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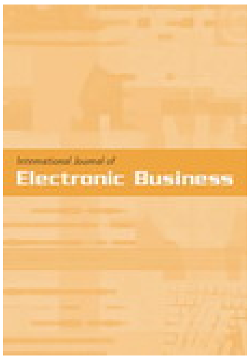

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Cândida Sofia Machado, Cláudia Cardoso, Natália Lemos

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Determinants of health apps' demand: a study on Google Play Store

Cândida Sofia Machado* and
Cláudia Cardoso

School of Management,
Polytechnic University of Cávado and Ave (IPCA), Portugal
Email: cmachado@ipca.pt
Email: ccardoso@ipca.pt
*Corresponding author

Natália Lemos

2Ai,
Polytechnic University of Cávado and Ave (IPCA), Portugal
Email: nslemos@ipca.pt

Abstract: Markets for health apps are complex, with multiple actors and interactions between them. Therefore, a successful business model must guarantee adequate revenues for app developers, and simultaneously value for users to guarantee demand. To a sample of 200 health apps in the Portuguese Google Play Store, we applied ordinal regression models to understand what characteristics of health apps influence their demand, measured in terms of downloads. We find that monetisation strategies are crucial to explain health apps' demand. Free to download, in-app purchases and in-app ads increase downloads. Additionally, the quality of the app is of significant importance to ensure users' satisfaction and to enhance the visibility and demand of the app. By presenting a comprehensive analysis of the factors that impact the success of a mobile app, these findings should be of interest to researchers and app developers.

Keywords: mobile apps; e-Health; demand for health apps; app characteristics; monetisation mechanisms; Google Play Store.

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Biographical notes: Cândida Sofia Machado holds a PhD in Economics, and she is an Assistant Professor at the School of Management of the Polytechnic University of Cávado and Ave, Portugal. With over 20 years of teaching experience, her research interests focus on microeconomics and industrial organisation.

Cláudia Cardoso holds a Bachelor's, Master's, and PhD's in Economics from the Faculty of Economics of Porto, Portugal; she is a Professor in the disciplinary area of Economics, at the School of Management (ESG) of the Polytechnic University of Cávado and Ave (IPCA), since 2002.

Natália Lemos holds a Master's in Management from the Polytechnic University of Cávado and Ave (IPCA), Portugal. She was a Research Fellow in the area of Management at the Applied Artificial Intelligence Laboratory (2Ai), and nowadays she is a Research Fellow in the area of Management at the Research Center for Accounting and Taxation (CICF), both of the Polytechnic University of Cávado and Ave (IPCA).

1 Introduction

As in other fields of society, digitalisation plays a central role in transforming the provision of healthcare services (Odone et al., 2019). Medical informatics apps and e-Health solutions, while easing 'the management and delivery of healthcare' [Pagliari et al., (2005), p.10] show the potential 'to improve healthcare locally, regionally, and worldwide' [Eysenbach, (2001), p.1].

This potential of e-Health solutions, such as health apps, to create additional value for users should be harnessed, and institutions should learn to devote part of their efforts to building value relationships because, in an approach focused on value co-creation (such as e-Health platforms), it is crucial to value and strengthen interdependencies between different user groups (Chesbrough, 2010; Fehrer et al., 2018; Foresti and Varvakis, 2018; Ketonen-Oksi et al., 2016; Lusch and Vargo, 2014).

In the specific case of m-Health (mobile health), such as health apps and wearable devices, these solutions enable continuous digital monitoring of citizens' health data by monitoring vital signs such as heart rate, blood glucose level, blood pressure, body temperature, brain activities, among others (Aydin and Silahtaroglu, 2021; Belliger and Krieger, 2018; Comissão Europeia, 2014; Demiris et al., 2019; Guo et al., 2017; Manogaran et al., 2017; World Health Organization, 2011).

In the market of health apps, monetisation strategies can be based, mainly, on revenues from the payment by download of the app (in the case of paid apps), on revenues from ads (mostly present in free apps) or revenue from in-app purchases (mechanism common to both free apps and paid apps) (Aydin and Silahtaroglu, 2021; Krishnan and Selvam, 2019; Lee et al., 2021).

Revenue from app download payments depends on a steady influx of new users, while ad revenue requires a large installed user base and revenue from in-app purchases requires the continuous involvement of users with the app and its conversion from users to buyers within the app. Indeed, most of the monetisation mechanisms of health apps (and apps as a whole) are affected or conditioned by the size of the active users' base of the app, so the main goal of health apps is to attract users and to achieve a critical mass of users that triggers network effects (Aydin and Silahtaroglu, 2021; Fu et al., 2017; Krishnan and Selvam, 2019; Lee et al., 2021).

In this paper, we intend to answer the following questions: what app-level characteristics impact health apps' demand? How influential are monetisation strategies in explaining the success of an app? Our aim is to show how various characteristics of health apps influence demand, measured in terms of downloads. To do so, we use a sample of 200 health apps available on the Portuguese Google Play Store platform. Previous studies have shown that the price on an app and other monetisation schemes are important determinants of mobile apps' demand (Arora et al., 2017; Ghose and Han, 2014; Lupiáñez-Villanueva et al., 2020; Dinsmore et al., 2017).

