze distributions and trends in metrics such as num_downloads, rating_app, and price_gplay. We categorized applications into six monetization levels based on binary indicators: is_free, in_app, and has_ads. Price values were processed to distinguish between free and paid applications.

To identify paired sample and premium applications within level 2, we applied Term Frequency-Inverse Document Frequency (TF-IDF) vectorization combined with cosine similarity on application names. This approach is effective for measuring textual similarity between documents (CITE Source 2). Subsequent filtering involved prefix matching and the identification of indicative terms (e.g., “Free,” “Pro”) to ensure logical pairing based on naming conventions and shared developers.

To adjust ratings for applications with few reviews, we calculated a Bayesian average. This method provides a more robust measure of user satisfaction by accounting for the number of ratings and the overall average rating across all applications (CITE Source 3). Visualizations, including scatter plots and box plots, were employed to explore relationships between monetization levels and user engagement metrics which will be displayed in the results section.

3.3.1 Handeling of Assumptions

We addressed missing values by removing rows with critical nulls, such as those in num_downloads, to maintain data integrity. Text-based variables like content_rating_app were standardized to ensure consistency. For price_gplay, currency symbols were removed to facilitate the classification of applications into free or paid categories.

Outliers in metrics like num_downloads were retained if they represented industry-leading applications, as their exclusion could skew the analysis. The use of Bayesian averages mitigated bias in rating_app due to low review counts, providing a more accurate reflection of user satisfaction. Covariance checks were conducted to ensure the absence of multicollinearity among numerical variables, thereby enhancing the reliability of correlation and regression analyses.

Some applications exhibited rare combinations of is_free, in_app, and has_ads that did not fit within the predefined monetization levels. These applications were excluded from the analysis but documented as a limitation. Edge cases in level 2 application pairing were flagged for potential mismatches due to naming ambiguities, ensuring transparency in the classification process.

These methodologies facilitated a systematic and accurate exploration of monetization models and their impact on application performance.

4 Results

In this section, we will visualize the data through tables and visualizations. These plots largely explore the data around the hypotheses and research question, we discussed in the previous sections. The aim of this section is to present possible evidence in supporting a hypothesis. This will be discussed and concluded upon in the next section.

Before we look at the results, let's revisit the research question: "*How are the 5 different revenue models as proposed by Djaruma et al. (2023) correlate to the success of an app?*". Where we identify 6 different revenue models, described in this section as (revenue) levels.

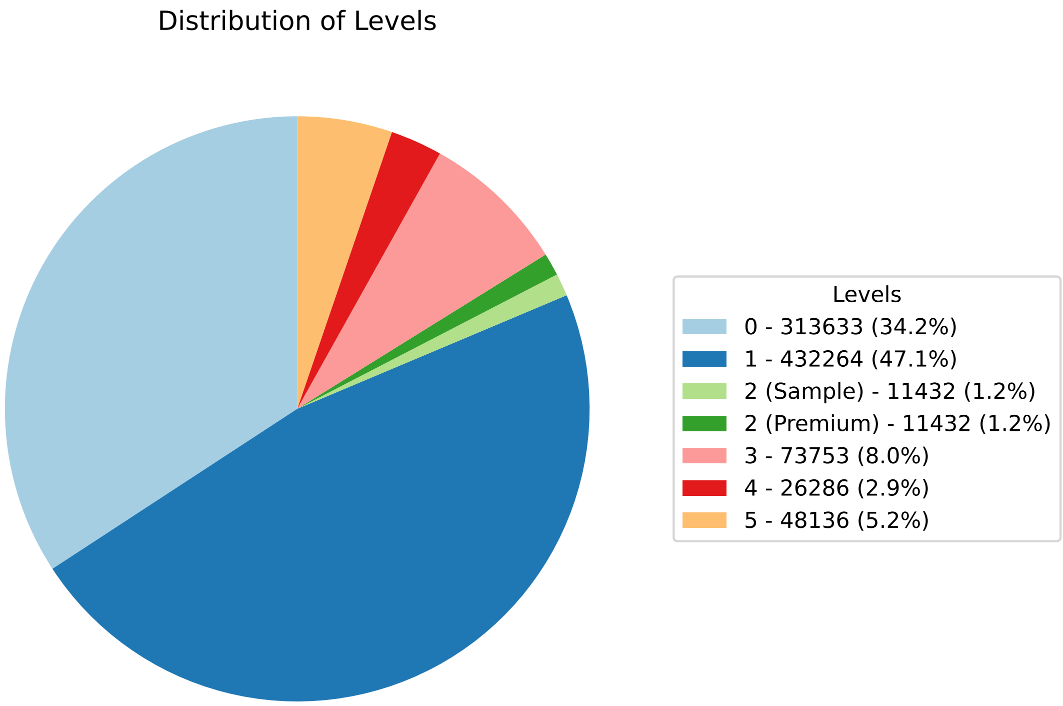
Strategy	Description
Level 5: Premium	Pay to use the application. This either happens up-front, or after a trial period.

