Journal of Business Research 101 (2019) 668–674

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Uncovering top-ranking factors for mobile apps through a multimethod approach[☆]

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A R T I C L E I N F O

Keywords:
Mobile apps
App success
Top grossing app
fsQCA
Multivariate logistic regression

A B S T R A C T

The increasing computational power of mobile devices and the advancements in network communications are enabling the emergence of new mobile services. Developers have created many mobile applications (mobile apps) to fulfill a wide range of personal and professional user needs. The present study aims to answer the following research question: what are the factors that influence an app's ranking and success? To answer this question, we define a set of antecedents that may explain the top rank of an app. We use a sample of 500 of Apple's top grossing apps to analyze the top 50 and bottom 50 apps. We then use a multivariate logistic regression to examine if factors such as user rating, category popularity, diversity as measured by the number of languages supported, package size, and release date are determinants of an app's success. We also apply a fuzzy-set qualitative comparative analysis (fsQCA) to find the existence of more causal paths for the mobile app's success. Multivariate results indicate that category popularity, diversity (number of languages supported), package size, and app release date are all factors that increase the probability that an app will be ranked inside the top 50. Nevertheless, contrary to our prediction, a high user rating is negatively associated with an app's success. The results of the fsQCA show that the importance of an app's attributes, functionalities, and longevity surpasses the importance of the user rating in explaining the app's success.

1. Introduction

Mobile devices are powerful tools that people use for personal and professional reasons. Following this trend, developers have created a large number of mobile applications (mobile apps or simply, apps). An app can be a web, native, or hybrid application. According to the statistics in a report by App Annie on mobile apps, 2017 was "a monumental year for the App Economy" (App Annie, 2018, p. 1). In fact, more than 175 billion downloads (60% more than in 2015) took place, and US consumers spent more than 86 billion USD (105% more than in 2005). The report estimated that each user spends nearly 1.5 months using apps per year (30% more than in 2015) (App Annie, 2018). As of March 2018, Android had around 3.6 million apps available, and the Apple App Store offered 2 million apps; by September of 2016 people downloaded apps 140 billion times (cumulative) (Statista, 2018a).

Mobile apps are a growing market with 69.7 billion USD in annual revenues in 2015 and a projected annual revenue of 188.9 billion USD by 2020 (Statista, 2018c). However, nearly half of IOS developers and two thirds of Android developers made less than 500 USD in revenue per month (Wilcox & Voskoglou, 2014). This revenue shows that not all developers are successful, and this is partly because there is limited knowledge about the factors that lead to the development of profitable apps. Furthermore, Garg and Telang (2013) find that the top-ranked paid apps have 150 times more downloads than the number 200 paid app in that same ranking. Indeed, being top-ranked in an app store increases the app's visibility, which is positively associated with its success (Ifrach & Johari, 2014; Liu, Au, & Choi, 2014). Existing research considers an app's rank as a measure of its success (e.g., Dibia & Wagner, 2015). Thus, we consider an app's success as its rank in the app store.

The literature proposes several measurable characteristics that may positively influence an app's success. Among these are the price, number of updates available, different languages supported by the app, the package size, and the popularity of the category to which the app belongs (Dibia & Wagner, 2015; Duarte & Picoto, 2016; Lee & Raghu, 2014; Shen, 2015). For example, gaming is the most popular category in Apple's App Store. It accounts for 25% of the available apps with an

☆ The authors gratefully acknowledge the financial support from FCT- Fundação para a Ciência e Tecnologia (Portugal), national funding through research grant (UID/SOC/04521/2019).

