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, and are briefly summarized in Table 1.

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.

Table 1: Six levels of monetization for apps

The monetization levels as shown in Table 1 are not meant to illustrate the revenue a firm will earn. It is meant to show how much customers may engage in paying for features or services at different levels.

Level 0 is an app that is completely free to use. This requires no payment nor ads, but may still make revenue through selling user data. This risks both ethical pitfalls, as well as scrutiny from customers (Djaruma et al. 2023).

Level 1 is an app that requires no user payment, and only makes revenue through ads. These may also make revenue by selling user information. Large social media apps such as Facebook and Instagram fall in this category (Djaruma et al. 2023).

Level 2 allows the user to purchase either a free or premium version. The free app has limit features; if the user wants to experience the app in full, they will have to purchase the premium version. However, this does run the risk of 'cannibalization', wherein users never upgrade to the premium version. Therefore, it is of the utmost importance to find the right amount of features to include in the free version (Djaruma et al. 2023).

Level 3 combines advertisement and purchases. Many pay-to-win games use this strategy (Nieborg 2016): users can sit through ads and wait a long time for certain rewards, or they can pay for immediate rewards.

Level 4 is similar to level 2: a user has a free trial version, and can upgrade to a premium version. This is often seen in subscription-style apps (Chen 2023).

Level 5 is a totally premium app, where a user has to pay up-front to access as features. This level requires a high-quality app, as users will not pay for an app that is not polished.

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 proposed by Djaruma et al. (2023) offer an opportunity to capture this nuance. However, no empirical study has yet applied their framework, as their paper was published only last year. By using this framework to examine how different revenue streams impact app popularity, this study aims to provide valuable insights into consumer preferences. Therefore, this paper seeks to answer the question: *How are the six different revenue models proposed by Djaruma et al. (2023) correlated with app success?*

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 six 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

According to Djaruma et al. (2023), there are six distinct revenue strategies for apps. However, it is important to point out they were not the inventors of these revenue strategies; these arose from the literature they analyzed. In the following section, we shall look at the previous research into these revenue strategies.

Firstly, biggest portion of apps are free to download. In fact, this contributes over 95% of all apps in both the Google Play Store as well as the IOS App Store (Statista 2023). But, this does not mean the apps do not generate revenue; they might implement advertisements, in-app purchases or sample and premium versions to still make a profit.

Tower (2023) has predicted global spending on in-app advertisements will reach over 233 billion U.S. dollars in 2026. These funds are an important source of income for mobile app developers (Gao et al. 2022; Maddodi and Upadhyaya 2023).

Aside from advertisements, there are two different revenue strategies to consider: in-app purchases, and a trial and premium version of the same app. Both of these are considered "freemium" in recent literature. Kumar (2014) describes freemium as apps for which users get basic features for free and can update it using a payment. This can be done both through in-app payments, as well as purchasing the premium version of an app.

Another revenue strategy used in apps are in-app payments. This strategy is often used in games. More specifically, games that fall in the "pay-to-win" category (Nieborg 2016).

These games often require the user to wait or watch advertisements, which they can circumvent by paying. Some games also allow users to buy special features, such as the look of their avatar or special powers. Nonetheless, while in-app purchases are a proven revenue strategy, it does come with risks. Notably, in-app payments are also prone to security risks, as it requires more complex interactions and involves more participants than traditional payment (Yang et al. 2019). Therefore, developers need to make sure their payment methods are secure before launching an app with this revenue strategy.

In-app purchases are not the only solution for offering freemium services. A different method is offering two different versions: a free one, and a paid one. The free version often has limit features combined with ads, meaning you make a profit by advertisements (Appel et al. 2020). This is combined with the revenue of the premium version.

To answer the question *"How are the six 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).

Building on this, we hypothesize that revenue models associated with fewer barriers to entry will drive higher downloads overall, but the impact of these models may vary by app type and market context.

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.

As Djaruma et al. (2023) has shown, the most highly ranked apps are level 1. These apps are the big social media platforms such as Instagram and Facebook. Therefore, we expect this to be reflected within our data and the following to be true.

H1b: The apps with the most downloads will be level 1.