Strategy	Description
Level 4: Semi-premium	Use a limited number of features for free. Unlock the app with all features through an in-app purchase.
Level 3: In-app advertisement and in-app purchases	Free application with ads, encouraging users to remove ads or to make in-app purchases.
Level 2: Sample and premium	Two different versions of the same app. One is a version with limit features and/or ads. The other version is a premium version.
Level 1: In-app advertisement	Only one version of the app, with only ads and no in-app purchases.
Level 0: Free	The app has no monetization. However, money can still be made through selling user information.

We have established in the "Literature Review" subsection, that the success of an app can be measured by:

1. Popularity: which can be measured by the number of downloads.
2. The rating of an application.
3. ~~Revenue estimation~~ (cannot be used, due to lack of data).
4.

Before we go into the descriptive statistics, let's look at the distribution of the apps across the revenue levels.

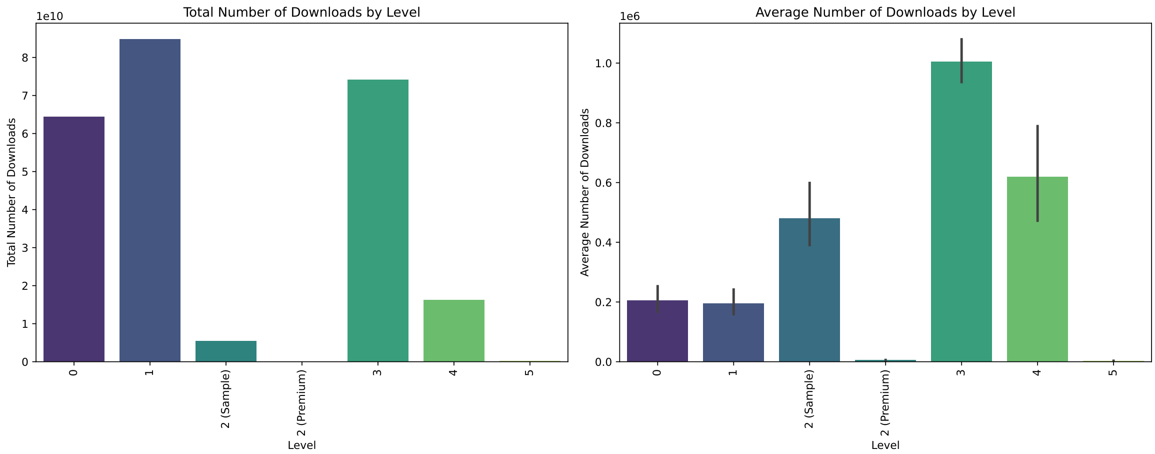


From this pie chart, we can make up that more than 75% of all the apps belong to level 0 and 1. With the smallest population being level 2 with two different version of the same app.

4.1 Number of Downloads.

The graphs below provides insights into the number of app downloads categorized by revenue levels. The left graph displays the total amount of downloads, while the right graph displays the average amount of downloads. In the next following three subsections, we will look into the key takeaways from these two graphs:

- Distribution of app downloads: how the downloads are distributed among the revenue levels.
- Gaming apps: analyzing the importance of gaming apps.
- Free vs Paid: comparing free and paid apps.



4.1.1 Distribution of app downloads

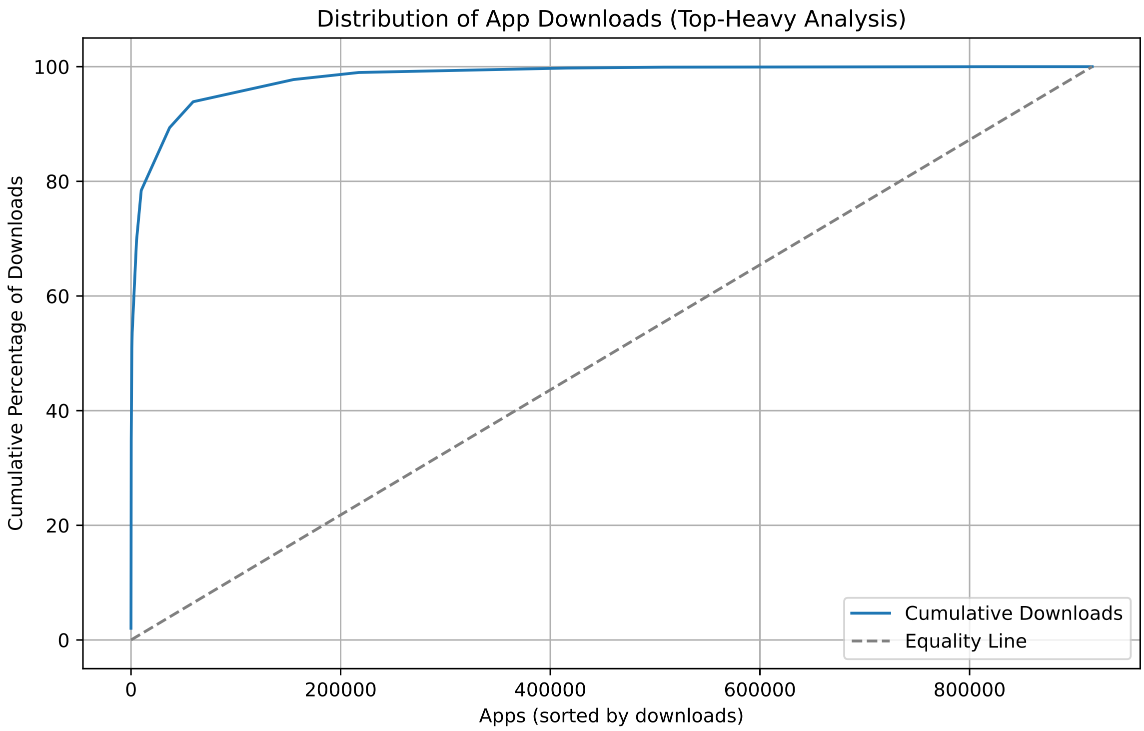
Important takeaway: Revenue levels 0 and 1 have a significant drop-off in terms of average number of downloads.