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https://doi.org/10.1016/j.jbusres.2019.01.038
Received 12 June 2018; Received in revised form 16 January 2019; Accepted 19 January 2019
Available online 07 February 2019
0148-2963/

expected global revenue of 105.2 billion USD by 2021 (Statista, 2018a). The academic research on the relation between app sales and their rankings (Garg & Telang, 2013; Lim & Bentley, 2013,) or on their success factors (Dibia & Wagner, 2015; Lee & Raghu, 2014; Tuckerman, 2014) mainly focuses on the developer's perspective. The existing research almost exclusively uses quantitative methods (Wang, 2017). Furthermore, the results are mixed (Wang, 2017). How different characteristics could lead an app to achieve a top ranking is not clear. The research question that guides the development of this study is: which are the factors that influence an app's ranking position and success? To answer this question, we draw on the literature to define a set of antecedents that can explain the reasons why an app is in the top-ranked position. The present study aims to enhance the research on the success factors for mobile apps by combining a traditional multivariate regression analysis with the fuzzy set qualitative comparative analysis (fsQCA). The combination of different research methods and the use of a qualitative approach is new in this area of research and may contribute to the current debate about the success of mobile apps.

The sample consists of the top 50 and bottom 50 apps out of the 500 that are Apple's top grossing apps. The top grossing rank refers to the apps with the highest total revenue, which includes not only the app's price and quantity sold (downloaded) but also its revenues from in-app purchases (Garg & Telang, 2013; Ifrach & Johari, 2014; Lee & Raghu, 2014; Ragaglia & Roma, 2014). Using public data available from the Apple App Store, namely the package size, supported languages, user rating, category popularity, and app release date (app age), we first apply a multivariate logistic regression in order to identify which factors influence the app's success. The results show that category popularity, number of languages supported, package size, and app age all have a positive influence on the app's success. Contrary to our prediction, a high user rating is negatively associated with the app's success. To further understand this particular result as well as to find the configurations of conditions that may lead to higher or lower success, we apply fsQCA to determine more causal paths that may explain the success of apps. As fsQCA considers different causal conditions that can explain the outcome of interest, several alternative configurations of conditions give a better understanding of what makes an app successful. The results of the fsQCA indicate that the absence of a user rating occurs in the combinations that lead to higher success of a mobile app because the importance of the app's attributes, functionalities, and longevity surpass the importance of the user rating in explaining its success.

This study makes several contributions to managers, developers, and researchers by giving a better understanding of what influences the development of successful, top-ranked mobile apps. As a result, developers and managers can focus more on these characteristics. A better comprehension of the mobile app's success also allows organizations to engage in successful mobile marketing initiatives and business-related apps for mobile devices. In addition, the study contributes in terms of applying a new method to this literature stream by comparing the empirical results of a multivariate logistic regression with those from fsQCA (Cheng, Huifen, & Zhongqi, 2016). This research supports the identification of the antecedents of an app's success as well as the determination of different possible success paths through the configuration theory. Accessing the different configurations that lead to the app's success may influence decisions when developing a new app or when improving an existing app. For researchers, this study presents a comprehensive analysis of influential factors for the success of mobile apps.

The remainder of this article is as follows: The next section comprises the literature review and theoretical background of this study. We then present multivariate regression and fsQCA methods. Finally, we present and discuss the results of this study and the conclusions.

2. Literature review and propositions

Native and hybrid applications are fostering the emergence and growth of mobile application marketplaces and ecosystems. Mobile apps are platform specific, and Google Play for Android devices and the Apple App Store for IOS devices are the most popular. Roughly 3.8 million applications are published for Android and 2 million applications are available for IOS devices (Statista, 2018a), and an estimated number of 5.5 million developers participate in this market (Wilcox, 2014). An application may generate revenues through the download price, in-app advertising, in-app purchases, and subscriptions. With paid downloads, the consumer is paying a fee for the app when acquired.

According to the literature, several measurable app characteristics exist that can positively influence its success: selling price, number of updates, different languages in which the app is available, number of operating system versions supported, the API functions, and the package size (Dibia & Wagner, 2015; Lee & Raghu, 2014; Liu et al., 2014). Additionally, the popularity of the category to which the app belongs appears to have a significant impact on success (Lee & Raghu, 2014; Shen, 2015) as well as the user rating (Lee & Raghu, 2014).