Freemium apps can be implemented with either in-app purchases or different versions. For the latter, we expect more downloads to be generated by the free app, than its premium counterpart. As demonstrated by Liu, Au, and Choi (2012), users tend to download the trial version before comitting to a premium version. Thus, the following is likely to be true.

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.

2.1.2 Rating

The downloads of an app are not everything. An app can be downloaded often, but may not be highly rated. Ratings provide valuable insights into user satisfaction, which often reflects the perceived quality and value of an app. Therefore, we hypothesize revenue models that prioritize short-term gains may achieve high download counts but could negatively affect ratings if users feel misled or dissatisfied.

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. This leads to the following hypothesis.

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 majority of the apps are free-to-use (Djaruma et al. 2023). However, this means there might be more difference in quality between these apps, as the barrier to downloading is lower for free apps than paid or freemium apps (Mileros and Forchheimer 2024). Therefore, we postulate the following.

H2b: Apps that allow the user to have free access to all features (level 0 and 1) will have more variance in their rating, as quality can vary for free-to-access apps.

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. Thus, the following should follow from our data.

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 in this research comprises 1,016,666 instances and 27 variables, offering a comprehensive overview of mobile applications across various revenue models. Each instance corresponds to a single app, capturing details about its characteristics, user engagement, and monetization strategies. Key variables include the app's unique identifier (my_app_id), the number of downloads (num_downloads), the average rating (rating_app), and the number of ratings received (nb_rating). These variables provide critical insights into app performance metrics.

Additional variables include pricing details (price_gplay), information about in-app purchases (in_app), and whether the app contains advertisements (has_ads). Other attributes, such as content ratings (content_rating_app) and metadata about the app developer (developer_name), further enhance the dataset's richness by adding contextual information.

Several variables, such as whats_new (completely null) and in_app_product (89.57% null), were excluded from the analysis due to their high proportions of missing data. Conversely, variables with minor missingness (e.g., date_published, privacy_policy) were retained after appropriate preprocessing. This curated dataset is the foundation for examining monetization strategies and their relationship to app performance metrics like downloads and user ratings.

3.2 Variable Selection

The analysis focuses on a subset of 13 variables selected from the dataset, as shown in Table 2 below. These variables were chosen for their relevance to our research questions, capturing information about app characteristics, user engagement, and monetization strategies.

Variable Name	**Description**
`my_app_id`	Unique identifier for each app.
`num_downloads`	Number of downloads for the app. Key indicator of app success.
`rating_app`	Average user rating. Measures user satisfaction.
`nb_rating`	Number of ratings received. Reflects user engagement.
`price_gplay`	Price of the app. Used to differentiate free vs premium apps.

Variable Name	Description
`in_app`	Boolean indicating whether the app has in-app purchases.
`has_ads`	Boolean indicating whether the app includes advertisements.
`content_rating_app`	Content rating of the app (e.g., Everyone, Teen).
`categ_app`	App category (e.g., Productivity, Games). Groups apps by functionality.
`developer_name`	Name of the app developer. Provides context on developer reputation.
`developer_info`	Additional metadata about the developer (e.g., location, website).

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**: Apps with no monetization, offering free services without ads or in-app purchases.
- **Level 1**: Free apps monetized solely through ads.
- **Level 2**: Freemium model, employing both free sample apps with limited functionality (and potentially ads) and paid premium apps with full features.
- **Level 3**: Apps combining ads and in-app purchases, monetizing through both strategies.
- **Level 4**: Freemium apps monetized entirely through in-app purchases, removing ads for a seamless user experience.
- **Level 5**: Fully premium paid apps, with no ads or in-app purchases, delivering a premium experience.

This classification is grounded in theoretical frameworks, such as the monetization levels proposed by Djaruma et al. (2023), 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, ensuring a rigorous approach to analyzing the dataset. Descriptive statistics were used to explore distributions and trends in key metrics such as num_downloads, rating_app, and price_gplay. Applications were categorized into six monetization levels using binary indicators (is_free, in_app, and has_ads), while preprocessing of price data facilitated the distinction between free and paid applications. These steps established a structured foundation for investigating relationships between monetization strategies and app performance.