This study contributes to the existing literature by giving a better comprehension of what explains the success of health apps, with emphasis on the role of monetisation strategies. For app developers, this research can provide valuable insights for the definition of the app's business model (Gokgoz et al., 2021; Scholz, 2016) and into how different revenue sources and other app characteristics contribute for an app's success.

The remainder of the paper is structured as follows: Section 2 presents the literature review on e-Health markets and on the determinants of apps' demand; Section 3 describes the data and the econometric setup; Section 4 reports the empirical results and sensitivity analysis is performed in Section 5; a summary and discussion conclude the paper.

2 Literature review

2.1 On e-Health markets

The health sector is constantly challenged in terms of efficiency, quality, and equity in the provision of healthcare. At the same time, this sector is increasingly facing challenges arising from the ageing population, the high incidence of chronic diseases, the lack of qualified health professionals, the scarcity of resources and the existing budgetary constraints (Arvanitis and Loukis, 2016; Aydin and Silahtaroglu, 2021; Comissão Europeia, 2014; Duque et al., 2017; Krishnan and Selvam, 2019; Mettler and Eurich, 2012; Pastorino et al., 2019; Vimarlund, 2017).

In this context, digital transformation has emerged as a solution with the potential to dramatically transform different areas of society, specifically the health sector. With this paradigmatic change in healthcare delivery, the health sector aims to maintain competitiveness in an evolving world (Arni and Laddha, 2017; Marques and Ferreira, 2020; Odone et al., 2019; Ruotsalainen, 2017; Schallmo and Williams, 2018; Vial, 2019; World Health Organization, 2010).

Digital transformation has enabled the evolution to an 'information age health system' in which users can ideally use information and communication technologies to gain access to information and control their own healthcare (Eysenbach, 2000; Pagliari et al., 2005). Thus, mobile technologies such as health apps that interact directly with wearable devices emerge as a fundamental tool to dramatically increase citizen engagement with healthy lifestyles and well-being (Comissão Europeia, 2014; Kostkova, 2015; World Health Organization, 2011).

With these solutions, such as health apps, health ecosystems have become dynamic systems that incorporate a variety of stakeholders (actors). Health ecosystems are now based on bilateral (or multilateral) markets whose objective is to develop products and deliver services that meet the needs of consumers (Kuziemsky and Vimarlund, 2018; Nykänen, 2017; Rochet and Tirole, 2006; Vimarlund and Mettler, 2017).

Multilateral markets, such as the e-Health market, correspond to 'markets in which one or several platforms enable interactions between end-users and try to get the two (or multiple) sides 'on board' by appropriately charging each side' [Rochet and Tirole, (2006), p.645]. A crucial feature of these platform-based markets is that they need to 'have both sides on board' to be sustainable, meaning that different user groups are interdependent, as they depend on each other to co-create value from their interaction (Armstrong, 2006; Schmalensee and Evans, 2007; Kuziemsky and Vimarlund, 2018; Muzellec et al., 2015; Osterwalder and Pigneur, 2011).

This particularity of multilateral markets is associated with the phenomenon of network effects that predicts that platforms with a higher number of users are more attractive, since users value direct connections with other consumers (direct network effects) and since they anticipate that platforms with a larger installed user base will be platforms with a greater offer and variety of products and services (indirect network effects). Taking into account the network effects, the success and viability of health apps are based on attracting as many users as possible, in order to reach the critical mass of users and finally trigger the network effects (Aydin and Silahtaroglu, 2021; Cennamo and Santalo, 2013; Eisenmann et al., 2011; Fehrer et al., 2018; Fu et al., 2017; Krishnan and Selvam, 2019; Lee et al., 2021; Osterwalder and Pigneur, 2011; Rochet and Tirole, 2003, 2006).

According to Antoja et al. (2019), the monetisation of health apps depends on the combination of the payment modalities allowed in the app and the concept that is paid. The main monetisation modalities on these platforms are payment by download, payment by in-app purchases, and ads revenues. In turn, the concepts for which you pay are essentially licenses of use, access to digital content, products and services and presence or space in the app to show sponsored content or ads.

Based on these payment methods, in health apps markets, monetisation strategies can include: the provision of a free health app, in which there is no financial return from the download, being the return based on revenues from in-app purchases and/or ads; or the provision of a paid health app, in which there is a financial return resulting from downloading and sometimes in-app purchases, since ads are less common in paid apps (Aydin and Silahtaroglu, 2021; Krishnan and Selvam, 2019; Lee et al., 2021).

There is also another possible monetisation strategy – called fragmented freemium – in which a free and a paid version of the health app is available simultaneously. Users are given a choice between the basic free version and the paid version with advanced and ads-free features (Aydin and Silahtaroglu, 2021; Krishnan and Selvam, 2019; Lee et al., 2021; Tidhar and Eisenhardt, 2020).

Regardless of the monetisation strategy adopted by health app developers, revenue from download payments as well as revenue from in-app purchases and ads, are affected and conditioned by the size of the installed base of users of the health app, so the goal of health apps, to ensure their viability and success in a highly competitive market, is to attract users, in order to achieve the critical mass of users to trigger network effects and maximise the returns of the different payment modalities (Aydin and Silahtaroglu, 2021; Fu et al., 2017; Krishnan and Selvam, 2019; Lee et al., 2021).