Over the past few years, with the increased computation power of mobile devices, their value has shifted to the data and software they can provide (Matos, Ferreira, & Krackhardt, 2014). The proliferation of mobile apps represents an opportunity for organizations and developers, but also a huge challenge, as it is not easy to stand out among 7.1 million apps (Statista, 2018a) on the major app stores. Achieving awareness is a complex and demanding task. The app market is not easily understood given the lack of information regarding the demand and sales of apps (Garg & Telang, 2013). Additionally, as users of mobile devices are dedicating more time to mobile apps than websites, organizations that seek to gain competitive advantage must also understand which factors affect an app's success in order to develop adequate mobile strategies and effective mobile marketing (Dibia & Wagner, 2015).

The actual algorithm that calculates the app's rank is a well-kept secret. Nevertheless, due to the developers' growing interest in understanding the factors that influence the rankings in app stores, it is becoming less of a secret. The most important factors that influence rankings are the number of downloads and revenue, both recent and aggregated, but also app launches, retention (uninstalls), social proof, number and value of reviews of users, keyword relevance, updates, and backlinks (Butters, 2014; Fuecks, 2015; Walz, 2015).

The success models in traditional Information Systems (IS) (such as the ones developed by Delone & McLean, 2003) may not be appropriate to evaluate the success of mobile apps (Dibia & Wagner, 2015). The reasons are because the characteristics of mobile app ecosystems are different from traditional IS applications in terms of development (through software development kits), distribution (attraction of all users to a single place making updates and marketing easier), and targeting (at the individual level only) (Dibia & Wagner, 2015). Although data on the number of downloads and revenue for each app from the app stores are not publicly available, a high rank infers an app is downloaded more often and thus generates more revenue (Garg & Telang, 2013). Garg and Telang (2013) propose a method, which uses the data available from the Apple App Store to infer the rank-demand relation.

Many studies have established the relation between top-ranked apps and the number of downloads (e.g., Garg & Telang, 2013). Furthermore, Lee and Raghu (2014) also acknowledge that when an app is at the top of the chart, it increases the chances of being purchased when users search for apps. Liu et al. (2014) establish a relation between the app's ranking and its sales volume. Therefore, the ranking of a mobile app is a proxy for its sales (Garg & Telang, 2013) and a measure of its success (Dibia & Wagner, 2015; Lee & Raghu, 2014). In the context of mobile apps, "success is restricted to appearance/reappearance of Apps in the top-charts over time" (Lee & Raghu, 2014, p. 9). Dibia and Wagner (2015, p. 4305) define a mobile app's success "in terms of the usage audience which an app is able to garner during its lifecycle and focus mainly on characteristics of apps such as app diversity (the number of geographic locales an app is built to support), an app cohesion (a measure of the tightness of integration with its parent platforms) as antecedents to its success."

The present study does not take the longitudinal perspective into analysis but rather a cross-sectional one, as it considers a snap shot of the top-grossing apps. Building on the two previous definitions of success in the context of mobile apps, this study proposes that success is the appearance at the top of the app stores' charts at a given moment, according to the app characteristics such as user rating, number of languages supported, package size, number of versions, and category popularity.

These factors are present in the literature as antecedents for a mobile app's success. For example, Song, Park, and Kim (2013) find that consumer rating and number of ratings are positively related with the app's number of downloads. Lee and Raghu (2014) conclude that free offers, high initial rankings, investment in less popular app categories, quality updates, high volume, and high user ratings have impacts on the app's success.

2.1. User rating

Based on the word-of-mouth literature, Song et al. (2013) identify the success factors that are related to the sales of mobile apps. They find that closed platforms (such as the Apple App Store) outperform the open ones (such as the Google Play Store), and the user rating is more important to open platforms than to closed ones. Indeed, the user rating can also play a role in the app's success (Lee & Raghu, 2014), as it indicates peer evaluation on a scale of one to five, (where one corresponds to “inadequate” and five means “excellent”). Mobile app platforms use this rating to allow new users to differentiate between apps with a high level of satisfaction and apps with a low level (Ruiz et al., 2017). The research has consistently studied the influence of peers as an antecedent to the adoption of information systems, thus the user rating is also expected to influence the mobile app's success. Accordingly, this study suggests the following proposition:

P1. The user rating is positively associated with the mobile app's success.