For the paired application analysis within Level 2, we applied Term Frequency-Inverse Document Frequency (TF-IDF) vectorization combined with cosine similarity to app names, allowing us to measure textual similarity (Widianto et al. 2023). Logical pairings were refined through prefix matching and the identification of indicative terms like “Free” or “Pro.” This process was further validated by ensuring paired apps shared the same developer, using metadata from developer_name and developer_info. While effective, this approach acknowledged potential limitations, such as ambiguity in naming conventions, which were flagged as edge cases for transparency.

To address potential biases in app ratings caused by low review counts, we calculated a Bayesian average, adjusting raw ratings by combining the global average with individual app ratings weighted by review volume (Moyeed and Clarke 2005). This provided a more balanced measure of user satisfaction, reducing the influence of apps with disproportionately few reviews. Scatter plots and box plots were employed to visualize the relationships between monetization levels and user engagement metrics, offering valuable preliminary insights into patterns within the data. These visualizations, alongside the Bayesian adjustments, laid the groundwork for robust and interpretable results, which are elaborated 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

This section analyzes the data using tables and visualizations to test the hypotheses and answer the research question: "*How do the six revenue models proposed by Djaruma et al. (2023) correlate with app success?*" These models, described in Table 1, form the basis of the analysis.

The Google Play Store data was categorized into these models, revealing that over 75% of apps fall into levels 0 and 1, while level 2 has the fewest apps (Figure 1).

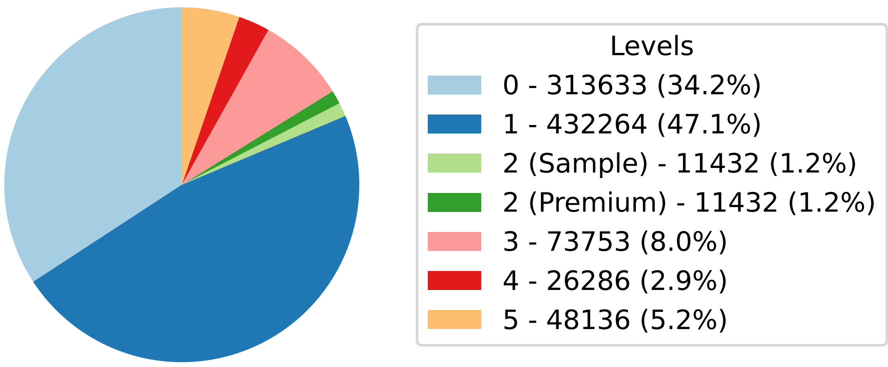


Figure 1: Distribution of the amount of apps across the revenue levels

App success is assessed using metrics like downloads (popularity) and user ratings, while revenue estimation is excluded due to insufficient data (Section 2.1). Downloads address hypotheses H1a–H1d, and ratings evaluate H2a and H2b.

4.1 Downloads

This section addresses hypotheses H1a–H1d in three subsections. In Section 4.1.1, download distribution is analyzed to address H1a and H1b. Section 4.1.2 explores download differences between sample and premium level 2 apps for H1c. Finally, Section 4.1.3 examines gaming app downloads to answer H1d.

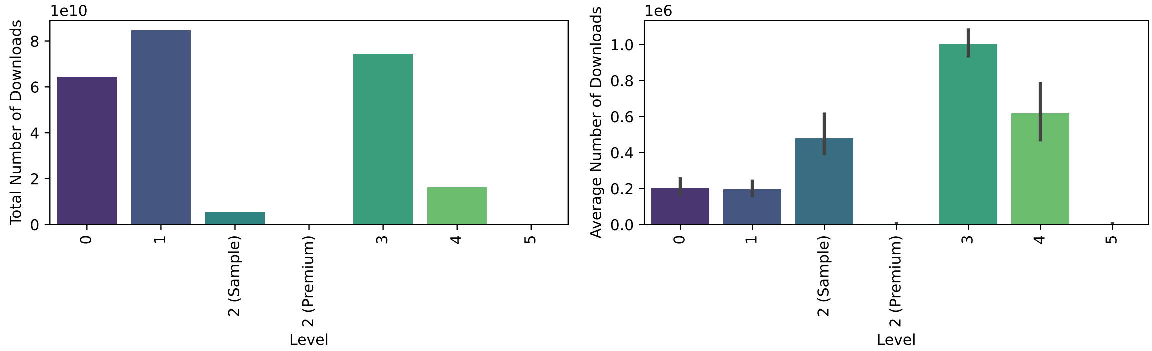
4.1.1 Distribution of app downloads

This section addresses:

H1a: Free-to-access apps (levels 0 and 1) will have the highest total downloads.

