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.

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 3. Many popular games use this type of 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, the data and methods used to test the hypotheses will be laid out.

3.1 Dataset Description

Omschrijf de data: hoeveel instances, welke variables, waar gaat de data over?

3.2 Variable Selection

Welke variabelen gebruiken wij? Welke hebben we eruit gehaald? (Hierover uitbreiden in Handeling of Assumptions).

Hoe definiëren we de 5 levels?

3.3 Statistical Methods

Omschrijf hoe we het daadwerkelijk hebben onderzocht.

3.3.1 Handeling of Assumptions

Hoe zijn we omgegaan met missing values, covariance, etc etc.

4 Results

4.1 Number of Downloads

4.1.1 Across Levels

4.1.2 Paid vs Free Version

4.1.3 Gaming

4.2 Ratings

4.2.1 Across Levels

4.2.2 Variance

4.2.3 Paid vs Free Version

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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