2.2 On the determinants of apps' demand

Previous literature has identified some characteristics of the apps as drivers for apps download. The price of the app is one of those drivers. Osterwalder and Pigneur (2011) argue that the demand generated by a product at zero prices is often higher than that generated by a product at a positive price. Arora et al. (2017) complements this argument by stating that app developers themselves are aware that app users, and Android users, particularly, do not like to pay for apps. Also because of this, most of the apps available on the Google Play Store are free apps and paid apps usually offer free versions. Ghose and Han (2014), in a comparative study between the platforms Google Play Store and Apple App Store, also identified a greater sensitivity on the part of Google Play Store users to price variations, visible by the greater impact on app demand in the face of price changes. Arora et al. (2017), however, conclude that the price of paid apps does not have a significant association with their speed of adoption, considering that paid apps have low prices.

The presence of other monetisation mechanisms also impacts the demand for mobile apps. Ghose and Han (2014) concluded that the availability of the in-app purchases option directly increases apps' demand in addition to having an indirect positive effect on demand, due to the decrease of apps' price. On the other hand, providing an in-app ad option has a negative impact on app's demand due to the hassle caused by these ads. Nonetheless, Ghose and Han (2014) consider that this mechanism, even if it damages the demand for the app, is worth it, given that, generally, the volume of ad revenues exceeds the loss of revenue with the decrease in downloads. Lupiáñez-Villanueva et al. (2020) and Dinsmore et al. (2017) argue that the presence of in-app ads does not decrease the intention of users' downloads, that is, it does not decrease the demand for the app in question, provided that potential users accept the ads as a non-monetary trade-off to access the app for free. Thus, even if the display of ads degrades the experience of using the app, some users accept this trade-off as necessary to enjoy the app.

The age of an app, that is, the time elapsed since the app was first released on the platform, is also a variable addressed in the literature. The study of the relationship between the age of the app and the respective downloads/demand has been conducted in various ways in the literature. For instance, Carare (2012) used the age of the app as a determinant of demand, from the perspective that, in the app market, there is a saturation effect that predicts that the demand for apps becomes saturated over time, the target audience of potential app users is large but finite. The notion of the age of the app has also been used, more indirectly, in studies on the survival retention of apps (Guo et al., 2017; Lee and Raghu, 2014), as well as in studies related to the analysis of versioning decisions over an app's life cycle (Appel et al., 2020; Arora et al., 2017). Ghose and Han (2014) and Krishnan and Selvam (2019) identify a positive relationship between the age of the apps and their demand, thus revealing a preference of users for 'long-standing' apps.

Furthermore, Ghose and Han (2014) found that the number of apps created by the same developer has a positive effect on the demand for the app. This occurs because, as ongoing marginal costs arise from various maintenance tasks after app development, some of the maintenance costs of a particular app can be shared by other apps created by the same developer. This finding further suggests that if a developer has created a large number of high-quality apps in the past, consumers can rely on that developer's apps, which influences the demand for such apps.

Some studies (Deng et al., 2022; Liu et al., 2014) have focused on the effect of a freemium strategy – that is, the simultaneous availability of a free version and a paid version of the same app – on apps' demand. Literature shows that the freemium strategy is positively associated with the increased demand for the paid version of the same app.

Liu et al. (2014) found that increasing the visibility of an app is essential to generate a high level of awareness of the app since most users find the apps they download through the ranking list published by the platform. Highly ranked apps, that is, with a higher position (closest to 1) in the top, are those that generate more interest among potential users, given that the position on the ranking list reflects the interest of other consumers and this peer influence is one of the main drivers of demand.

Krishnan and Selvam (2019) and Lee and Raghu (2014) use app ratings as a metric for the quality of the app and report a positive effect of good ratings on the number of downloads. Arora et al. (2017) also found a positive association between the rating and the adoption of an app. This association becomes significantly more positive in the later stages of an app's life. Erić et al. (2014) also concluded that, within the context of mobile apps, user ratings play a significant role, as they are used as a satisfaction metric for current users of the app and as a tool to support decision-making by potential users.

As for more technical characteristics of an app, Ghose and Han (2014) conclude that the increase in the size of the apps, measured in megabytes (MB), results in an increase in the time required to download the app and that, consequently, the longer waiting times negatively affects app demand. They also consider some technical restrictions, such as the minimum version of the Android operating system required to install the app, as a determinant of apps' demand.

Health apps need to attract a critical mass of users to unleash the typical network effects of platforms and maximise the returns arising from the different payment modalities adopted by app developers. Hence, knowing what and how app-level characteristics influence the demand for health apps is of particular interest to app developers and to the sustainability of their business model.

3 Methodology

Digital distribution platforms for mobile apps offer users many apps to buy or download for free. The largest global app distribution platforms are the Google Play Store and the Apple App Store, which is not surprising given that Android and iOS are the two main operating systems for mobile devices (Statista, 2022b).

Among those two leading platforms, the Google Play Store establishes itself as the largest app market in the world, in terms of volume, with a number of apps available that has been increasing since its launch in 2008 and peaked at 4.67 million apps at the end of 2021 (Statista, 2022b). As the Android operating system gained support from several smartphone manufacturers, it began to gain popularity in the market and, in 2021, it accounted for more than 70% of the market for smartphone operating systems (Statista, 2022a).