Hypothesis H1b serves as a guideline to explore the data, in particular on revenue level 1:

The apps with the most downloads will be level 1. Most social media platforms, which dominate our culture, tend to have this revenue stream (Djaruma et al. 2023).

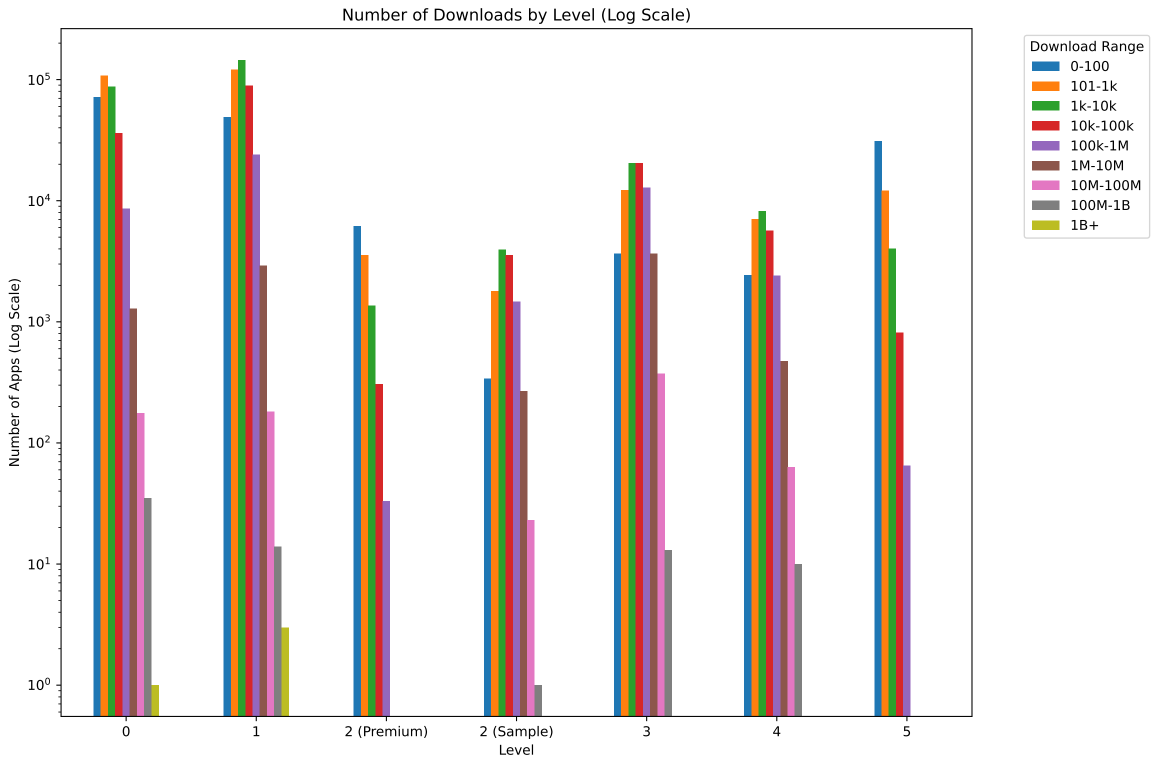
4.1.1.1 h1b

It's interesting to investigate the drop-off in average number of downloads.

