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IMPACT OF ONLINE CONSUMER RATINGS ON MOBILE APP DEMAND

Gina Maria Almeida Valle

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ADVISOR: Ana Isabel Almeida Costa

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ABSTRACT

People can now freely interact online in order to gather and share information about products and services. Consequently, it becomes very important for firms to understand how these developments shape demand.

Online consumer ratings are an evaluative, numerical form of eWOM that reduces the information asymmetry for current and potential customers on the Internet and is thus expected to impact sales. Because of this, several studies have investigated their effect on demand since it is still not clear the extent to which their valence, volume and/or dispersion affect product sales.

This dissertation studies the impact of online consumer ratings on demand by determining the effects of valence and volume of mobile apps ratings on sales at two online stores, in the last trimester of 2015. Additionally, it also investigates the potentially moderating effects of apps characteristics, namely perceived hedonicity, thereby making a novel contribution to the topic.

Consequently, 360 surveys were collected to assess numerically the apps' perceived hedonicity. Furthermore, ratings and publicly available data of 250 apps was collected from Google Play and Amazon App Store to be evaluated in a regression analysis.

The results show that the volume is what matter on apps' demand since the average rating was not significant in the regressions. Therefore, firms should focus on increasing the number of ratings regardless of the valence. Still, the hedonic/utilitarian concept is a moderator for the average rating and the volume, thus the more hedonic the app the fewer will be impact of both variables on sales.

SUMÁRIO

As pessoas agora podem interagir livremente na Internet, a fim de reunir e compartilhar informações sobre produtos e serviços. Consequentemente, é muito importante para que as empresas entender como estes desenvolvimentos afetam a demanda.

Online consumer ratings são uma avaliativa numérica do eWOM que reduz a assimetria de informação para os clientes na Internet e, portanto, se espera que impactem as vendas. Devido a isso, vários estudos têm investigado o seu efeito, pois ainda não está claro em que medida a sua valência, volume e / ou dispersão afeta as vendas.

Esta dissertação estuda o impacto dos *online consumer ratings* sobre a demanda das aplicações móveis em duas lojas on-line no último trimestre de 2015. Além disso, também investiga os efeitos de moderação potenciais, do grado hedônico percebido, adicionando assim uma nova contribuição para o tópico.

Consequentemente, 360 questionários foram coletados para avaliar numericamente o grado hedônico das aplicações. Além disso, os *ratings* e os dados publicamente disponíveis de 250 aplicativos foram coletados no Google Play e Amazon App Store para ser avaliados em uma análise de regressão.

Os resultados mostram que o volume é o que importa na demanda dos aplicativos por quanto a valência não foi significativa nas regressões. Portanto, as empresas devem se concentrar em aumentar o número de *ratings*, independentemente da valência. Ainda assim, o conceito hedônico /utilitário é um moderador para a valência e o volume, assim, o mais hedônico o aplicativo o menor impacto das duas variáveis sobre as vendas.

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GLOSSARY

Amazon App Store (AAS): The second largest online store to download and purchase mobile apps for Android operating system.

Average rating: Mean of the numerical ratings given by website users.

Electronic WOM (eWOM): Process of sharing information about products or services through the Internet.

Google Play (GP): is the largest online store to download and purchase mobile apps for Android operating system.

Mobile Phone Applications: Software designed to perform different activities on mobile phone devices.

Online Customer Rating (OCR): Numerical evaluation about a product or service. It is given in different scales, such as stars or points.

Online Customer Reviews (OCRev): Type of eWOM in which users post public products' evaluations on websites in terms of open-ended reviews.

User generated content (UGC): Any kind of online content generated by website users.

Volume of ratings: Absolute number of ratings given by website users.

Word-of-mouth (WOM): Process of sharing information person-to-person about a product or service.

CHAPTER 1: INTRODUCTION

This chapter briefly introduces the research topic and contents of the dissertation. It starts by providing background information about eWOM, followed by the problem statement, aim, scope and a brief description of the research methods used. It ends by presenting the academic and managerial relevance of the dissertation and the outline for upcoming chapters.

1.1.Background

WOM is one of the most important sources of information affecting consumers' attitudes and perceptions, and hence shaping their behavior when making purchase decisions (Brown & Reingen, 1987). This topic has been extensively studied since the early 50's. A general consensus about its relevance in the consumer decision journey as one of the most reliable sources of information for customers, has been reached (Day, 1971).

Thanks to technological progress, WOM has transcended from the physical to the digital world. In recent times, the internet has enabled consumers to share and consult information about products and services in a more efficient way, allowing them to take advantage of its scalability, anonymity, accessibility, speed of dispersion, variety of formats and other relevant characteristics (Barreto, 2015; Cheung & Thadani, 2012; King, Racherla, & Bush, 2014). Consequently, this has changed the nature of WOM, giving rise to eWOM, that is, people's online interaction that aim to gather and share information about products and services.

The importance of understanding eWOM has been growing for companies and the academic community alike, not the least because, contrary to what happens WOM, eWOM can be easily tracked and measured.

Online customer reviews and ratings (OCRev/OCR) are types of eWOM designed to reduce information asymmetry and thereby help to lower the risk of buying unfamiliar goods through the Internet (Chen & Xie, 2008). Their importance and huge popularity are mainly due to Amazon's pioneering role in requesting, compiling and displaying this type of information on its website since 1995. At present Amazon has one of the richest reviews' data base in the world with more than 10 million OCRev, which has become one of its most successful sales tool. OCRev and OCR have also become mainstream in social network sites, online discussion forums and topic-related communities where they are crucial for both product brand's and the website's value proposition (i.e. TripAdvisor). Such sites increase consumer welfare by enhancing the transparency and accessibility of information about offers' price and quality and hence promoting competition between firms (Brynjolfsson, Hu, & Smith, 2003).