H1b: Level 1 apps will have the most downloads.

Download data (Figure 2) shows significant variation for levels 0 and 1, which account for 75% of apps (Figure 1). However, levels 0 and 1 do not dominate in average downloads.



(a) Total Number of Downloads by Level (b) Average Number of Downloads by Level

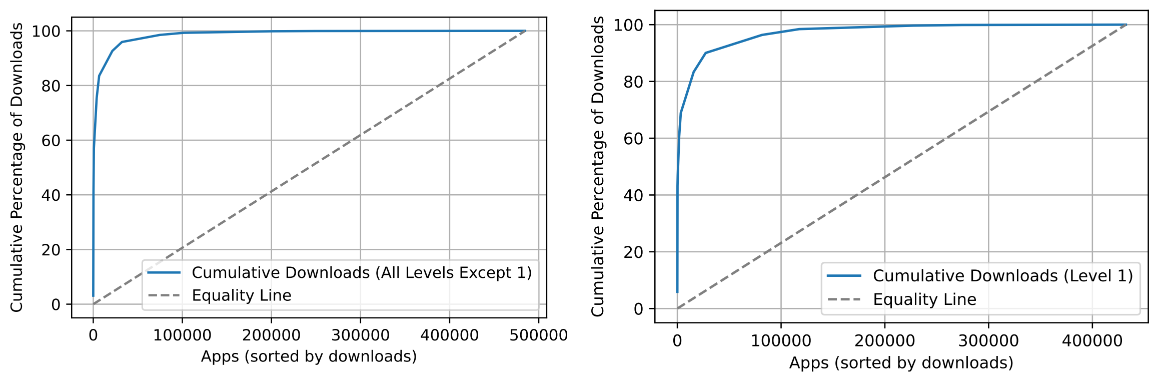
Figure 2: Comparison of Total and Average Downloads by Level

As the majority of apps fall under level 0 and 1, these do have the highest overall downloads, as shown in Figure 2a. Table 3 shows just how big the difference between the total downloads is. The apps that are completely free to use (level 0 and 1) have over 40 billion more downloads than the apps that are paid to some extend (levels 2 through 5).

	category	num_downloads
0	Free all access	149140785038
1	Freemium and Premium	96093512270

Table 3: Difference Total Number of Downloads

Figure 3 reveals significant inequality in download distribution, with a small proportion of apps accounting for the majority of downloads. Figure 3a and Figure 3b show similar patterns, suggesting this dominance may not be exclusive to levels 0 and 1, as other levels could exhibit similar trends.



(a) All levels except 1 (b) Level 1 Only

Figure 3: Distribution of App Downloads (Top-Heavy Analysis)

The download range of apps in Table 4 illustrates that level 1 dominates in terms of apps with over 1 billion downloads. Furthermore, level 0 also has a few apps with over 1 billion downloads. Level 0 has the most app downloads between 500 million and 1 billion with 18.

	0-1M	1M-100M	100M-500M	500M-1B	1B+
0	312119	1469	17	18	1
1	429133	3105	7	7	3
2 (Premium)	11431	0	0	0	0
2 (Sample)	11140	291	1	0	0
3	69699	4040	10	3	0
4	25738	538	8	2	0
5	48124	0	0	0	0

Table 4: Number of Downloads by Level

Taking a closer look at the apps provided by Djaruma et al. (2023) in Table 5. We do see that Facebook, Instagram, Spotify, Snapchat and Amazon Shopping fall under level 1.

	App Name	Downloads (in B)	Category	Level
0	WhatsApp	1	Communication	0
1	Facebook Lite	1	Social	1
2	Instagram	1	Social	1
3	Facebook Messenger	1	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

Table 5: Top 8 Apps by Downloads (in Billions)

Free apps are downloaded more often than paid ones (Table 3) but not on average (Figure 2b). While levels 0 and 1 dominate in total downloads (34.2% and 47.1%, Figure 1), their average downloads are not the highest, making evidence for H1a inconclusive.