2.2. Category popularity

The popularity of the app's category may also be important to explaining its success (Lee & Raghu, 2014; Shen, 2015). Many studies have examined the category to which the app belongs when considering the app's success, ranking, and adoption (Ghose & Han, 2014; Ifrach & Johari, 2014; Lee & Raghu, 2014; Petsas, Papadogiannakis, Polychronakis, Markatos, & Karagiannis, 2013; Shen, 2015). Liu et al. (2014) study the impact of an app being hedonic (i.e., games, entertainment, and other leisure or fun related apps) or non-hedonic (i.e., utility and business apps) on its ranking. They find that the impact of the ranking is more relevant to hedonic applications. In fact, as of September 2018, the top ranked shares of active apps in the Apple App Store were categorized as games (24.86%), business (9.77%), and education (8.5%) (Statista, 2018b). Therefore, if an app belongs to a popular category, then that category increases the odds of reaching a top ranking (Lee & Raghu, 2014; Shen, 2015). Hence, this study puts forward the following proposition:

P2. The category's popularity is positively associated with a mobile app's success.

2.3. Diversity

High network effects that transcend the frontier of one country (Bresnahan, Davis, & Yin, 2014; Ifrach & Johari, 2014) often characterize the mobile platform's ecosystem. Most platforms and rankings are available to global audiences (Dibia & Wagner, 2015). Diversity refers to an app being available in different geographic locations because of specific language characteristics. Dibia and Wagner (2015) show that this characteristic is a significant and positive antecedent for the mobile app's success. Thus, this study puts forward the following proposition:

P3. An app's diversity is positively associated with its success.

2.4. Package size

Package size, measured in megabytes, “may be a proxy for the richness of its content potential value thus reducing uncertainty about its performance” (Dibia & Wagner, 2015 p. 4309). The literature considers the package size as a positive factor for an app's success, as it can be a proxy for the richness of its content, sophistication, and functionalities that have potential value for users (Dibia & Wagner, 2015; Ghose & Han, 2014). The app's characteristics depend both on the technology and on features used in its development. The fact that an app provides more functionalities increases its package size when compared to apps that must have network connections to perform certain tasks. However, even though larger apps can provide higher value for users in terms of the available content and functionalities, they also can deter users from installing these apps due to a lack of storage space in their devices (Dibia & Wagner, 2015). Nevertheless, storage limitations are decreasing as mobile devices increase their computational power and storage space at more affordable prices. Hence, this study proposes the following:

P4. The package size is positively associated with a mobile app's success.

2.5. Application age

The days since the release of an app or the app's age can be defined as “the number of days elapsed after an app was released” (Lee & Raghu, 2014, p.16). If an app has existed for a long time and still appears at the top of the chart, then it has a higher sustainability and survival rate (Ghose & Han, 2014; Lee & Raghu, 2014). This combination indicates that users are more engaged with the app and that they judge its quality and value as superior. Thus, this study proposes the following research proposition:

P5. The application's age is positively associated with a mobile app's success.

3. Method

3.1. Data

Based on the literature review, we select the characteristics that can explain an app's level of success. We focus on the Apple App Store in this study. This store is the preferred platform in the USA for 42% of developers (Wilcox & Voskoglou, 2015). The sample is composed of the top 50 grossing apps and the bottom 50 grossing apps out of 500 apps on the chart at the Apple App Store (USA data). For each app, we collect the data on the package size, number of supported languages, user rating, app age, and category popularity from the Apple App Store and App Annie websites on October 30, 2017. The app price was not included in this analysis because only five apps were not free in this sample (Liu et al., 2014).

3.2. Multivariate regression method

To test the propositions presented above, this study applies a multivariate logistic regression in which the outcome is measured by the position of the app in the top 500 grossing apps in the Apple App Store. The independent variables are the different factors that influence the position of the app in this ranking. Therefore, we estimate the following model:

$$\ln[P(Y=1)] = \beta_0 + \beta_1 RATING + \beta_2 CATPOP + \beta_3 LANG + \beta_4 SIZE + \beta_5 AGE + \varepsilon$$

where Y = RANK is a variable that equals one if the app is in the top 50 grossing apps and zero if it is in the bottom 50 of the same ranking. RATING is the user rating, which is evaluated on a scale of one to five, where one corresponds to "inadequate" and five means "excellent." CATPOP represents the popularity of the app's category as measured by the percentage in share for each category (games, music, and entertainment among others), based on Statista data for 2018 (Statista, 2018b). LANG is the natural logarithm of the number of languages supported by the app. SIZE is the natural logarithm of the application size measured in megabytes. Age is the natural logarithm of the number of days between the app's release and October 30, 2017.