1.2.Problem Statement

Currently, the biggest challenge for companies and marketing researchers is related with understanding how the eWOM affects the consumer decision making process and thus, determining the influence that it has on demand. For this reason, specific metrics have been developed to assess the consumers' eWOM, an important part of which result from the analysis of the volume, valence and dispersion of OCRev. Volume refers to the absolute number of OCRev/OCR (that is offer mentions and evaluations) and can work as an indirect measure of an offer's awareness among consumers. Valence refers to whether the OCRev/OCR reflect more or less positive offers assessment and hence gauge consumer attitudes about it, whereas dispersion relates to the spread of OCRev/OCR across different communities. (Dellarocas, Zhang, & Awad, 2007)

The impact of the eWOM on demand has been studied in several product categories, such as hotels, books, movies & TV programs, beers and other electronic devices (Chevalier & Goolsbee, 2003; Chevalier & Mayzlin, 2006; Chintagunta, 2010; Clemons, Gao, & Hitt, 2006; Dellarocas et al., 2007; Ho-Dac, Carson, & Moore, 2013; Liu, 2006; Mudambi & Schuff, 2010; Sun, 2012; Vermeulen & Seegers, 2009; Ye, Law, & Gu, 2009). Generally speaking, however, there is still no consensus about the true impact of OCRev/OCR on sales performance (Floyd, Freling, Alhoqail, Cho, & Freling, 2014). On one hand, some researchers have shown that volume rather than the valence, has explanatory power on sales (Ho-Dac, Carson, & Moore, 2013; Liu, 2006). On the other hand, others have suggested that valence should matter more than volume (Chevalier & Mayzlin, 2006; Chintagunta, 2010; Sun, 2012). Therefore, this dissertation aims to solve this strong unanimity about the impact of OCR valence and OCR volume on sales.

Moreover, the OCR topic lacks of studies about moderating effect of the characteristics of the products. Because of this, the hedonicity effect is included in the study since it has not been included in previous studies in the field and it is referred as a relevant driver of online shopping attitudes (Childers, Carr, Peck, & Carson, 2002; Jones, Reynolds, & Arnold, 2006).

1.3. Aim

This dissertation aims to study the impact of OCR on demand and the potentially moderating effects of product characteristics. To achieve this goal, answers to the following research questions were specifically sought:

RQ1: What is the impact of OCR valence and OCR volume on product sales?

RQ2: Does the hedonic vs the utilitarian character of products moderate the impact of OCR volume and/or valence on the corresponding sales?

1.4.Scope

The dissertation is focused on the analysis of OCR because they are easily measurable and publicly accessible, while OCRev, as open-ended post, are more difficult to assess. Besides, the dissertation excluded the dispersion from the analysis since there is no access to information to calculate it. As was said before, attention is focused on studying valence and volume because there is no consensus about their impact on sales.

Particularly, to explore an industry that has not been extensively treated in the OCR literature, this dissertation is focused mainly on the analysis of the impact of OCR on mobile phone applications.

The importance of this industry is reflected by its statistics. The number of smartphones worldwide exceeded 1 billion and industry revenues reached US$ 74 billion (Kim, Briley, & Ocepek, 2015). Currently, iOS and Android are the major two major operating systems around the globe. Android is, however, the most popular operating system, as everyday there are more than 1.5 million new Android users and, by 3Q 2012, 70% of smartphone shipments were Android phones (Rollins & Sandberg, 2013). The dissertation is focused on Android operating systems due to its relevance in the industry.

Smartphone applications, in particular, are changing people's life. They are becoming a universal source of information, value and entertainment, made readily available by tech service providers. U.S. consumers, for instance, have increased their access to mobile apps from less than five to more than seven times a day between 2012 and 2013 (The Nielsen Company, 2014). It is thus unsurprising that, by 2015, global sales of mobile apps are expected to reach US$38 billion (Kim et al., 2015). Google Play and Apple Store are the two most important players in this market. In the first quarter of 2013, Google Play offered over 700.000 apps and recorded more than 25 billion downloads, generating a growth of 90% in revenue (Rollins & Sandberg, 2013).

Mainly, the analysis is focused on the analysis of the impact of OCR on apps performance in the most important mobile app distribution platforms for Android (Google Play and Amazon App Store) because they represents more than 80% of the app store market share for Android operating system (Statista, 2015a).

Additionally, as most of the previous studies referred to paid items, the scope of the study is restricted to the paid apps because it would be interesting to have comparable results with previous researches. Therefore, free apps, other kind of platforms (i.e. iTunes) and other products (i.e. Movies, Books, Music, etc.) were not considered in the analysis.

1.5.Research Methods

In view of the aim stated above, explanatory research approach was undertaken. Methodologically speaking, this approach entailed an econometric analysis of a cross-sectional data set about the sales and characteristics of 250 top paid apps across the two top download platforms for Android (Google Play and Amazon App Store). Thus, information about the selected paid apps was recorded in terms of ranking, average star rating, total number of ratings, distribution of ratings according to stars, app size and release date.

Inferred sales were used as dependent variable while volume and average rating were taken as the independent variables. The platform of origin (Amazon or Google Play) and the hedonicity were used ad interaction terms. To that end, primary data was collected from 360 people by doing an online survey to classify the apps according to perceived hedonicity. Price, size, category, creator popularity and the number of retailed days were taken as the control variables.

1.6.Relevance

eWOM represents a huge challenge for the companies. On one hand, considering the current digital environment, companies have little control over user-generated content. On the other hand, WOM is one of the most credible sources of information for users. According to Nielsen studies, for instance, almost 60% of consumers of electronic devices consider online reviews before making purchase decisions, while 45% and 37% of consumers consult the reviews prior purchase decisions of cars and software respectively (The Nielsen Company, 2010). Generally speaking, the OCR are extremely important in the buying decisions for half of the visitors of online retailers (Chen & Xie, 2008). Therefore, it is crucial for managers to measure the impact of the electronic word-of-mouth (eWOM) on critical metrics such as sales.