Level 1 apps, including many social networks (Table 5), are the most downloaded (Figure 2a), though downloads are concentrated among a few (Figure 3), supporting H1b.

4.1.2 Sample and Premium Apps

This section tests H1c: Free versions of level 2 apps will have more downloads than their paid counterparts.

Levels 2 (premium) and 5 have the lowest total and average downloads (Figure 2). A significant disparity exists between level 2 sample and premium app downloads (Figure 2b). Only 1.1% of level 2 downloads are attributed to premium apps (Figure 4), highlighting the vast discrepancy.

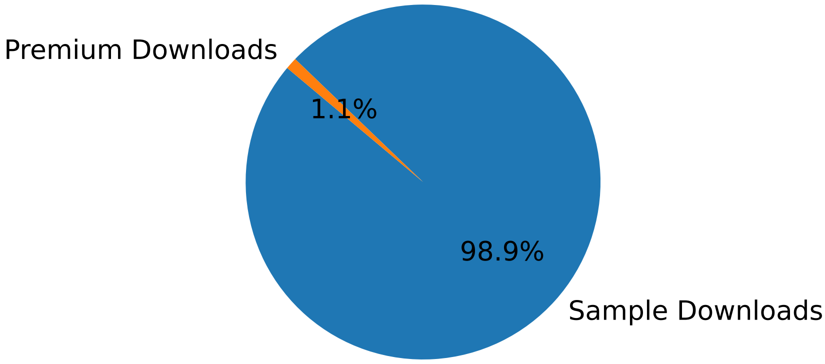


Figure 4: Proportion of Total Downloads: Sample vs Premium

High disparity is also evident in the average downloads, as shown in Table 6. Where the average download difference is close to 500.000. With an average download ratio of nearly 27%. Meaning that about one in fourth users that download the sample app, also download the premium app.

	Metric	Value
0	Average Sample Downloads	480358
1	Average Premium Downloads	5213.22
2	Average Download Difference	-475145
3	Average Download Ratio	0.265126

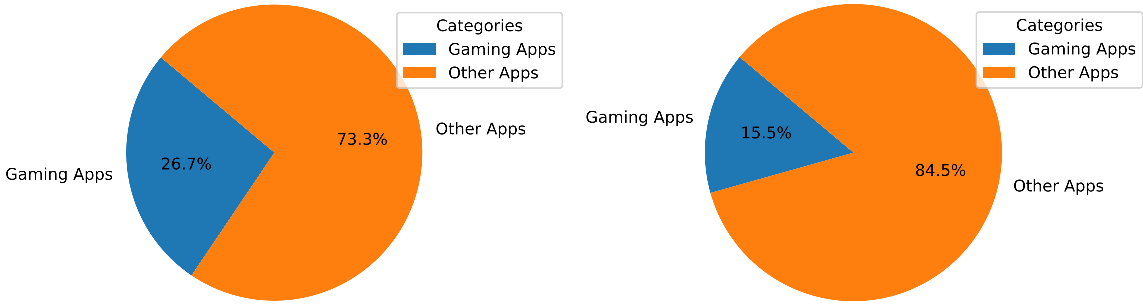
Table 6: Sample and Premium download metrics

Hypothesis H1c claims that sample versions have more downloads than their paid counterparts. Figure 2 and Figure 2b show an imbalance in download rates, further supported by Figure 4 and the disparities in Table 6. These findings confirm H1c, and the hypothesis is accepted.

4.1.3 Games in the Google Play Store

This section tests H1d: Most downloaded gaming apps will fall under levels 3 and 4.

Levels 3 and 4 show high total and average downloads (Figure 2). Games, making up 15.5% of apps (Figure 5b), account for 26.7% of total downloads (Figure 5a), with average downloads 98.6% higher than other apps (Table 7).