3.3. fsQCA method

This research applies fsQCA in order to understand alternative configurations of mobile app characteristics that lead to the outcome of a "mobile app's success". As fsQCA applies a holistic approach that considers several conditions together while multivariate logistic regression does not (Woodside, 2013), it enhances the understanding of the complex interconnected factors that can lead to the success of a mobile app.

FsQCA leverages Boolean algebra to qualitatively and systematically analyze cases to explain an outcome of interest. Furthermore, fsQCA focuses on the analysis of set relations (Feurer, Baumbach, & Woodside, 2016) and conceptualizes cases as combinations of attributes (Fiss, 2011) that lead to an outcome (dependent variable). We use the software version 3.0 of fsQCA for our analysis.

The procedures follow the ones used by Fiss (2011) and Feurer et al. (2016). The variables are calibrated using the fsQCA software and full membership corresponds to the original values above the 95th percentile, the crossover point is the median or average value, and full nonmembership is the original value below the 5th percentile. Table 1 presents the calibration of the set membership and the descriptive statistics for each condition and the outcome. Table 2 presents the descriptive statistics on the categories of apps in the sample.

The sample contains the top 50 grossing apps and the bottom 50 ones out of the 500 apps that are ranked. Because of the calibration method we use in this investigation, a higher value of a rank corresponds to a lower rank. For example, the top app has a rank value of one, and the last app in the list has a rank value of 500. Thus, the variable of interest in this case is the absence of TopRank.

4. Results

Table 3 shows the correlation matrix between the different variables. The correlation values are all low, which indicates that no multicollinearity concerns exist for our tests. Contrary to the literature, a negative correlation exists between the probability of the app being in the top 50 and having a top user rating. Table 4 presents the results for the logistic regression.

The results show that, in line with our propositions, attributes such as the popularity of the app's category, its diversity (the number of languages supported), its package size, and its longevity all have positive and significant relations. Contrary to our first proposition and the majority of the literature, the results show a negative relation between the user ratings (user-perceived quality) and the app's success.[1] Therefore, our results indicate that apps with a higher user rating have a lower probability of being in the top 50 grossing apps in the Apple App Store. For example, the top app is Netflix, which presents a user rating of only 3.5 out of 5.

We analyze the five conditions to determine the outcome ~Ranking Position (corresponding to the highly successful applications) and the outcome Ranking Position (corresponding to the less successful applications). First, we use fsQCA to assess the existence of necessary conditions. A condition is necessary if it is always present when the outcome is present (Ragin, Drass, & Davey, 2006), which means the outcome is a subset of the condition (Ragin, 2008). The necessary analysis shows that no condition presents a consistency score above the threshold of 0.9 (Ragin et al., 2006). Therefore, no necessary condition exists for this model as the highest consistency score is 0.717 for the combination between the absence of the User Ranking Score and the absence of Category Popularity, which is also below the threshold value for an almost always necessary condition (between 0.8 and 0.9).

The fsQCA computations for sufficient conditions present three different solutions: the complex solution, parsimonious solution, and

[1] As a robustness test, we estimate an OLS linear regression that uses as the dependent variable the transformation of the percentile rank scores of mobile apps into z-scores (standard normal scores) by using an inverse normal function that is normally distributed. The results remain unchanged.

Table 1
Calibration of the causal conditions and the outcome.