Based on this, the present dissertation was focused on better understand the impact of ratings valence and volume on sales since in the academic ground there is not consensus about the topic. Additionally, the attention of the study is directed to the mobile phone applications industry which has not been studied in depth. Besides, the introduction of the hedonicity moderation effect aims to provide additional insights in the OCR subject.

After doing this analysis, brand managers and digital marketers could understand the impact on OCR rating on demand and businesses performance, giving them tools to comprehend the current app performance based on up-to-date ratings. By doing so, the enterprises can direct their efforts to improve their ratings in the online applications stores making the apps more profitable. Therefore, online retailer can enhance its resources though the app store optimization. For instance, online retailers can invest more resources in obtaining more ratings in the product categories in which the volume of rating is worth more according to the hedonicity feature.

1.7. Dissertation outline

The second chapter presents a literature review on the evolution of eWOM and the online consumer reviews (OCRev). Based on the literature review, some conclusions were determined and some hypotheses were formulated accordingly. The third chapter describes the research methods, data sets and statistical analysis performed to come up with the conclusion about the impact of the ratings on brand performance. The fourth chapter presents and discusses the main results obtained from the statistical analysis to assess the proposed research hypotheses. Finally, the conclusions about the research are exposed in the fifth chapter along with the limitations of the study and some recommendations for further research in the area of eWOM and ratings.

CHAPTER 2: LITERATURE REVIEW

The second chapter presents a review of extant literature on WOM and more specifically its evolution into eWOM. In this regard, the different types of eWOM are going to be discussed along with its differences compared to the traditional WOM concept. Then, the online consumer reviews concept is evaluated regarding the metrics that have been used to assess it. Moreover, the extant studies about eWOM among different industries are going to be considered to analyse how the rating valence, dispersion and volume have been studied in recent years. Based on the findings of this review, 4 research hypotheses are formulated for further statistical testing.

2.1. WOM

WOM was originally defined as “oral, person-to-person communication between a receiver and a communicator whom the receiver perceives as non-commercial, regarding a brand, product or service” (Arndt, 1967). This type of communication has been studied in depth since the late 50’s to assess its impact on business performance. For instance, in one of the first studies about the topic in 1954, it was revealed that the diffusion of air conditioners

usage in Philadelphia was due to the spread of information about the product among a neighbours' network in the suburbs of this city (Brown & Reingen, 1987).
WOM is considered one of the most important sources of information for customers in their purchase decision process (Breazeale, 2009; Brown & Reingen, 1987; King et al., 2014). While brand awareness stage of the consumer decision making process is dominated by mass media and advertising, WOM is a crucial in the evaluation stage, shaping the final decision (Arndt, 1968). Further investigations about WOM and mass media indicated that word of mouth is "seven times as effective as newspapers and magazines, four times as effective as personal selling and twice as effective as radio advertising in influencing consumers to switch brands" (Brown & Reingen, 1987). So, overall, the probability of purchase is higher when the consumer has been exposed to favorable word of mouth and it decreases as the consumer is exposed to unfavorable comments about the product (Arndt, 1967).
A long stream of research about WOM has identified the drivers of word-of-mouth activities, such as, altruism, product involvement, anxiety reduction, vengeance, advice seeking, among others (Kim et al., 2015). Extant literature has shown that other factors are important as well, like time-saving search, interaction needs, seeking retaliation, compensation, bargaining power, or showing connoisseurship, among others (Barreto, 2015). Moreover, the impact of WOM on demand has been shown to be moderated by the characteristics of the message, the receiver, the sender and the step of the purchase decision process. For instance, negative WOM can be more influential than positive WOM (Breazeale, 2009), highly loyal users are less involved with effective WOM than less loyal one because they have smaller incremental gains from WOM due to their networks' saturation (Barreto, 2015) and the likelihood of receiving WOM about a product is higher for people predisposed to purchase than for those who have not consider it yet (Arndt, 1968).

2.2. eWOM

eWOM has been defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). eWOM formats can be classified according to the supporting medium. According to Cheung & Thadani, there are 5 types of eWOM channels, as follows: online discussion forums, online consumer review sites, blogs, social networking sites and online brand/shopping retailer sites (Cheung & Thadani, 2012). However, further researches have proposed alternative typologies, for instance, based on the communication scope and the level of interactivity

(Figure 2.1), hence the channels can be classified between asynchronous (i.e. Blogs) or synchronous (i.e. Chat with a friend /instant chatting) but also depending on the scope: some channels link single consumers (i.e. emails) while others link a single consumer with many others (i.e. product review sites) (Wilde, 2013).

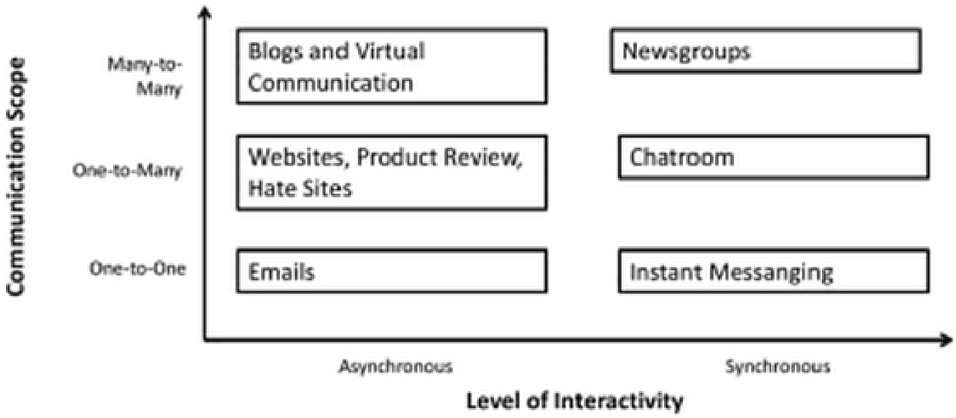

Figure 2.1: Typology of eWOM communications (Wilde, 2013)