Apps for Android devices have fewer download barriers and can be obtained by users in alternative app markets as well as through the open web. The Google Play Store hosted 3.5 million apps as of the second quarter of 2022, being a continuously expanding platform, which added nearly 90,000 apps in June 2022 alone and saw a 6.35% increase in apps available to users between the first and the second quarters of 2022. During the third quarter of 2022, more than 3.55 million mobile apps were available on the Google Play Store, up 1.3% from the previous quarter. In the third quarter of 2022, users downloaded approximately 27 billion apps from the Google Play Store (Statista, 2022c, 2022e, 2022f).

With so many users downloading and interacting with apps daily, it's not surprising that brands and marketers have begun to explore the hugely profitable app industry and capitalise on the growing demand for apps (Statista, 2022d).

To study how the various characteristics of health apps influence the demand for health apps, we collected data on health apps marketed in the Google Play Store platform, for it stands as the app store with greater relevance worldwide, namely in terms of downloads.

3.1 Data and variables

As mentioned, the data used in the empirical analysis refer to health apps available on the Google Play Store platform. The Google Play Store releases daily ranking lists, namely the top free and the top paid lists, which include, respectively, the free and paid apps with greater relevance based on the number of downloads.

Since the Google Play Store does not publish comprehensive data on health apps, we analysed third-party websites to ascertain their potential as a source of data collection for this research. We used data made available by the third-party website AppBrain (https://www.appbrain.com.) for it provides a detailed summary of rich information regarding Android mobile apps that appear on the Google Play Store ranking lists.

On November 7, 2022, we collected information on health apps figuring in the top free and top paid categories ‘health and fitness’ and ‘medical’ on the Google Play Store, totalling a set of 200 health apps. Sample values are summarised in Table 1.

Table 1 Sample values

Type of health app	*Total*	*Category of health app*	
		Health and fitness	*Medical*
Paid	100	50	50
Free	100	50	50
Total	200	100	100

For the dataset, in addition to the name of the health app (*id*) and its developer (*developer*), several other variables that we present below were collected.

Since we intend to study the determinants of health apps’ demand, the variable downloads is our dependent variable. For each observation, we have data on the download ranges, but we do not know the specific value of the observation. More downloads means being positioned in a higher number category of downloads, in accordance with the information presented in Table 3. There are 11 categories for the variable downloads and the table shows that there is a small percentage of apps either with less than 1,000 downloads (category 0) or with 100,000,000 or more downloads (category 10), 4% or 3.5%, respectively. The most prominent categories of downloads are category 3 (from 10,000 and up to 49,999 downloads), reflecting 24%, and category 5 (from 100,000 and up to 499,999 downloads), representing 17%.

Looking at the distribution of downloads by type of health app (Table 4) we can see that free apps are prevalent in higher categories of downloads (from categories 5 to 10, with the exceptions of categories 5 and 7, free apps are the only type of apps downloaded) whereas paid apps are dominant in lower categories (categories 0 to 4). Not surprisingly, data shows that free health apps have more downloads than paid apps.

Table 2 Variables description

Variables	*Description*
downloads	A categorical variable that identifies the range of downloads in which the app falls into
type	A dummy variable that indicates if the app is free or paid
age	A discrete quantitative variable that identifies the age of the app, in months
same_developer	A discrete quantitative variable that specifies the number of apps provided by the developer
category	A dummy variable that specifies the category in which the app is in
screenshots	A discrete quantitative variable that states the number of screenshots available on the web page
iap	A dummy variable that specifies whether the app has in-app purchases options
ads	A dummy variable that specifies whether the app has ads
other_version	A dummy variable that identifies if there is another version of the app (freemium strategy)
rank	A discrete quantitative variable that specifies the position of the app in the ranking list
rating	A continuous quantitative variable that specifies the classification/rating of the app
size	A continuous quantitative variable that specifies the size, in megabytes (MB), of the app
android_version	A categorical variable that states the minimum version of the Android operating system required

Note: Except for the variable *ads* – collected from the Google Play Store – the remainder of the variables were obtained from the AppBrain website.

Table 3 Data description for the dependent variable *downloads*

Downloads category	*Downloads range*	*Frequency*	*Percent*
0	< 1,000	8	4.00
1	1,000 to 4,999	21	10.50
2	5,000 to 9,999	20	10.00
3	10,000 to 49,999	48	24.00
4	50,000 to 99,999	13	6.50
5	100,000 to 499,999	34	17.00
6	500,000 to 999,999	9	4.50
7	1,000,000 to 9,999,999	19	9.50
8	10,000,000 to 49,999,999	13	6.50
9	50,000,000 to 99,999,999	8	4.00
10	≥ 100,000,000	7	3.50
	Total	*200*	*100.00*

The descriptive statistics of the independent variables collected to study the determinants of demand for health apps are exhibited in Table 5.