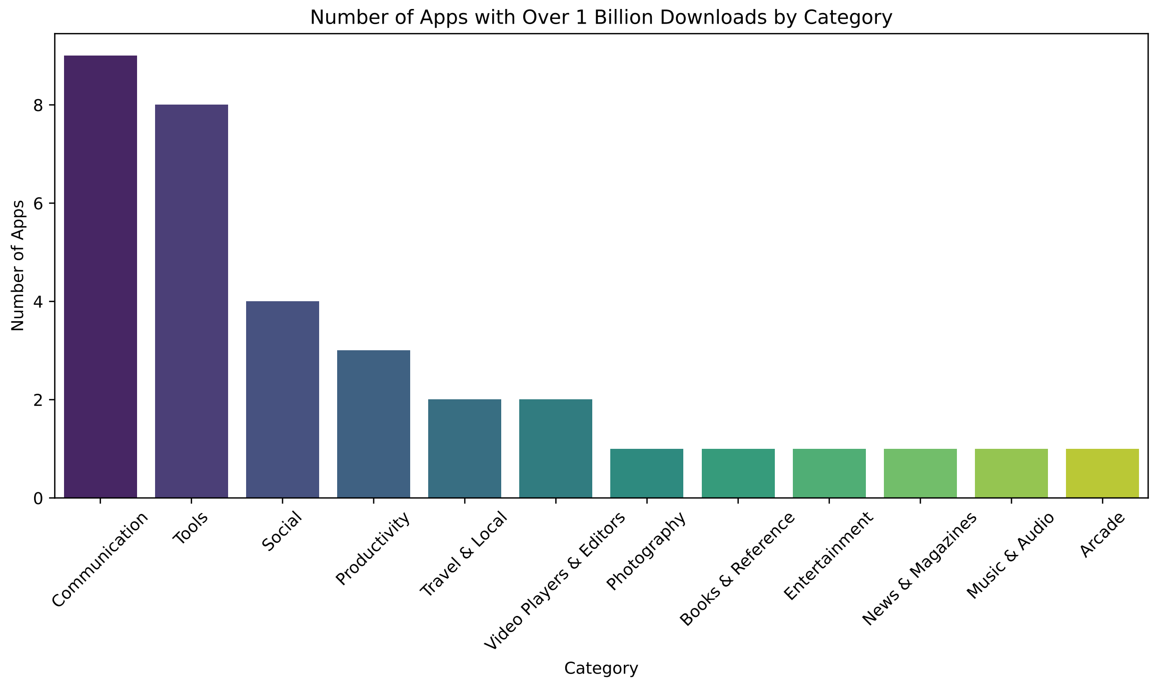


For instance, we see that the apps are top-heavy. So, a small proportion of the apps make up for almost all the app downloads.

We also look at the download bins per level:



It can be seen that level 0 and level 1 have the most by far 1 billion+ downloaded apps.



The social media platform mentioned in the paper by (Djaruma et al. 2023). (TikTok didn't exist up until 2019)

	App Name	Downloads (in B)	Category	Level
0	WhatsApp	1.0	Communication	0
1	Facebook Lite	1.0	Social	1
2	Instagram	1.0	Social	1
3	Facebook Messenger	1.0	Communication	4
4	Spotify	0.5	Music & Audio	1
5	Snapchat	0.5	Social	1
6	Netflix	0.5	Entertainment	4
7	Amazon Shopping	0.1	Shopping	1

4.1.2 Gaming apps

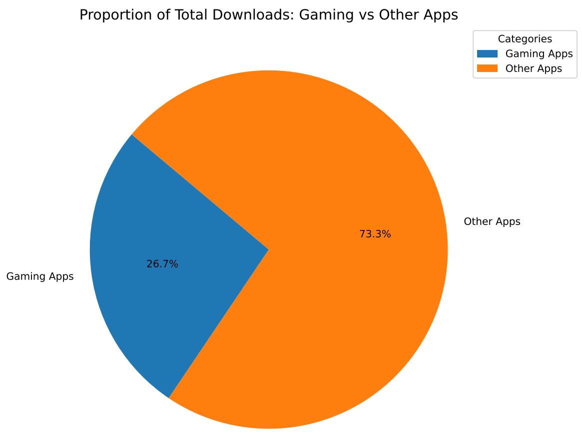
Important takeaway: Revenue level 3 and 4 stands out with high average app downloads. Suggesting these revenue levels can be considered as the most popular revenue level. Important to note is that they have two things in common, they are free and contain in-app purchases. The only difference is that level 3 contain ads.

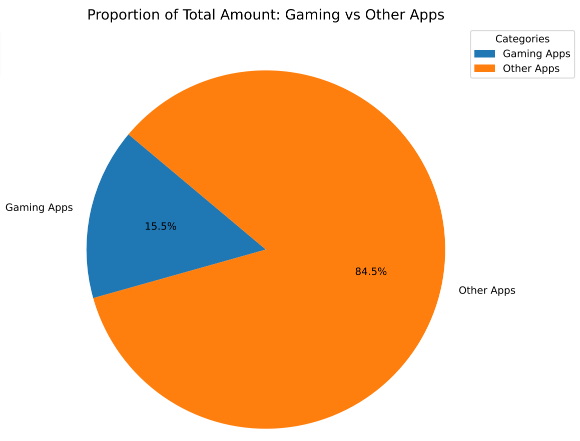
Hypothesis H1d takes a closer look into these 2 revenue levels:

The most downloaded apps in the gaming category will likely fall under level 4. Many popular games use this type of "pay-to-win" mechanism (Nieborg 2016). Therefore, it would be expected this same pattern would arise from our data.