Besides internet support, there are other important distinctions between WOM and eWOM such as, scalability, speed of diffusion, accessibility, measurement, anonymity and credibility (Cheung & Thadani, 2012). When compared to WOM, eWOM also offers enhanced volume, higher dispersion, higher persistence, more anonymity, more saliency of valence and higher community engagement (King et al., 2014). On the other hand, because of the lack of personal contact, eWOM messages may result less credible than WOM: consumers may wary of companies creating positive posts, disguised of individual recommendations, to foster sales of their products (Barreto, 2015). In fact there is some evidence of the existence of dishonest positive reviews made by retailers, to boost their ratings, as well as of fake negative reviews attempting to damage competitors' reputation (Floyd et al., 2014).

2.3. Online Customer Reviews

OCRev and OCR are UGC that pertain to product evaluation and hence one of the most important types of eWOM (Cheung & Thadani, 2012). They have been defined as "peer-generated product evaluations posted on company or third party websites" and typically take the form of open-ended reviews and numerical ratings (i.e. 1 to 5 stars), respectively (Mudambi & Schuff, 2010).

E-tailer Amazon was one of the first companies allowing customers to post entries with their opinions, namely about books sold at the website. At the beginning, this move appeared to be a bad strategic decision, as experts and customers alike were now able to rant about the products on offer. However, as time passed, Amazon became one of the first successful online retailers to prosper on the back of customer reviews. These became a crucial tool in the value proposition of the company, giving relevant and convenient information to customers in their decision making process. Over time, the importance of customer reviews increased and they have evolved in the website accordingly (Bloomberg L.P, 2009). In 2005, Amazon implemented customer discussion areas for specific products and in 2009 it allowed customers to share and rate specific product attributes (e.g. the battery life for a PC). Nowadays, many other online businesses use customer reviews as an informational value proposition: TripAdvisor for travelling purposes, Yelp and Foursquare for entertainment businesses, Yahoo Movies and Netflix for movies, among others (Bloomberg L.P, 2009).

Currently, one of the biggest challenges for companies and marketing researchers with a steak on e-commerce is understanding how eWOM affects the consumer decision making process and thus, determining the influence that it has on demand. For this reason, specific metrics have been developed to assess the consumers' eWOM, an important part of which are related with the analysis of the volume, valence and dispersion of OCR. Volume refers to the absolute number of OCR. Valence refers to whether OCR reflect more or less positive offer assessments and dispersion relates to the spread of OCR across different consumer segments (Dellarocas et al., 2007).

2.3.1. Movie industry

Dellarocas and colleagues (2007) developed a revenue forecasting model for movies based on online reviews. They collected 55.156 online reviews of 80 movies from Yahoo! Movies, BoxOfficeMojo and Hollywood Reporter, as well as information about movie genre, MPAA ratings, pre-release marketing, availability, star power, release strategy, expert critics and early box office revenues. They then estimated the movies' revenues trajectory after initial release by using a non-linear diffusion Bass model. Based on the results, they concluded that the volume, valence, and dispersion of online movie reviews have positive and statistically significant relationship with upcoming box office sales and thus the early volume of customer online ratings can be used as a proxy of early ticket sales (Dellarocas et al., 2007).

Liu (2006) investigated the impact of OCRev on movies´ box office revenue. This author collected a total of 12.136 reviews from Yahoo Movies, posted about 40 movies during the first eight weeks in the movies' run (a period in which movies are assumed to make 97% of their revenue). Such messages were further classified into five categories according to their valence (positive, negative, mixed, neutral and irrelevant) by 3 independent judges. Information about movie genres, MPAA rating, star power and critical reviews was also collected. Results show that OCRev have significant explanatory power for both aggregate and weekly box office revenue; however most of this power comes from volume rather than valence (Liu, 2006).

More recently, Chintagunta (2010) measured the impact of valence, volume and variance of OCR on offline ticket purchase in the US movie market. To that end, they used 16-month period data from 148 movies including online review data from Yahoo! Movies. Based on the results obtained, and in contrast with extant research, the author concluded that ratings' valence, and not their volume, seems to be the main driver movie box office performance (Chintagunta, 2010).

2.3.2. Book sales

Chevalier and Mayzlin (2006) investigated the effect of OCR on book sales. To do so, they selected randomly a sample of 2394 books and collected information about them in two important online book stores (Amazon.com and Barnesandnoble.com) including shipping, price and the 500 most recent reviews. Importantly, they were able to estimate book sales based on a Pareto distribution of their ranking in both web stores. Their results show that the marginal impact of a 1-star rating is greater than the effect of a 5-star one. Moreover, they concluded that long written views do not necessarily stimulate sales (Chevalier & Mayzlin, 2006).

Subsequent researches about OCR impact on book sales studied the variance in ratings. For instance, Sun (2012) used a difference-in-differences (DID) analysis based on Hoteling´s law to study the effects of OCR variance on sales. To that purpose, data about consumer ratings, price, sales rank and shipping information were collected about 667 bestseller books in Amazon.com and Barnesandnoble.com. Results showed that that higher variance in ratings is related with niche products. Consequently, products with a low average rating and high rating variance could trigger sales in a particular segment since they signal that the product might fit the expectation of a niche, thereby increasing demand. In turn, for products with high average ratings, a higher rating variance leads to the loss of consumers and reduces demand (Sun, 2012)..