Variables	Calibration values			Descriptive statistics				
	95%	50%	5%	Median	AVG	STD	Max	Min
RATING	5	4.2	3	4.5	4.2	0.7	5	1.5
CATPOP	0.3	0.2	0	0.3	0.2	0.1	0.3	0
LANG	44.1	8.5	1	8.5	12.6	14.8	73	1
SIZE	298.2	126.7	25.2	126.7	161.1	221.4	2200	1.4
AGE	2913.5	1155.5	222.3	1155.5	1392.5	895.9	3460	110
RANK	495.1	248.5	6	248.5	249.8	225.9	500	1

RATING is the user rating, evaluated on a scale of one to five, where one corresponds to "inadequate" and five means "excellent." CATPOP represents the popularity of the app category as measured by the percentage share for each category. LANG is the natural logarithm of the number of languages supported by the app. SIZE is the natural logarithm of the application size measured in megabytes. Age is the natural logarithm of the number of days between the app's release and October 30, 2017.

Table 2
App categories in the sample.

Category	% in the sample	Share of popularity[a]
Games	57%	24.86%
Music	9%	2.48%
Entertainment	8%	6.03%
Social network	6%	2.11%
Lifestyle	4%	8.32%
Productivity	4%	2.66%
Health and fitness	3%	3.01%
Business	2%	9.77%
Photos and videos	2%	2.2%
Sports	2%	2.17%
Utilities	2%	5.06%
Education	1%	8.5%

[a] Source: Statista, 2018b.

Table 3
Correlation matrix.

	RANK	RATING	CATPOP	LANG	SIZE	AGE
RANK	1.00					
RATING	−0.17	1.00				
CATPOP	0.06	0.31	1.00			
LANG	0.20	0.02	−0.08	1.00		
SIZE	0.21	0.21	0.19	0.00	1.00	
AGE	0.19	−0.15	−0.36	0.07	−0.08	1.00

RATING is the user rating, evaluated on a scale of one to five, where one corresponds to "inadequate" and five means "excellent." CATPOP represents the popularity of the app category as measured by the percentage share for each category. LANG is the natural logarithm of the number of languages supported by the app. SIZE is the natural logarithm of the application size measured in megabytes. Age is the natural logarithm of the number of days between the app's release and October 30, 2017.

Table 4
Results of multivariate logistic regression.

Independent variables	Coefficient	Predicted sign	Coeficient	*P*-value
Intercept	β_0	?	−4.538	0,100
RATING	β_1	+	−3.013	0.007
CATPOP	β_2	+	4.128	0.079
LANG	β_3	+	0.341	0.030
SIZE	β_4	+	0.619	0.001
AGE	β_5	+	0.659	0.021
N° of observations			100	
Pseudo-R^2			14.87%	
$LRChi^2$			20.61	
Prob > Chi^2			0.000	

RATING is the user rating, evaluated on a scale of one to five, where one corresponds to "inadequate" and five means "excellent." CATPOP represents the popularity of the app category as measured by the percentage share for each category. LANG is the natural logarithm of the number of languages supported by the app. SIZE is the natural logarithm of the application size measured in megabytes. Age is the natural logarithm of the number of days between the app's release and October 30, 2017.

the intermediate solution. The complex solution does not include configurations without a solution, the parsimonious solution includes all the configurations including the ones without a solution, and the intermediate solution, which is the one recommended by Ragin (2008), includes the configurations selected by the researcher.

We use the fsQCA software to compute the sufficient solutions for the following models:

$$\sim ranking\ position = f\,(UserRating, CategoryPopularity, SupportedLanguages, PackagedSize\ and\ AppAge)$$
− model for evaluating configurations that lead to high success;

and

$$ranking\ position = f\,(UserRating, CategoryPopularity, SupportedLanguages, PackagedSize\ and\ AppAge)$$
− model for evaluating configurations that lead to low success.