4.1.2.1 h1d

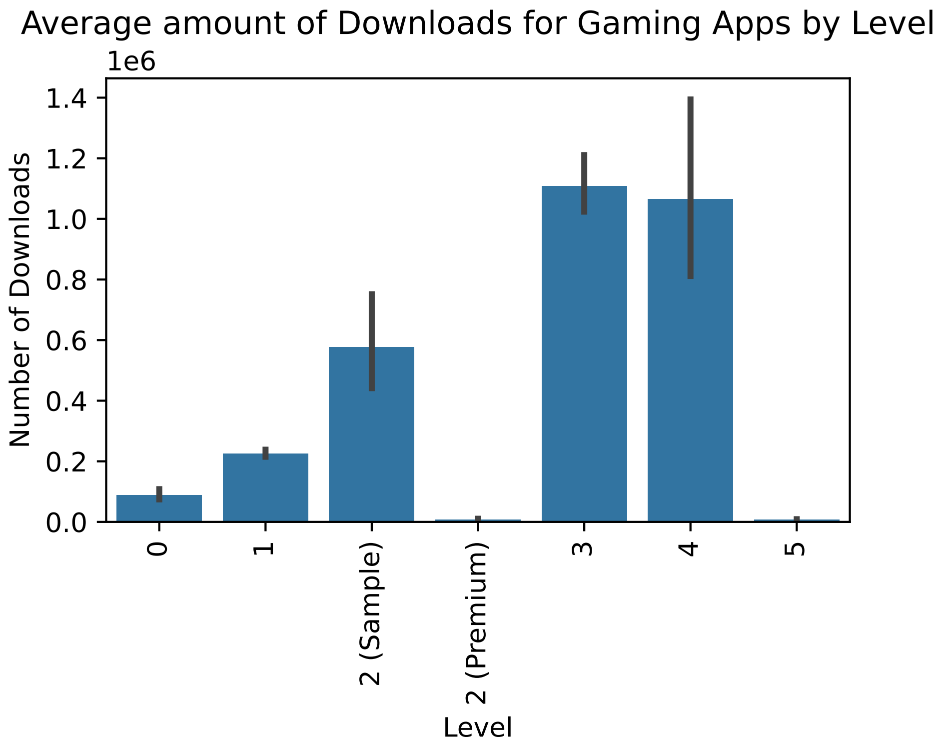
Games are hugely popular on the Google Playstore. In the graphs below, you'll find that they are responsible for more than 25% of the total downloads, while only populating 15% of the total apps.





The gaming apps are therefore downloaded more on average than the other apps, by nearly 100%. Making gaming apps hugely popular on the Google Playstore.

	Category	Avg Downloads	% Diff vs Baseline	% Diff Gaming vs Other
0	Gaming	460828.45	72.30	98.6
1	Other	232040.53	-13.24	-98.6
2	Baseline	267449.74	0.00	NaN



By filtering on the gaming categories we can see that the average downloads is also significantly higher in level 3 and 4. With level 4 having a higher variance than level 3 and 4. To further explore this we have the top 5 most downloaded games are from each revenue level:

	App Name	Downloads (in Billions)	level
0	Subway Surfers	1.0	3
1	Hill Climb Racing	0.5	3
2	Temple Run 2	0.5	3
3	My Talking Tom	0.5	3
4	Pou	0.5	3
5	Candy Crush Saga	0.5	4
6	Clash of Clans	0.5	4
7	Pet Rescue Saga	0.1	4
8	Farm Heroes Saga	0.1	4
9	Candy Crush Soda Saga	0.1	4

Here, you can already clearly see the variance in level 4 is much larger than in level 3. With the Downloads going from 0.5 to 0.1 for level 4 and 1.0 to 0.5 for level 3.

4.1.3 Free vs Paid

Key takeaways:

- Revenue level 2 premium and 5 have the least amount of total and average app downloads. These apps cost money upon downloading the app.
- Revenue level 2 sample and premium have a high download offset in both average and total amounts.

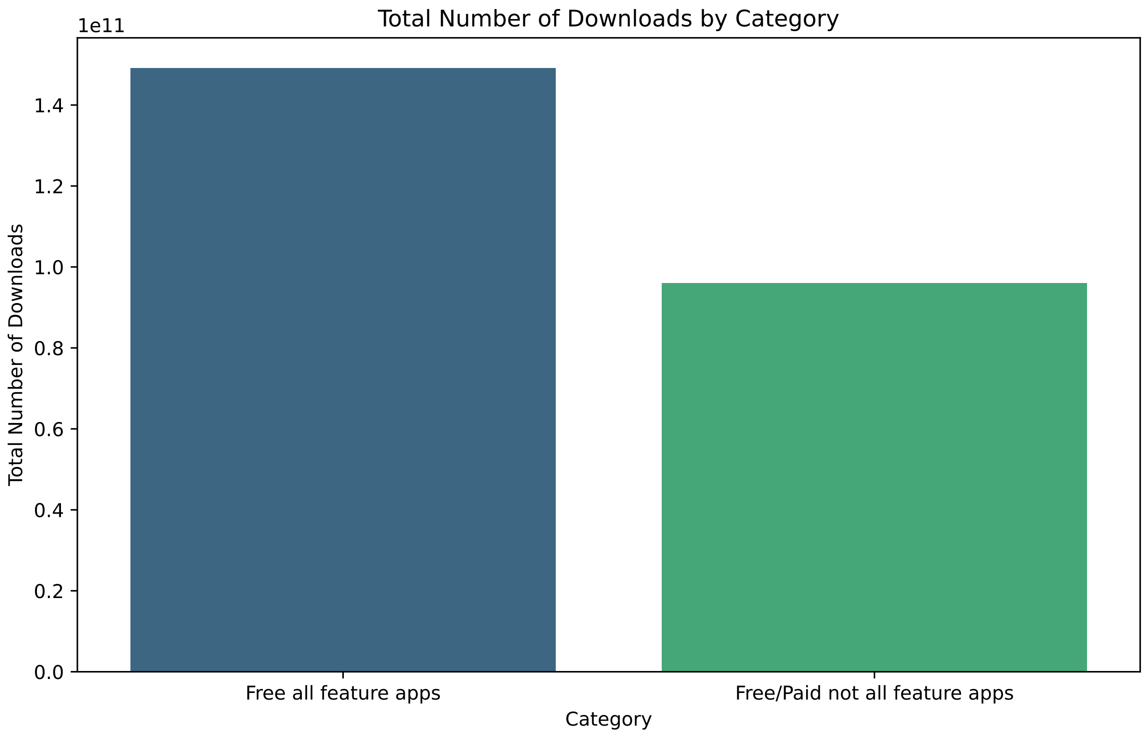
We see high disparity in downloads between free (-mium) and paid apps. To further investigate this we follow the guideline of hypotheses: H1a and H1c.