2.3.3. Beers

Clemens and colleagues (2006) calculated the extent to which the variance of reviews is determinant for product positioning in the current context of hyper-differentiation, that is, where firms can virtually produce almost everything users wants. Accordingly, as consumers are highly informed, companies that produce highly differentiated goods should have higher growth rates. In this context, the variance of the ratings can be interpreted as a form of horizontal differentiation. Using data about 224 craft beer brewers, these authors showed that rating variance and the most positive quartile of reviews have explanatory power for sales growth. This occurs because it is more important to be the first option for a niche segment than to be an acceptable option for a larger number of customers who would prefer buying a product that fit their tastes in a better way (Clemons et al., 2006)

2.3.4. Electronics Industry

Ho-Dac and colleagues (2013) investigated how brand equity moderates the potential effects of OCR on sales, by studying two electronics´ markets with different maturity: the emerging Blue-ray market and the mature DVD players'. The authors run a regression analysis with 3.341 OCR in the Blue-ray category and 1.664 OCR about DVD players collected from Amazon. They concluded that, there is a positive feedback loop between sales and positive OCR of weak brands. This implies that OCR improve the penetration of weak brands but also increase its brands equity. Meanwhile, the impact of OCR on sales is generally low for strong brands. Consequently, as weak brands become stronger, the impact of positive OCR is reduced (Ho-Dac et al., 2013).

2.3.5. Tourism industry

Ye and colleagues (2009) studied the impact of OCR on the number of hotel booking, by collecting data in Ctrip (the largest travel website in China) about 248 hotels in three different Chinese cities. They found that three out of four travellers consider OCR when planning trips and a 10% improvement on average rating led to 4.4% more bookings (Ye et al., 2009).

Another study in this segment of the tourism industry focused on the potentially moderating roles of brand familiarity and reviews expertise on the effect of the valence of OCR on hotel consideration (Vermeulen & Seegers, 2009). A sample of 168 Dutch respondents were randomly assigned to one of eight groups in a factorial design 2x2x2x2, which varied in review valence, hotel familiarity, reviewer expertise and review exposure. As expected, hotel awareness and consideration grew significantly after respondents were exposed to the reviews. However, this effect was more important for lesser-known hotels than for well-known ones. In spite of having a detrimental effect on consumer attitudes towards and hotel, negative reviews improved its brand awareness. Finally, review valence did not significantly affect consideration for well-known hotels, although it did negatively impact the attitude of customers towards lesser-known ones (Vermeulen & Seegers, 2009).

2.3.6. Meta-analytical studies

In an attempt to synthetize the knowledge about the impact of customer reviews on demand, a meta-analysis was performed on the results of 26 studies related to products as diverse as books, beer, movies, videogames and hotels, sold at e-tailers (Floyd et al., 2014). Results showed that in addition to customer review valence, the existence of a critic's review and the placement of the review on a non-seller website positively influenced retail sales elasticities. Moreover, the level of product involvement was shown to moderate such influences, with customer reviews of high-involvement product having a relatively higher impact on sales elasticities.

2.4. Potentially moderating effects for OCR impact on demand

Prior studies have included some moderating effects to analyze the OCR impact on demand. For instance, product differentiation and niche segments (Sun, 2012; Clemons et al., 2006), brand equity (Ho-Dac et al., 2013), category maturity (Ho-Dac et al., 2013), brand familiarity and reviewers expertise (Vermeulen & Seegers, 2009) have been moderating effects under study. In the considered literature the moderating effect of hedonic/utilitarian motivation on OCR was not treated.

2.4.1. Hedonic/Utilitarian motivations

Hedonic benefits are related with experiences, fun, pleasure, and excitement, whereas products with utilitarian benefits are mainly instrumental and functional. Due to their different nature, the buying process of utilitarian products tend to be driven by rational motivations while hedonic products are determined by emotional incentives (Sloot, Verhoef, & Franses, 2005).

According to Jones and colleagues, both hedonic and utilitarian shopping values are key drivers of retailer outcomes. They referred that satisfaction, positive WOM and loyalty are moderated by the hedonic aspects of the purchase (Jones et al., 2006). On the other hand, hedonicity can affect other variables such as expending preferences. In terms of effort and money, customers are willing to spend more in money for utilitarian goods while devote more effort for hedonic products (Okada, 2005).

Previous researches catalogued app categories between utilitarian and hedonic according to the type of consumption: while utilitarian value refers to extrinsic motivation in efficiency needs and informational based services, hedonic consumption is related with intrinsic motivation of entertainment and fun experiences in mobile services (Heinonen & Pura, 2006;

J. Kim, Park, Kim, & Lee, 2013). Kim and colleagues (2013) classified the apps categories in either utilitarian or hedonic according to Figure 2.2.

Segment	Category
Utilitarian	Business, education, finance, healthcare and fitness, medical, navigation, news, productivity, reference, utilities, weather
Hedonic	Books, entertainment, games, lifestyle, music, photography, social networking, sports, travel

Figure 2.2: Classification of app Categories based on Utilitarian or Hedonic content (Kim, Park, Kim, & Lee, 2013)

2.5. Conclusions and formulation of research hypotheses

At present, one of the biggest challenges for companies is understanding how eWOM affects the consumer decision making process and thus, determining the influence that it has on demand. However, there is still no consensus about the true impact of customer online reviews on sales performance (Floyd, Freling, Alhoqail, Cho, & Freling, 2014). Specifically, talking about the online ratings, some researchers have shown that volume, rather than the valence, has explanatory power on sales (Ho-Dac, Carson, & Moore, 2013). On the other hand, others have suggested that the ratings valence should matter more than volume (Chevalier & Mayzlin, 2006; Chintagunta, 2010; Sun, 2012, Ye et al., 2009; Clemons et al., 2006). In this regard, this dissertation aims to test if valence and volume have positive impact on mobile app sales.