Table 4 Distribution of *downloads* by *type* of health app (percent)

Downloads category	*Downloads range*	*Type of app*	
		Free (n = 100)	*Paid (n = 100)*
0	< 1,000	25.00	75.00
1	1,000 to 4,999	23.81	76.19
2	5,000 to 9,999	15.00	85.00
3	10,000 to 49,999	29.17	70.83
4	50,000 to 99,999	30.77	69.23
5	100,000 to 499,999	52.94	47.06
6	500,000 to 999,999	100.00	0.00
7	1,000,000 to 9,999,999	89.47	10.53
8	10,000,000 to 49,999,999	100.00	0.00
9	50,000,000 to 99,999,999	100.00	0.00
10	≥ 100,000,000	100.00	0.00

Table 5 Descriptive statistics of the independent variables

Variable	*Mean*	*Standard deviation*	*Percent*	*Min*	*Max*
type (= 1 if the app is paid)	--	--	50.00	0	1
age (in months)	66.9	39.569	--	0	154
same_developer	12.515	26.252	--	1	207
category (= 1 if medical)	--	--	50.00	0	1
Screenshots	7.42	1.836	--	0	10
iap (= 1 if the app contains in-app purchases)	--	--	25.50	0	1
ads (= 1 if the app contains adds)	--	--	17.50	0	1
other_version (= 1 if there is another version of the app)	--	--	11.50	0	1
Rank	25.5	14.467	--	1	50
Rating	3.03	1.93	--	0	5
size (in MB)	62.217	154.934	--	0.09	1,710
android_version	4.04	2.975		0	11

Note: Number of observations: 200.

To study how the characteristics of the health apps impact downloads, variables such as the type of app (free or paid), the age of the app (measured in months), the number of apps provided by the *same_developer*, the category of the app (‘health and fitness’ or ‘medical), or the number of *screenshots* available in the web page were considered in the empirical analysis. Paid apps account for 50% of the observations, the same percentage as the apps belonging to the category ‘medical’. For the health apps in our sample, the mean time elapsed since the release date of the app (variable age) is 66.9 months, and, on average, the app developers provide over 12 apps on the Google Play Store platform. As for the variable *screenshots* its inclusion can reveal if user’s value visual information provided about the app to allow them to ascertain whether the app is of interest. In our sample, the average number of *screenshots* in the health apps under study is 7.42 screenshots.

In addition, the variables *iap* and *ads* specify whether the app has alternative monetisation mechanisms, in addition to payment by download. Of the health apps present in the sample, 74.5% do not have in-app purchases options. As for the dummy variable *ads* – a binary variable that indicates the absence (*ads* = 0) or the presence (*ads* = 1) of ads in the app, we have 82.5% of health apps without in-app ads in the sample. Thus, the majority of the health apps in the sample do not have in-app purchases options or in-app ads as additional monetisation strategies.

The existence of another version of the app in question (*other_version*), which indicates whether an app is marketed based on a fragmented freemium approach, that is, through the simultaneous availability of a free version and a paid version of the same app. This variable allows us to determine the absence (*other_version* = 0) or the presence (*other_version* = 1) of another version (free or paid) of the same app and, in the study sample, only 11.5% of the health apps have both free and paid versions of the same app available on the platform.

The variable *rank* measures the market visibility of the app, and it is expected to influence demand positively. This variable assumes values from 1 to 50, where 1 means that the app is in the first position of the rank and 50 means that it is in the last position. Purchase decisions of other users, generating highly ranked apps, may promote the interest of potential users.

To address the quality of the app and how it influences demand, the variable rating indicates how users rate the app, using a five-point scale evaluation that reflects the level of user satisfaction with the app (Erić et al., 2014). In our dataset, the average *rating* of the health apps under study is 3.03 points. The inclusion of this variable will reveal how the satisfaction of current users (reflected by the *rating*) triggers interest and trust in the app by potential users and consequently, triggers an increase in demand for the app in question.

There is also other technical information available on the app's web pages that can potentially influence a health app's download decision. For that, we have also collected data on the size of the app (*size*) and the minimum version of the Android operating system required to install the app (*android_version*). The variable size is a continuous quantitative variable that specifies the size, in megabytes (MB), of the app. In our sample, the average size of the health apps is 62.22 MB. An increase in the size of the app may imply an increase in the time required to download the app and this longer waiting times may harm demand. Finally, as for the variable *android_version*, this variable has 12 categories that include: '4.0.3 Ice Cream Sandwich' (which is the oldest), '4.1 Jelly Bean', '4.2 Jelly Bean', '4.3 Jelly Bean', '4.4 KitKat', '5.0 Lollipop', '5.1 Lollipop', 6.0 Marshmallow', '7.0 Nougat', '8.0 Oreo', '8.1 Oreo', and '9.0 Pie' (which is the newest). In our sample, 29% of the apps need the minimum version 5.0 for the app to work, while 10.5% of the apps need the minimum version 4.4 for the app to work. The percentage of apps that require newer versions, such as version 9.0, is minimal (0.50% of the sample), and a large number of apps, approximately 23.5%, only require version 4.0.3 for the app to work. These technical restrictions can also influence the demand for the apps and, therefore, were considered in the empirical analysis.

3.2 Econometric models

Ordinal regression models, such as the ordered probit model and the ordered logit model, are used to estimate relationships between a categorical and ordered dependent variable and a set of regressors. Our dependent variable, *downloads*, classifies as a categorical and ordered variable. As shown in the previous section, this variable has 11 categories and identifies the interval of downloads into which the health app falls. Although we cannot observe the actual number of downloads, we know that a higher number category implies more downloads.