(a) Total Downloads: Gaming vs Other Apps (b) Total Amount: Gaming vs Other Apps

Figure 5: Proportion of Games compared to other apps

	Category	Avg Downloads	% Diff Gaming vs Other
0	Gaming	460828	98.6
1	Other	232041	-98.6
2	All	267450	-

Table 7: Average Downloads Games vs Other Apps

Up until now, these findings suggest that games are hugely popular, regardless of their revenue level. Figure 6 shows that particularly games in levels 3 and 4 accrue a lot of downloads, compared to other levels.

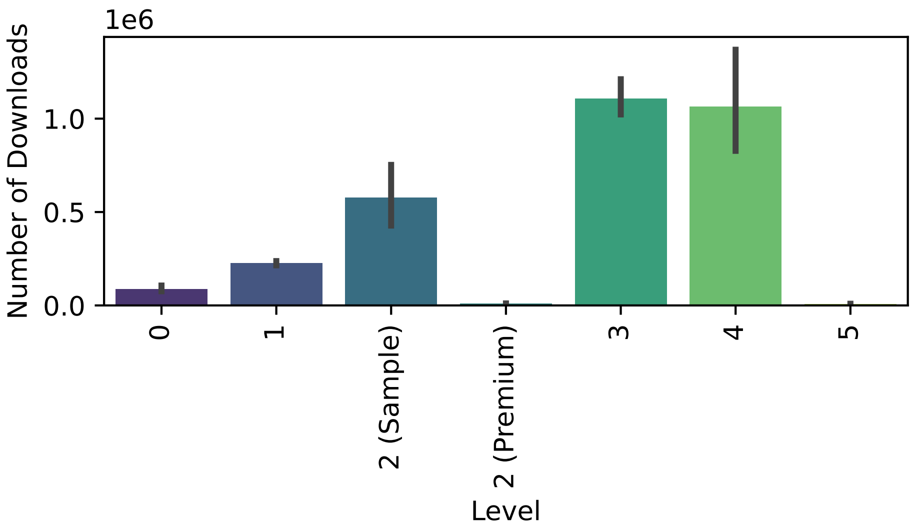


Figure 6: Average amount of Downloads for Gaming Apps by Level

Games on the Google Play Store account for 26.7% of total downloads (Figure 5a), with average downloads nearly doubling those of other apps at ~0.5 million (Table 7). In levels

3 and 4, average downloads exceed 1 million (Figure 6). These findings provide sufficient evidence to support H1d.

4.2 Ratings

In this section, we will venture to answer hypothesis H2a and H2b. In Section 4.2.1, we will try to find fluctuations in ratings that might be by the quality in order to answer hypothesis H2a and H2b.

4.2.1 Quality of Free and Paid Apps

This section tests the following hypotheses:

H2a: Apps requiring payment to unlock features (levels 2, 3, and 4) will have lower ratings than upfront payment apps (level 5).

H2b: Free-to-access apps (levels 0 and 1) will show greater rating variance due to varying quality.

According to Figure 7, premium apps have higher average ratings than free apps requiring payment to unlock features, while free apps display greater rating variability.

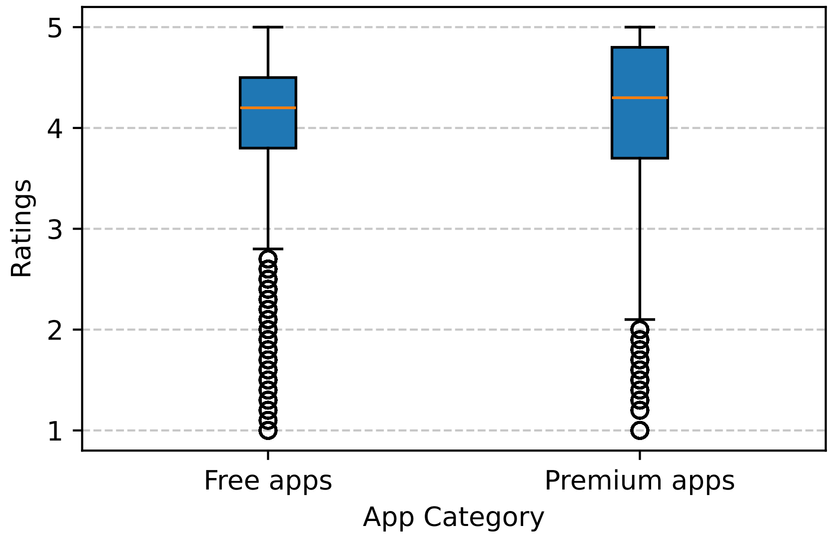


Figure 7: Boxplot of Ratings for Free and Premium Apps

Paid apps have higher average ratings than free apps (Figure 7), indicating perceived higher quality, while the wider spread in free app ratings supports H2a.