Table 5 presents the results of the sufficiency analysis for each of the two models. A black circle indicates the presence of the condition, and a white circle indicates its absence. Large circles correspond to core conditions and small circles to peripheral conditions (following, e.g., Crilly, Zollo, & Hansen, 2012; Misangyi & Acharya, 2014). Core conditions are present both in the parsimonious and intermediate solutions whereas peripheral conditions are the ones that appear in the intermediate solution but do not appear in the parsimonious one. According to the results, two solutions exist that lead to the high success of a mobile app, and three solutions exist that lead to low success. The solutions for high success (~Ranking Position) show consistency slightly above the threshold of 0.75 and coverage above the threshold of 0.25 that indicates they are informative solutions (Woodside, 2013). However, the solutions for low success (Ranking Position) do not achieve the minimum recommended value of consistency as they are below the threshold. Although 0.75 is commonly accepted as a threshold for consistency, some studies claim that this value should account for the research context (Schwellnus, 2013). Furthermore, our main objective is to explain the conditions that lead to the app's success in terms of its ranking. We also analyze the conditions that lead to low success with the main objective of seeing if the paths are different from the ones that are sufficient to explain high success. Coverage is another criterion to evaluate the quality of the results, and it ranges from zero to one and "refers to the extent to which a configuration of antecedents accounts for high scores of the outcome set" (Feurer et al., 2016 p. 13); and this criterion is met by low success model solutions.

The results show that two configurations are sufficient for achieving higher success. The consistency of all configurations is above the recommended level of 0.75. The first configuration (H1) shows that larger

Table 5
Configurations for intermediate and parsimonious solutions.

	High success		Low success		
	H1	H2	L1	L2	L3
RATING	○	○	○	○	●
CATPOP	◦	◦	◦	◦	◦
LANG	●	●	○	●	○
SIZE	●		●	○	○
AGE		●	○	○	○
Consistency	0.767	0.763	0.676	0.683	0.700
Raw coverage	0.280	0.282	0.230	0.183	0.291
Unique coverage	0.041	0.043	0.041	0.034	0.090
Overall solution consistency		0.750	0.675		
Overall solution coverage		0.322	0.370		

Note: The presence of the condition is indicated by a black circle and absence is indicated by a white circle. Large circles correspond to core conditions and small circles to peripheral conditions.

package size, higher diversity, lower user rating, and less popular category lead to a mobile app's success. This configuration is highly consistent (consistency of 0.767) and represents around 28% of the cases (coverage of 0.280). The second configuration (H2) shows that apps with a higher diversity, lower user rating, less popular category, and longer time in the market also achieve success. This solution is also highly consistent (consistency of 0.763) and represents roughly 28% of the cases (coverage of 0.282).

The sufficient analysis for lower success shows three different solutions, so the paths that lead to high and low success are not the same. In this case, all conditions are always present or absent in the solutions. Configuration L1 shows that younger apps with lower diversity, lower user rating, larger package size, and a less popular category does not achieve success. This configuration is fairly consistent (consistency of 0.676) and represents around 23% of the cases. Configuration L2 indicates that younger apps with higher diversity, lower user rating, smaller package size, and a less popular category also lead to lower success. This configuration is fairly consistent (consistency of 0.683) and represents around 18% of the cases. Configuration L3 shows that younger apps with lower diversity, higher user rating, larger package size, and a less popular category achieve low success. This configuration is fairly consistent (consistency of 0.70) and represents around 37% of the cases. In fact, it is the solution that is the most representative of the solutions for low success.

5. Discussion and conclusions

This research analyzes the impact of five factors (user rating, category popularity, diversity (number of language supported), package size, and app age) on our outcome as measured by the ranking of an app in the top 500 grossing apps in the Apple App Store. This study uses a multivariate logistic regression to find how each determinant influences the probability of an app being ranked in the top 50. This study also uses an fsQCA approach to identify the existence of more causal paths that lead to a mobile app's success to gain a deeper understanding of our results from multivariate logistic regression.

The data validates all the research propositions except for the first one (P1: user rating is positively associated with a mobile app's success) in both analyses. The multivariate logistic regression's results provide evidence that the app's category popularity, supported languages, package size, and app age have a positive influence on its success. According to Lee and Raghu (2014), the category influences the success of sales. Our findings show that the popularity of the category increases the probability of being in the top 50. Diversity also increases the app's success. An increase in the number of languages increases the probability of being in the top 50 by 1.4 times. This is in line with the literature as diversity, and consequently the number of users capable of using the application, positively contributes to the increase in an app's success (Dibia & Wagner, 2015). Finally, both the package size and app age also make a positive contribution to the app's success. The package size can be viewed as a proxy for the app's functionalities that increases its richness (Dibia & Wagner, 2015) while app age showcases the app's continued interest and survival (Lee & Raghu, 2014).