Furthermore, to our best knowledge, there are no studies that analyze the extent to which this impact is moderated by hedonic/utilitarian consumption, which is an important predictor of online shopping attitudes (Childers et al., 2002; Jones et al., 2006). Utilitarian products differ from hedonic ones in terms of motivations because they are driven by rational incentives and emotions respectively (Sloot et al., 2005). Thus, as ratings have numerical nature and they can be seen as a rational incentive, it would be expected that ratings' valence and volume have higher impact for utilitarian products.

From these conclusions and taking into account the research questions mentioned in the first chapter, the following research hypotheses are formulated to be tested:

RH1: Average rating has a positive impact on mobile app sales.

RH2: Volume of ratings has a positive impact on mobile app sales.

RH3: Hedonicity moderates the effect of average rating on mobile app sales.

RH4: Hedonicity moderates the effect of volume of ratings on mobile app sales.

CHAPTER 3: METHODOLOGY

This chapter describes the kind of research approach used in the study. Furthermore, the population, data, sampling process, data collection methodologies and the analytical tools used to analyse the data in this dissertation are described in this chapter.

3.1. Research Approach

The topic of OCR has been studied in depth for the academic community in the last years and there is a lot of information about researches on the field. So, there is no need to clarify the understanding of the problem or its nature (exploratory research) or representing an accurate profile about the OCR (descriptive research) (Saunders, Lewis, & Thornhill, 2009a). So, in general terms, the purpose of the thesis goes beyond understanding or describing the phenomenon; instead, the study is based on the explanatory research method because the aim of the thesis is focused on finding a causal relationship between the OCR's ratings and the companies' performance in terms of sales.

3.2. Population and samples

The general description of the performed sampling process is depicted in figure 3.1.

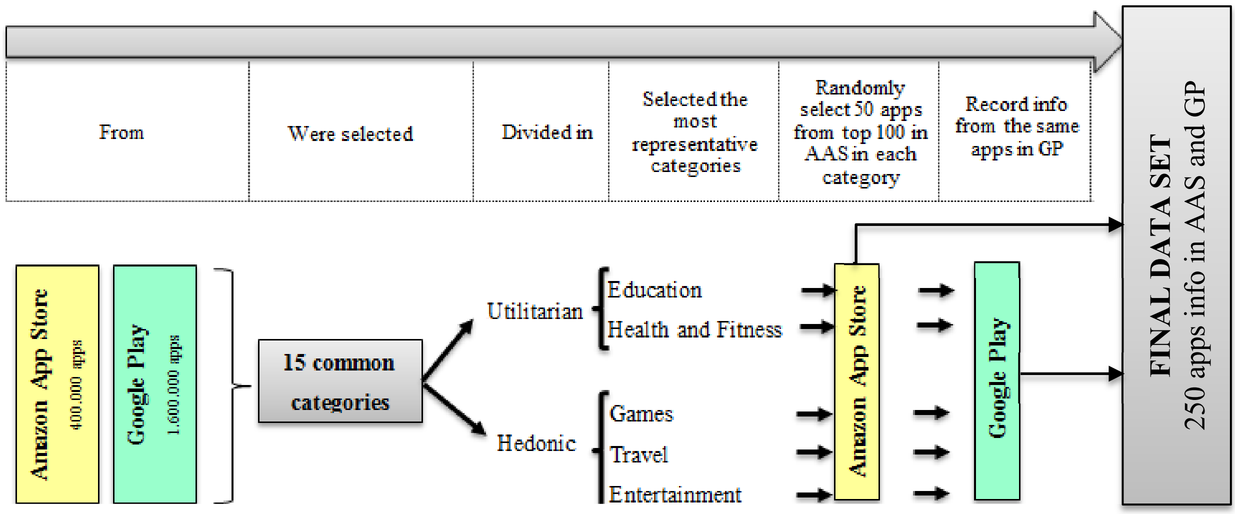

Figure 3.1: Description of sampling process step by step

Data collection was focused on the Android app market since this is the most important operating system around the globe. More specifically, this thesis analysed the relationship between ratings and performance for a given paid app across the two leading app stores for android devices (Google Play and Amazon App Store) (Annex 1). Both have being growing in the last years in terms of available apps (Statista, 2015a), as show in Annexes 2 and 3.

Apps were selected first from AAS since it has a quarter of the total number of apps of GP, so the probability of finding an AAS app sold on GP is higher than the other way around. The population of interest to this thesis was thus defined as the paid apps available at AAS that were also sold in GP till October 2015. This represented 35% of the total number of apps sold in AAS (148.775 out of 426.381 apps).

Annex 4 shows the categories of apps sold at AAS and GP. It can be seen that there are 15 common categories between the two sites. These categories were first classified by the thesis author according to previous typologies of mobile services in terms of their hedonic versus utilitarian nature (Kim, Park, Kim, & Lee, 2013). As a result, as is shown in table 3.1, the most representative categories in each group were selected to perform the final sample selection (Education and Health & Fitness for the utilitarian type and Games, Travel and Entertainment for the hedonic category, which represent more than 80% of the total number of apps in each group respectively).