Levels 0 and 1, with free access to all features, lead in downloads (~40 billion; Table 3). H2b suggests rating variance reflects quality disparity, but minimal differences in variance and standard deviation (Table 8) indicate no significant difference.

	category	variance in rating	standard deviation in rating
0	Free all access	0.531282	0.728891
1	Freemium and Premium	0.511318	0.715065

Table 8: Variance (and std) difference. Between free access to all feature apps and free access to not all features or paid apps

Figure 8 visualizes variance with outliers. It shows that both categories have a similar median rating close to 4.5, with "Free/Paid not all feature apps" being slightly lower. Both categories seem to have a lot of outliers under 3, with 'free all feature apps' having more outliers in 2 and 1.

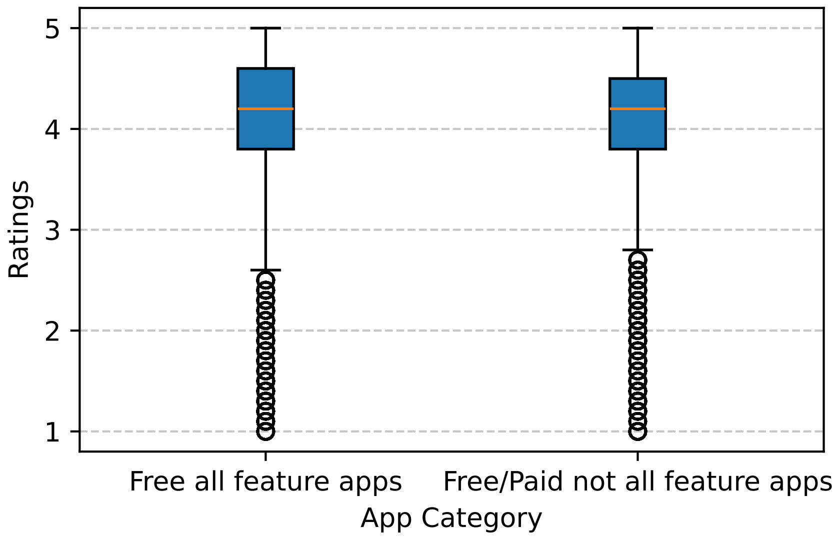


Figure 8: Boxplot of Ratings by App Category

The variance and standard deviation between the two categories are minimal (Table 8). Figure 8 shows both receive high ratings, with notable outliers reflecting variability in user satisfaction. The slightly higher median for "Free all feature apps" suggests a preference but is marginal and likely requires statistical validation. Thus, evidence for greater variance in levels 0 and 1 is inconclusive, and H2b is rejected.

4.3 Conclusion

The six revenue strategies by Djaruma et al. (2023) show distinct trade-offs between accessibility and user satisfaction.

Levels 0 and 1 dominate with ~40 billion downloads but have variable ratings, prioritizing accessibility over quality. Freemium models (levels 2, 3, and 4) balance popularity and user expectations, while fully premium apps (level 5) achieve the highest, most consistent ratings but limited reach.

Games account for 26.7% of downloads (Figure 5a) and average nearly double the downloads of other apps (~0.5M, Table 7). Levels 3 and 4 surpass 1M average downloads (Figure 6), supporting H1d.

In summary, free models maximize reach, freemium models balance flexibility and satisfaction, and premium models prioritize quality. Each strategy meets different user needs.

4.4 Ethical Considerations

This research uses publicly available Google Play Store data, ensuring user privacy (Tikkinen-Piri, Rohunen, and Markkula 2018). However, such data can reveal sensitive business insights, like proprietary strategies. To mitigate this, we avoid highlighting specific apps. The findings offer value to developers, marketers, and policymakers by revealing profitable monetization methods, but they also raise ethical concerns, potentially encouraging exploitative practices that prioritize profits over user experience (Mileros and Forchheimer 2024). This highlights the need to balance actionable insights with ethical responsibility.