Following Long and Freese (2001), we can present the ordinal regression model as a latent variable model where y^* stands as a latent variable ranging from $-\infty$ to ∞. For a set of independent variables **x**, the structural model is:

$$y_i^* = \mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i$$

where i is the observation and ε is a random error. Having more than two outcomes, y^* is divided into J ordinal categories:

$$y_i = m \text{ if } k_{m-1} \le y_i^* < k_m \text{ for } m = 1 \text{ to } J$$

where the cutpoints k_1 through k_{J-1} are estimated.

In ordinal regression models, a score is estimated as a linear function of the regressors and the set of cutpoints. The coefficients and cutpoints are estimated using maximum likelihood. There is no constant in the model since the effect is absorbed into the cutpoints.

The probability of observing outcome m corresponds to the probability that the estimated linear function, plus random error, is within the range of the cutpoints estimated for the outcome:

$$Pr(y = m \mid \mathbf{x}) = Pr\left(k_{m-1} \le y^* < k_m \mid \mathbf{x}\right)$$

Replacing y^* for $\mathbf{x}\boldsymbol{\beta} + \varepsilon$, the predicted probability in the ordinal regression model will be given by:

$$Pr(y = m \mid \mathbf{x}) = F\left(k_m - \mathbf{x}\boldsymbol{\beta}\right) - F\left(k_{m-1} - \mathbf{x}\boldsymbol{\beta}\right)$$

where F is the cumulative distribution function for ε. In the ordered probit model, F is the standard normal cumulative distribution function while, in the ordered logit model, F is the logistic cumulative distribution function.

4 Results

Table 6 exhibits the regression coefficients for both the ordered probit and the ordered logit models. The signs of the estimates as well as their statistical significance are similar for both models and between the different specifications of the models. Nonetheless, the goodness of fit metrics allows us to conclude that the ordered logit models fit the data better than the ordered probit models since the former present higher log-likelihood and lower AIC values than the latter. Moreover, among the ordered logit models, specification (3) is the one performing better for it shows the highest log-likelihood and the lowest AIC values (the predicted probabilities mentioned below refer to the results of this model specification).

Table 6 Estimation results for the ordered probit and logit models (coefficients)

	Ordered Probit models			*Ordered Logit models*		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Type	–2.097***	–2.912***	–2.770***	–3.792***	–5.206***	–4.950***
	(0.214)	(0.252)	(0.259)	(0.406)	(0.487)	(0.499)
Iap	0.858***	0.547***	0.484**	1.493***	0.950***	0.805**
	(0.203)	(0.210)	(0.221)	(0.355)	(0.367)	(0.387)
Ads	0.932***	0.532**	0.587**	1.959***	1.145**	1.307***
	(0.244)	(0.259)	(0.264)	(0.450)	(0.461)	(0.481)
age	0.019***	0.017***	0.016***	0.033***	0.030***	0.029***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)
same_developer	0.003	0.002	0.002	0.007	0.005	0.007
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)
category	–0.913***	–0.935***	–0.938***	–1.581***	–1.729***	–1.768***
	(0.160)	(0.164)	(0.167)	(0.283)	(0.295)	(0.300)
other_version	–0.076	–0.208	–0.108	–0.109	–0.483	–0.304
	(0.251)	(0.259)	(0.262)	(0.417)	(0.431)	(0.436)
screenshots	–0.045	–0.016	–0.009	–0.081	–0.052	–0.036
	(0.042)	(0.042)	(0.043)	(0.072)	(0.073)	(0.073)
rank	--	–0.018***	–0.018***	--	–0.033***	–0.033***
	--	(0.006)	(0.006)	--	(0.010)	(0.010)
rating	--	0.413***	0.383***	--	0.712***	0.671***
	--	(0.055)	(0.056)	--	(0.102)	(0.103)
size	--	--	0.000	--	--	0.000
	--	--	(0.001)	--	--	(0.001)
android_version	--	--	0.084***	--	--	0.153***
	--	--	(0.032)	--	--	(0.056)
/						
cut1	–3.081***	–3.508***	–3.269***	–5.628***	–6.881***	–6.392***
	(0.410)	(0.460)	(0.471)	(0.783)	(0.910)	(0.933)
cut2	–2.070***	–2.229***	–1.972***	–3.651***	–4.258***	–3.717***
	(0.375)	(0.409)	(0.423)	(0.685)	(0.752)	(0.774)
cut3	–1.489***	–1.479***	–1.182***	–2.600***	–2.869***	–2.265***
	(0.366)	(0.392)	(0.409)	(0.654)	(0.698)	(0.727)
cut4	–0.401	–0.189	0.166	–0.675	–0.613	0.093
	(0.355)	(0.380)	(0.404)	(0.624)	(0.660)	(0.706)

Notes: Dependent variable: downloads of the app. Standard errors in parentheses: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Source: Own computations

Table 6 Estimation results for the ordered probit and logit models (coefficients) (continued)