Table 3.1: Most representative categories for Utilitarian and Hedonic Classification

	App category	Number of apps in AAS	Number of paid apps in AAS	%	% Cumulative
UTILITARIAN	Education	25827	9841	60%	60%
	Health & Fitness	10681	3808	23%	**83%**
	Productivity	7023	1824	11%	
	News & Magazines	8859	651	4%	
	Shopping	2635	214	1%	
	Weather	720	159	1%	
	Total		**16497**		
HEDONIC	Games	151003	38835	52%	52%
	Travel	23690	18371	25%	77%
	Entertainment	38266	6668	9%	**85%**
	Lifestyle	20056	3268	4%	
	Music	14720	2928	4%	
	Sports	6975	2262	3%	
	Photography	5911	1022	1%	
	Communication	5996	754	1%	
	Social Networking	3668	663	1%	
	Total		**74771**		

So, each one of these 5 selected categories represents strata in which stratified random sampling is made among the top 100 paid apps in the category. Previous studies have demonstrated that the top 100 paid apps follow a Pareto distribution, and the log-sales are exponentially distributed, so the most of the downloads are concentrated in this 100 top sellers (Carare, 2012; JA Chevalier & Mayzlin, 2006; Garg & Telang, 2012; Ghose & Han, 2014; Ho-Dac et al., 2013). Due to time constraints and restricted access to the entire stratum apps' ranking, the sample size was defined using the statistical rule of thumb of 30 as the minimum number in each category within the overall sample required to different statistical analysis (Adanza, 2006; Saunders et al., 2009b). Thus, in each category 50 apps were selected randomly in AAS among the top 100 to perform the analysis, each one of the records were analysed in order to determine the suitability for the analysis. To that purpose, were discarded the entries:

1. Which were not found in both web sites. (Listed in AAS but not in GP)
2. Which were listed in different categories across the two web sites. (i.e. Listed as travel in AAS but referred as Communication in GP)
3. Which has only free version available in GP
4. Which has either none ratings in AAS or GP
5. Which information about the exact ranking position in the category was not available.

So, resampling was made until the quota of 50 was met in each stratum (category). So, a total sample size of 250 apps that were studied across both Amazon App Store and Google Play.

3.3. Data Collection

3.3.1. Secondary Data

Data about the 250 apps sampled were collected between October 27th and November 13th from AAS and GP; behavioral data of consumers (ratings given by the users) were recorded along with general information about the apps. In general, the table 3.2 describes the recorded information in each platform.

Table 1.2: Information collected in each platform (Google Play & Amazon App Store)

SOURCE	DATA COLLECTED
Amazon App Store (AAS)	• Ranking position assigned randomly (used to estimate the DV-sales) • App name • Creator (CV) • Classification (all ages, guidance suggested or mature) (CV) • Price in USD (CV) • Release date (CV) • Size in MB (CV) • Average rating (IV) • Total number of ratings (volume) (IV) • Number of 5, 4, 3,2 and 1 stars
Google Play (GP)	• Ranking position in the category (used to estimate the DV-sales) • App name • Creator (CV) • Classification (everyone, parental guidance, PEGI 3, PEGI 7, PEGI 12, PEGI 16 or PEGI 18) (CV) • Price in USD (CV) • Update date (CV) • Size in MB (CV) • Average rating (IV) • Total number of ratings (volume) (IV) • Number of 5, 4, 3,2 and 1 stars

Based on the rank information gathered from AAS and GP, the inferred sales were calculated according to the extent literature (Brynjolfsson, Yu, & Smith, 2010; Erik Brynjolfsson et al., 2003; Chevalier & Goolsbee, 2003; Chevalier & Mayzlin, 2006; Garg & Telang, 2012; Ghose & Han, 2014). In this way, the sales were calculated following the Pareto distribution:

$$Sales = b * rank^{a}$$

So, the shape (a) and scale (b) parameters used in each of the platforms were determined based on the extent literature as follows (Annex 6):

- GP: Specifically, the figures were taken from an existent research (Garg & Telang, 2012). In the case of the b parameter, it was estimated as the average of the b parameters of iPad and iPhone.

$$Sales(GP) = 33.237 * rank^{0.985}$$

- **AAS**: a and b parameters were calculated as the average of these parameters in all the analyzed literature.

$$Sales(AAS) = 17.198 * rank^{0.962}$$

3.3.2. Primary Data

The hedonic/utilitarian classification made from the literature was improved. First of all, because each one of the 5 original categories may contain apps that might not be compatible with the assigned typology. Secondly, it was interesting to include real opinion about customer opinions in order to determine a quantifiable hedonicity scores for each app. So, in order to better classify apps in utilitarian or hedonic, each one of the apps in the sample was classified in a subcategory to assign a final hedonicity score. To the end, the apps were divided among 12 more functionality specific subcategories according to table 3.3.

Table 3.3: Apps subcategories used in the survey to obtain hedonic/utilitarian score

SUBCATEGORY	NUMBER OF APPS
Action & Adventure Games	29
Diet & Carb-control	7
Educational & Brain Games	60
Maps & GPS	18
Measurement tools	18
Media & Video	26
Relaxation & Better Sleep	17
Simulation & Pretend Games	19
Transport Tracking	10
Trip planners & Guides	14
Workout & Routines	17
Photography & Drawing	15
Total general	**250**

Then, by performing a Qualtrics survey in English and Spanish (Annex 5), the main objective was to quantify the score by which an app can be classified as hedonic or utilitarian. First of all, the survey begin with an introduction and a brief description about the objective of the survey, then it presents three filter questions regarding the minimum age to participate in the survey (16 years) and the apps usage & download pattern for each respondent. Following this, 6 out of 12 of the subcategories were assigned randomly to each respondent to be classified in terms of hedonic content in a scale from 1 to 6 (1=not hedonic at all, 6=extremely hedonic) and then each respondent was asked to classified the remaining categories in terms of the utilitarian content in a scale from 1 to 6 (1=not utilitarian at all, 6=extremely utilitarian). Finally, demographics data were collected in terms of gender, age, occupation and country of residence. In total, 360 surveys were collected from November 22th to 28th through Facebook.