H1a: Apps that allow the user to have free access to all features (level 0 and 1) will have the highest amount of downloads overall. However, the ratings may fluctuate, as quality can vary for free-to-access apps.

H1c: For apps that utilize a sample and a premium version of the same app (level 2), the free versions of an app will have more downloads than their paid-for counterpart. Most, if not all, users will download the free version first, and then might upgrade. This means there should be a disparity between the number of downloads between the apps, as is also demonstrated by Liu, Au, and Choi (2012).

Now that we have seen the download metrics per revenue model, we cannot definitely determine that level 0 and 1 has the highest overall downloads.

4.1.3.1 h1a

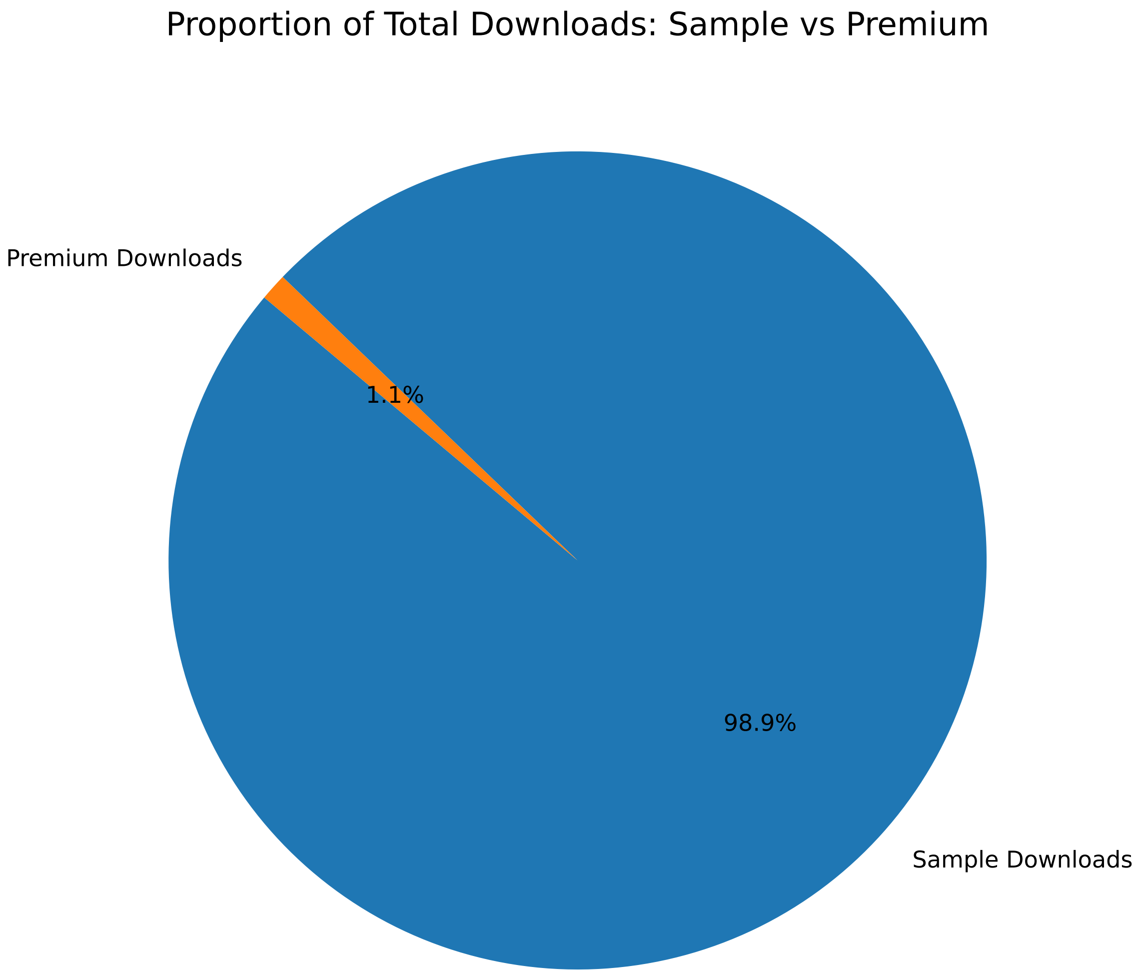


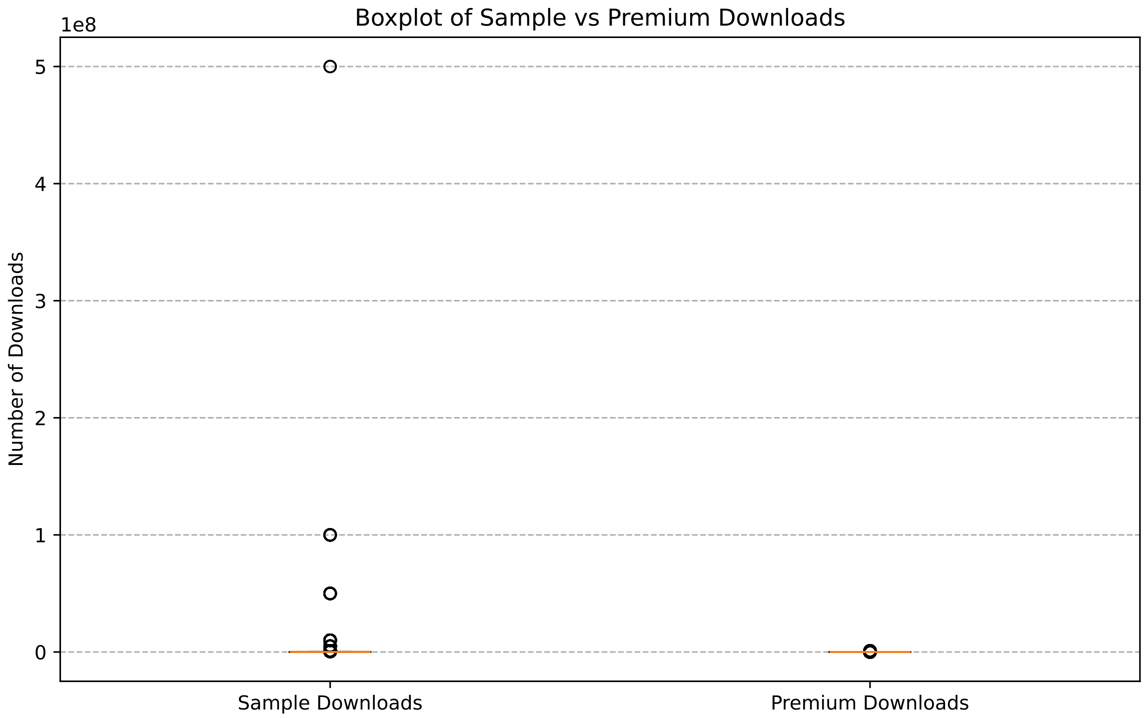
TODO: explanation.

4.1.3.2 h1c

H1c the proportion of total downloads between sample and premium app versions.

	Version Type	Total Downloads
0	Sample Downloads	5491457990
1	Premium Downloads	59597548