	Ordered Probit models			*Ordered Logit models*		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
cut5	–0.100	0.181	0.551	–0.143	0.028	0.761
	(0.355)	(0.381)	(0.406)	(0.623)	(0.661)	(0.711)
cut6	0.822**	1.403***	1.823***	1.520**	2.254***	3.107***
	(0.358)	(0.395)	(0.427)	(0.634)	(0.690)	(0.759)
cut7	1.110***	1.781***	2.205***	2.058***	2.971***	3.832***
	(0.361)	(0.402)	(0.433)	(0.644)	(0.704)	(0.774)
cut8	1.824***	2.666***	3.073***	3.409***	4.573***	5.419***
	(0.375)	(0.425)	(0.453)	(0.693)	(0.754)	(0.821)
cut9	2.549***	3.436***	3.813***	4.797***	5.965***	6.763***
	(0.402)	(0.452)	(0.473)	(0.769)	(0.821)	(0.876)
cut10	3.277***	4.159***	4.506***	6.148***	7.278***	8.059***
	(0.444)	(0.488)	(0.503)	(0.861)	(0.901)	(0.952)
Log-likelihood	–330.9	–294.9	–291.1	–326.8	–291.9	–287.7
AIC	697.7	629.9	626.1	689.7	623.9	619.5
LR Chi2	219.9	291.7	299.5	227.9	297.7	306.1
N	200	200	200	200	200	200

Notes: Dependent variable: downloads of the app. Standard errors in parentheses: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Source: Own computations

As expected, the *type* of app has a negative impact on downloads. Holding the other variables at their mean values, the predicted probability[1] of having a number of downloads situated in category 3 (10.000 ≤ *downloads* < 50.000) – the mode of the distribution, is 0.476 if the app is paid (*type* = 1) and 0.043 if the app is free (*type* = 0). Conversely, the predicted probability of having a number of downloads situated in category 7 (1.000.000 ≤ *downloads* < 10.000.000) – the highest category where we can find both downloads from paid and free apps, is 0.003 if the app is paid (*type* = 1) and 0.234 if the app is free (*type* = 0). Indeed, these results suggest that paid health apps have fewer downloads than free health apps which is consistent with previous studies, such as Osterwalder and Pigneur (2011), Arora et al. (2017) and Ghose and Han (2014). These studies have identified a higher demand for products (in this case, health app) with reduced prices or, in the extreme, free. Given that our study focuses on the Google Play Store, it is relevant to state that Android users are particularly price-sensitive (Arora et al., 2017; Ghose and Han, 2014).

As for the alternative monetisation mechanisms of health apps, the presence of in-app purchases (*iap* = 1) or the presence of in-app ads (*ads* = 1) both show a positive impact on the predicted probability of health apps' downloads. Again, holding the other variables at their mean values, the predicted probability of having a number of downloads situated in category 3 (10.000 ≤ *downloads* < 50.000) is 0.2154 if the app contains in-app purchases (*iap* = 1) and 0.3564 otherwise (*iap* = 0). On the other hand, the predicted probability of having a number of downloads situated in category 7 (1.000.000 ≤

downloads < 10.000.000) is 0.0535 if the app has in-app purchases and 0.0251 if it has not. As for the in-app ads variable (*ads*), the predicted probability of having a number of downloads situated in category 3 (10.000 ≤ *downloads* < 50.000) is 0.1489 if the app contains ads (*ads* = 1) and 0.3607 otherwise (*ads* = 0), but the predicted probability of having a number of downloads situated in category 7 (1.000.000 ≤ *downloads* < 10.000.000) is 0.0821 if the app contains ads and 0.0245 if not. Thus, health apps that contain in-app purchases or in-app ads present higher downloads. Ghose and Han (2014) also concluded that the availability of the in-app purchase option directly increases the demand for the app, but they found that providing an in-app ad option has a negative impact on app demand. However, this mechanism works as a trade-off for price reduction. Our results are aligned with Lupiáñez-Villanueva et al. (2020) and Dinsmore et al. (2017) who also argued that the presence of ads in the app does not decrease the intention of users' downloads. The presence of in-app ads option allows developers to establish lower app download prices or even offer the app for free. It compensates the loss of revenue derived from a price reduction (Lemos et al., 2023). Nevertheless, this trade-off may originate distraction and time opportunity cost (Appel et al., 2020; Ghose and Han, 2014; Guo et al., 2019), with negative impact on downloads. From the developers' perspective, downloads can be potentiated if they offer an app at a lower price (or for free) that displays ads, regardless of what advertisers are paying for those ads. From the users' perspective, they can choose to use a version of the app with ads, benefiting from a price discount, or they can eliminate the inconvenience of ads for a price (Appel et al., 2020; Guo et al., 2019).

As for the age of the health app (*age*), results suggest a positive effect on demand. In line with our results, and corroborating the preference of users for apps that have been established for the longest time in the market, Ghose and Han (2014) and Krishnan and Selvam (2019) have also identified a positive relationship between the age of the apps and their demand, thus revealing a preference of users for 'long-standing' apps.

Our results also indicate that health apps that belong to the 'medical' category, instead of the 'health and fitness' category, are expected to have fewer downloads. In effect, holding other variables at their mean values, the predicted probability of having a number of downloads situated in category 3 (10.000 ≤ *downloads* < 50.000) is 0.4694 if the health app belongs to the 'medical' category and 0.1738 if the health app belongs to the 'health and fitness' category, while the predicted probability of having a number of downloads situated in category 7 (1.000.000 ≤ *downloads* < 10.000.000) is 0.013 if the app is a 'medical' app and 0.0697 if it is a 'health and fitness' app. As so, the decision by the app developer as to the most appropriate category to include the health app is increasingly relevant. Considering that there are more than 30 categories currently in the Google Play Store platform, some categories often overlap and vary in specificity, which is precisely the case of 'health and fitness' versus 'medical'. App developers should dedicate attention to the choice of the best category for their health app to make it easier for consumers to find new apps that match their specific interests and needs. Making matters more complex, it cannot be assumed that selecting a category will make the app achieve the best possible results. In this context, our study provides real insights into this problem that is still poorly addressed in the literature on health apps and mobile apps in general.