5 Discussion

This study examined the relationship between six revenue strategies and app success, measured by downloads and ratings. The findings reveal clear trade-offs among these models, offering insights into app monetization strategies.

5.1 Reflection on the Findings

We found that free apps (Levels 0 and 1) dominate in terms of downloads. However, these apps also have higher variance in ratings, suggesting they struggle with consistent quality. While this aligns with existing literature suggesting that free apps attract a broad audience but often deliver inconsistent experiences (Mileros and Forchheimer 2024), it does raise the question of whether the amount of downloads should be the primary measure of success. Free apps may have more downloads, but without understanding the deeper dynamics of user engagement and satisfaction, these figures could be misleading. For example, apps with high ratings but fewer downloads could still represent significant success in specific niches.

Freemium models (Levels 2 and 3) show promise as a balanced strategy, combining accessibility with opportunities for revenue generation. These models cater to both casual users and those willing to pay for premium features, reflecting their flexibility. Prior research supports this notion, emphasizing the interplay between user retention and monetization in freemium models (Kumar 2014). However, the disparity in downloads between sample and premium versions suggests that other factors, such as app quality or external influences like marketing, also play significant roles in shaping success (Stocchi et al. 2022).

Premium apps (Level 5) stand out for their high average ratings, reinforcing the perception of superior quality. This is consistent with user expectations: those who pay upfront often demand a polished product. However, premium apps trade reach for exclusivity, as shown by their lower download numbers. This dynamic aligns with theories of optimal distinctiveness, where firms strive to balance conformity to market norms with differentiation to reduce competition (Zhao et al. 2018). For premium apps, moderate differentiation appears optimal, allowing for high-quality perceptions while catering to a specific user base.

This finding aligns with the broader literature on optimal distinctiveness, which explores how firms should manage the balance between conformity and differentiation in order to achieve superior performance (Zhao et al. 2018). On the one hand, products need to conform to category norms to build legitimacy, but on the other hand, they should differ enough to avoid intense competition. The study by (Angeren et al. 2022) further extends this line of inquiry by considering how the relationship between differentiation and performance varies based on the product's revenue model. For premium apps, moderate differentiation appears to be an optimal strategy, allowing for both quality perception and enough market fit, but with the trade-off of a smaller, more specific user base.

5.2 Limitations

This study has several limitations. Downloads are not a comprehensive measure of app success, particularly for freemium models. Metrics such as user retention, in-app purchases, and time spent on the app may better reflect profitability and user engagement (Ross 2018). Additionally, the dataset predates the rise of TikTok, a platform whose unique revenue model could alter findings, particularly for levels emphasizing in-app purchases (e.g., Level 3). Including more recent data could provide a fuller picture of trends and revenue strategies.

Causality is another challenge. While the study identifies correlations between revenue models, downloads, and ratings, these relationships are influenced by external factors such as marketing efforts, app category, and regional preferences. Therefore, the results should not be interpreted as causal. Moreover, the exclusion of revenue estimates due to data limitations prevents deeper insights into profitability, a critical dimension of app success.

5.3 Practical Implications for Businesses

For app developers, these findings offer valuable guidance. Free models (Levels 0 and 1) are effective for maximizing reach, but ensuring quality remains critical to sustaining user engagement. Freemium models provide a flexible approach, appealing to both casual users and paying customers. However, success in these models requires a strong focus on user retention and feature quality. Premium models, while catering to niche audiences, demand significant investment in quality to meet high user expectations.

Businesses should consider these trade-offs when selecting a revenue model, aligning their choices with the app's target audience and objectives. However, over-reliance on these findings should be avoided, as they reflect correlations rather than definitive success drivers.

5.4 Future Research Directions

Future studies should address limitations by integrating newer datasets that include platforms like TikTok and expanding metrics to capture user engagement and in-app purchases. Exploring additional dimensions of app success, such as long-term user retention, would provide a more nuanced understanding of monetization strategies.

Ongoing research is crucial in this dynamic field. By building on these findings, future work can contribute to more effective and user-centric app monetization strategies, supporting businesses in navigating the ever-evolving app market.

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