Although the majority of the literature concludes that high user ratings have a positive impact on an apps' sustainability and success as they confer product quality to customers (Lee & Raghu, 2014; Liu et al., 2014), our results do not support this proposition. In fact, the coefficient for RATING ($\beta_1 = -3.013$) is negative and statistically significant at the 1% level, which indicates that apps with higher user ratings have a lower probability of being in the top 50. Ruiz et al. (2017) find that the method for calculating the store rating is static and cumulative so it is not able to capture changes in the users' satisfaction, which could occur given the dynamic nature of app releases. Additionally, top ranking apps may have millions of users but only a small group rates the apps, which could indeed bias the overall rating system. This case could explain the results that we achieved in the present study.

The extent to which reviews affect consumers' decisions can differ due to a variety of factors (Liu et al., 2014). Therefore, we supplement our research with fsQCA to verify if multi-configurations of causal conditions are able to better explain our findings.

Regarding high app success, the solutions indicate that apps that have a lower user rating, less popular category, higher diversity and higher size achieve a top grossing rank (solution H1). On the other hand, the findings also show that highly successful apps are associated with lower user rating, lower category popularity, higher diversity, and longer time on the market (solution H2). One possible explanation for why a low user rating appears as a core condition in highly successful apps is that their attributes such as the number of supported languages, package size and app age increase their functionalities and enhance visibility. In fact, the importance of an app's attributes surpasses the importance of the user rating. This is in line with Ruiz et al. (2017), who conclude that the actual rating system available at the app stores is not capable of capturing changes in the user satisfaction of mobile apps, as new versions and updates could change it. Additionally, 95% of the sample is free mobile apps. Liu et al. (2014) find that user ratings can have lower relevance for free apps because they do not always indicate the users' satisfaction with an app. The fact of being free and being in the market for a long time can lead users to experience the app regardless of user rating. The high functionalities of those apps can then justify their high rank. Furthermore, Liu et al. (2014) also find that in the case of apps that adopt a freemium strategy, the fact that the user could experiment with the app reduces the importance that he or she may give to user ratings. On the other hand, Song et al. (2013) conclude that a user rating is less important in closed mobile app platforms (such as the Apple App Store) than in open ones (such as Google Play Store). Nevertheless, further research could apply a content analysis to explore the richness of user comments about an app, which could contribute to a deeper understanding of the reasons why top-ranking apps are negatively associated with their user ratings.

Contrary to the results from the regression analysis, fsQCA shows that the category popularity is not important to the app's success. This result may indicate that the category popularity loses importance in conjunction with the other factors. This evidence may be also influenced by the fact that the majority of the sample (57%) belongs to the category of "games." These findings are reinforced by the solutions L1, L2, and L3, which explain low app success. All the solutions are different from the ones that lead to high success after accounting for the causal asymmetry of the absence and presence of the outcome (RankPosition). Less popular categories and younger apps are associated with lower success for an app.

This research contributes to enhancing the knowledge about the success of mobile apps. The application of fsQCA complements results from multivariate logistic regression by determining the multiple combinations of conditions that explain the outcome (Woodside & Zhang, 2013). In a systematic literature review, Wang (2017) concludes that quantitative methods dominate the stream of research regarding the determinants of mobile app downloads.

For academics, this study provides an examination of the antecedents of the success of mobile apps by contributing to uncovering the underlying configurations that lead to their top ranking. For practitioners, this research highlights that diversity, package size, and longevity are important conditions for an app to achieve a top ranking.

This research also has some limitations. First, the sample size and the use a US ranking chart limit the generalizability of the results. Second, the data was collected at a single point in time but top charts are calculated on a daily basis. However, despite this limitation, app rankings may be considered fairly stable (Liu et al., 2014). Third, the consistency values for the overall solutions for low success are below the threshold of 0.75. However, these values do not compromise the validity of the results of this study, as the main focus of this study is highly successful apps. Finally, the study of possible interactions between the apps' characteristics considered in the present study could lead to interesting results. Nevertheless, as this analysis requires a longitudinal study and a different research approach at the developer level, it is a potential topic for further research.

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