The variables related to the visibility and the quality of the health app (*rank* and *rating*, respectively) is both statistically significant. The position of the health app in the top *rank* impacts downloads negatively. A lower number for this variable indicates that the app is in a better position in the top rank and, inversely, a higher number for this variable indicates a worse position in the top rank. Thus, health apps that have a better position in the top rank (and, consequently, a lower number for the *rank* variable) are expected to have more downloads. For instance, holding all other variables at their mean values, the predicted probability of having a number of downloads in category 3 (10.000 ≤ *downloads* < 50.000) is 0.1830 if the health app is in the first position (*rank* = 1) of the rank against a predicted probability of 0.4601 if the health app in the last position of the rank (*rank* = 50). In contrast, the predicted probability of having a number of downloads situated in category 7 (1.000.000 ≤ *downloads* < 10.000.000) is 0.0652 if the health app is in the first position of the rank and 0.0138 if the health app in the last position of the rank. The variable that relates to how the users assess the quality of the health app, *rating*, shows a positive sign which means that a better rating is expected to promote downloads. If a health app gets a rating of 0 by users (the lowest possible rating), holding other variables at the mean, the predicted probability of having a number of downloads in category 3 (10.000 ≤ *downloads* < 50.000) is 0.5193 and the predicted probability of having a number of downloads in category 7 (1.000.000 ≤ *downloads* < 10.000.000) is 0.0042. Nonetheless, if an app gets a rating of 5 (the highest rating), the predicted probability of having a number of downloads in category 3 (10.000 ≤ *downloads* < 50.000) is 0.1216 and the predicted probability of having a number of downloads in category 7 (1.000.000 ≤ *downloads* < 10.000.000) is 0.1011. As supported by previous literature, positive evaluations made by users tend to promote apps' demand (Dellarocas et al., 2007; Lee and Raghu, 2014; Li et al., 2011).

Finally, a technical characteristic of the app such as the minimum *Android version* required for app download shows a positive impact on downloads. Apps requiring more recent Android versions are expected to have more downloads. Similar findings were obtained by Liu et al. (2014).

5 Sensitivity analysis

Considering the nature of our dependent variable, *downloads* – in which outcomes face interval censoring, we can use an interval regression model as an alternative econometric possibility (Wooldridge, 2002). The interval regression model is a generalisation of censored regression. Indeed, we do not know the precise value for downloads, but we know the ordered category into which each observation falls. Hence, to check for the robustness of the results presented in the previous section, we have also run an interval regression model. To do so, we had to create two dependent variables: the interval's *lower limit* and the interval's *upper limit*. The lowest category of *downloads* (category 0) is left-censored, and the highest category of *downloads* (category 10) is right-censored. The other categories are interval censored, being both left-and right-censored. After creating the two dependent variables, we estimated the interval regression models considering the same set of independent variables as for the ordered probit and logit models presented in the previous section. Compared to the ordered probit and logit models, results remain generally unchanged in the interval regression model. Nonetheless, the ordinal regression models seem to fit the data better than the interval regression model as we can see in Table 7.

Table 7 Interval regression models and ordinal regression models comparison – selected statistics

	Interval regression models			*Ordered probit models*			*Ordered Logit models*		
	(1)	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*	*(1)*	*(2)*	*(3)*
Log likelihood	–1,226.2	–1,224.8	–1,222.4	–330.9	–294.9	–291.1	–326.8	–291.9	–287.7
AIC	2,472.5	2,473.6	2,472.8	697.7	629.9	626.1	689.7	623.9	619.5
LR Chi2	114.2	117.0	121.8	219.9	291.7	299.5	227.9	297.7	306.1
N	200	200	200	200	200	200	200	200	200

Comparing the log likelihoods for the interval regression models estimated and the ordinal regression models, which are directly comparable, the log likelihoods for the ordinal models are significantly larger.

6 Conclusions

Understanding what influences health apps demand is of great importance for app developers. Our study shows that the different monetisation strategies significantly impact demand. We find that paid health apps have fewer downloads than free health apps, and that in-app purchases option and in-app ads increase downloads. Indeed, in e-Health markets the price structure and pricing decisions are crucial for the creation of network externalities and for increasing the market value of the platform. In-app purchases and/or in-app ads are additional sources of revenue and users accept them as a trade-off to enjoy the app for free or at a lower price.

Likewise, developers should devote attention to the quality of the app and users' satisfaction. Health apps with better ratings perform better in terms of downloads. If the experience is satisfactory to users, it can potentiate an app's visibility, and highly ranked apps are expected to have more downloads.

Our study presents some caveats that can be overcome in future research, namely the expansion of the sample to include other health apps, besides those figuring in the top free and top paid ranking lists, and the consideration of other app stores, besides Google Play Store, for a better understanding of health app's demand across different platforms. Also, the cross-sectional nature of the dataset used does not allow to have a dynamic perspective over demand. Longitudinal data would help to explain demand changes over time.

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Notes

1 Predicted probabilities were computed using the predict command in Stata.