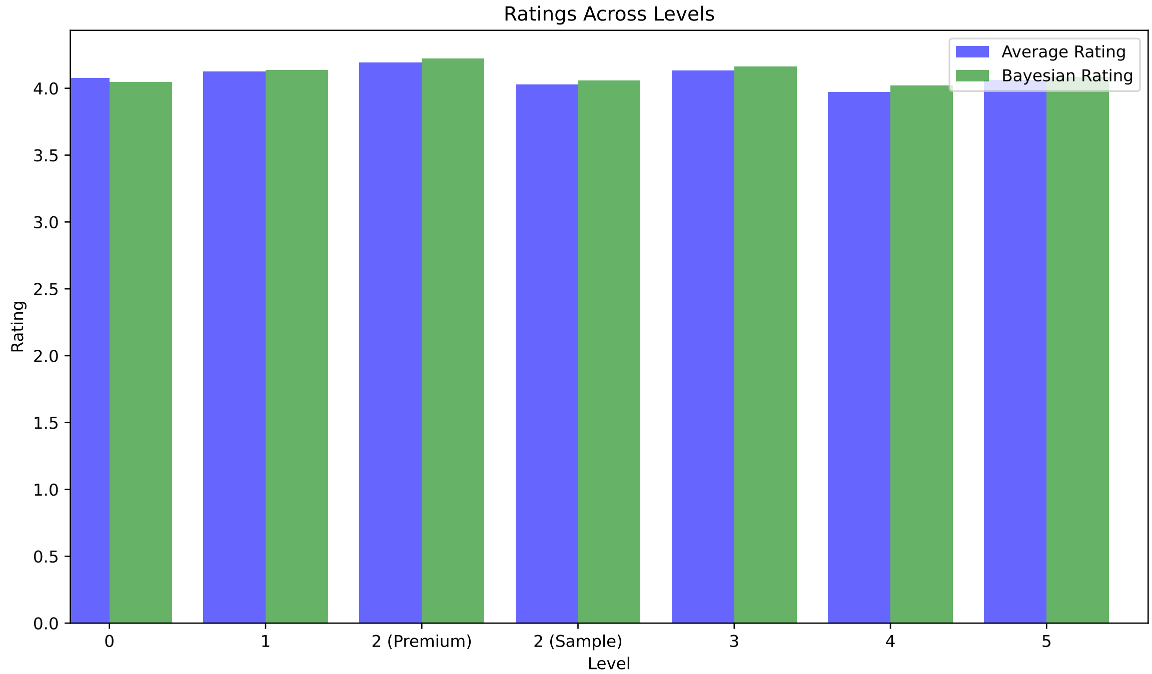




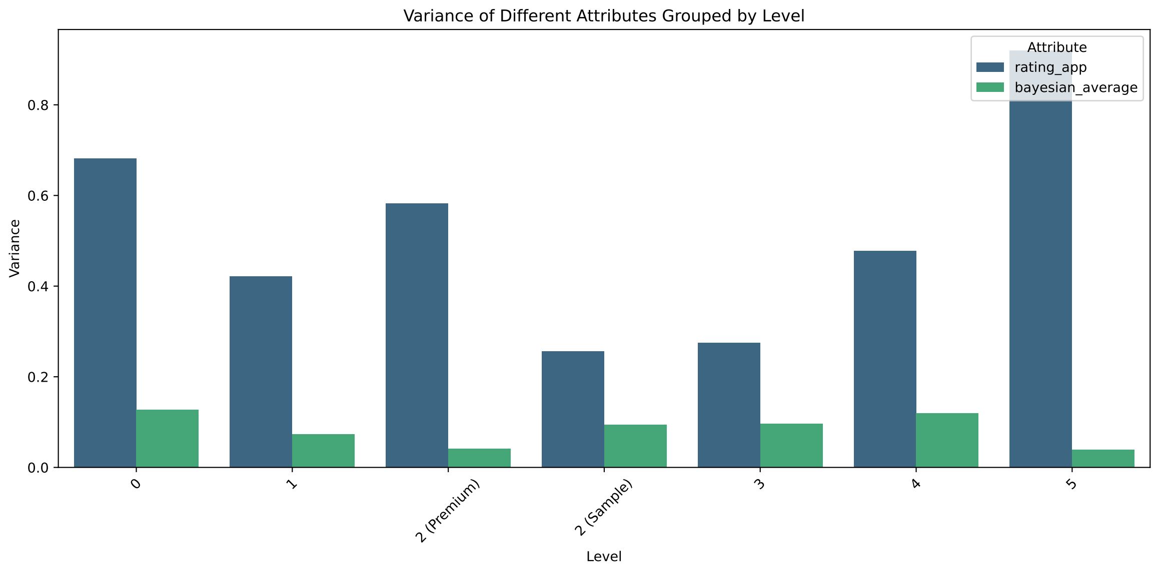
	Metric	Value
0	Average Download Difference	-475145.245101
1	Average Download Ratio	0.265126

4.2 Ratings

Plotting the distribution of the ratings across all the different revenue models doesn't have the same effect as with the number of downloads. As can be seen below, the ratings in itself doesn't vary all that much within the revenue levels.



When plotting the variance of the ratings across the different levels, we do see a lot of variance. But when looking at the bayesian average, this is no longer the case.



4.2.1 Variance

H1a: Apps that allow the user to have free access to all features (level 0 and 1) will have the highest amount of downloads overall. However, the ratings may fluctuate, as quality can vary for free-to-access apps.

H2b: Fully premium apps (level 5) will have less variance in their ratings, while all other levels will have more. In the same vein as H2a, users have more realistic expectations of paid apps compared to apps that require you to unlock features (Kumar 2014). Therefore, more users downloading premium apps will be satisfied with their purchase, leading to less variance.

4.2.2 Paid vs Free Version

H2a: Apps that require the user to pay to unlock features (level 2, 3, and 4) will tend to have lower ratings than the version that requires payment upfront (level 5). The main draw of a freemium model is to attract users, and have them update to a paid version (Kumar 2014). However, as Kumar (2014) points out, this can be a double-edged sword. Too few features, and it may not be attractive to users. Too many features, and the users will not update.

H3: For apps that utilize a sample and a premium version of the same app (level 2), the rating of the paid-for version is positively associated with the rating of the free version of the same app. This was true for the study on the most popular apps in the Google Play Store by Liu, Au, and Choi (2012), so it is expected a similar pattern should arise for this dataset.

5 Discussion

5.1 Reflection on the Findings

Downloads do not necessarily indicate revenue for freemium models (Djaruma et al. 2023). The time the user spends on an app and the purchases made within this app (Ross 2018) are better measures of the revenue for freemium applications.

5.2 Practical Implications for Businesses

5.3 Future Research Directions

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