3.4. Data preparation and analysis

3.4.1. Secondary data

The data cleaning was performed. In this regard, the data preparation was focused on solving three main issues: First of all the missing values, secondly the correction of the variables that do not follow a normal distribution and finally the exclusion of extreme observations. In this regard, Size was the only variable that had to be treated to complete the missing values (58 missing values of this variable were corrected in SPSS replacing them using the series mean method). Then, by analysing the frequencies of the variables, it was discovered that some variables did not follow a normal distribution (Annex 8) -Sales (DV), Total OCR (IV), Average rating (IV), Price (CV), Size (CV), Days the app has been retailed (CV), AND Creator's Popularity (CV)-, so they were linearized through transformations (natural logarithm/ exponential) or transformed into dummy variables. Finally, two observations (App Code 177) were excluded due to their extreme values in the variable Price that bias the normal distribution of the transformed variable LogPrice.

Hedonic score and source were included as interaction terms since they were supposed to have a moderation effect on the independent variables. On the one hand, it was expected that OCR have higher impact for utilitarian apps. On the other hand, due to the presence of two different platforms in the study, it was expected that the effect of OCR could vary according to the source.

Table 3.4 summarizes the variables considered in the analysis along with their main descriptive statistics.

Table 3.4: Descriptive statistics of variables taken into consideration in the regression analyses.

TYPE	VARIABLE	MIN	MAX	MEAN	STD DEV
Dependent	Log(Inferred Sales)[a]	1.83	4.52	2.7447	0.5172
Independent	Exp(Average rating)[b]	2.72	148.41	65.0778	30.4247
	Log(Total OCR Volume)[a]	0	6.05	2.3501	1.1766
Interaction terms	Hedonic score	-2.09	1.88	0.0783	1.1609
	Source	Amazon =1 ; Google Play =0			
Control	Rated	Guidance suggested =1; Other =0			
		Mature=1; Other=0			
	Log (Price in USD)[a]	0	1.18	0.4202	0.2795
	Log (Size in MB)[a]	-1.47	3.38	1.2293	0.7312
	# of days the app has been retailed (Days.year)[c]	Less than a year retailed =1 Other=0			
	Creator popularity [c]	Creator has more than 1 app in the best seller rankings=1 Other = 0			

N= 498

[a] Variable normalized through a natural logarithm transformation.

[b] Variable normalized through an exponential transformation.

[c] Dummy variable created to normalize the original function.

Following this process, the final dataset was analyzed with a linear OLS regression to assess the impact of online ratings (Average rating and volume) on apps' demand.

3.4.2. Primary data

Only 2,78% of the respondents were excluded from the subcategories survey analysis (10 respondents in total: 7 respondents were 16 or less, 1 respondent referred she/he has never used an app and 2 respondents said that they have never downloaded an app). Most of the users (86%) said that they use mobile apps every day, however the pattern of the download frequency is less homogeneous: 25% download apps once a month, 24% less than one a month and 20% 2 or 3 times a month (See Annex 7 for other survey's descriptive statistics). For the rest of the respondents, the apps were rated in terms of hedonic and utilitarian consumptions. However, as was done in previous studies, the difference between the average scores of the two scales was calculated to discover the total hedonism rating for each subcategory depicted in table 3.5 (Okada, 2005). So, the more positive is the hedonism rating, the more hedonic is the category while, on the contrary, the more negative score is related with utilitarian apps. Finally, an hedonicity effect was attributed to each app according to the subcategory it belonged in the data set with the secondary data.

Table 3.5: Hedonism score obtained from the survey (n=360)

	HEDONIC		UTILITARIAN		
SUBCATEGORY	**Number of respondents**	**Hedonic Mean ± Std dev**	**Number of respondents**	**Utilitarian Mean ± Std dev**	**Hedonism rating for subcategory**
Action & Adventure Games	175	4.08 ± 1.83	150	2.2 ± 1.57	1.88
Diet & Carb-control	150	3.31 ± 1.75	175	3.52 ± 1.56	-0.21
Educational & Brain Games	158	3.5 ± 1.84	167	3.32 ± 1.51	0.18
Maps & GPS	149	2.95 ± 1.7	178	5.04 ± 1.31	-2.09
Measurement tools	177	2.41 ± 1.54	147	4.13 ± 1.68	-1.72
Media & Video	195	3.41 ± 1.64	132	3.33 ± 1.58	0.08
Photography & Drawing	168	3.79 ± 1.62	156	3.37 ± 1.5	0.42
Relaxation & Better Sleep	148	3.41 ± 1.71	174	3.01 ± 1.58	0.4
Simulation & Pretend Games	169	3.92 ± 1.83	155	2.08 ± 1.38	1.84
Transport Tracking	158	2.85 ± 1.77	163	4.6 ± 1.5	-1.75
Trip planners & Guides	157	3.85 ± 1.66	168	4.26 ± 1.46	-0.41
Workout & Routines	164	3.98 ± 1.57	161	4.26 ± 1.39	-0.28

As a way to test further the hedonic degree and best describe the result of this interaction, two additional regressions were tested. To do so, dummy variables were used as a way to classify the apps in five categories: Strongly utilitarian (less than -1.71 original score), Utilitarian (between -1.71 and -0.20), Neutral (between -0.19 and 0.19), Hedonic (between 0.20 and 0.45) and Strongly hedonic (higher than 0.45). The table 3.6 describes the number of cases in each category:

Table 2: Count of cases in hedonic dummies classification (n=498)

Subcategory_Classification				
Classification	**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Strongly Utilitarian	90	18.1	18.1	18.1
Utilitarian	76	15.3	15.3	33.3
Neutral	172	34.5	34.5	67.9
Hedonic	64	12.9	12.9	80.7
Strongly Hedonic	96	19.3	19.3	100.0
Total	498	100.0	100.0	

3.5. Bivariate Pearson Correlations amongst variables

Bivariate Pearson Correlation table (Annex 9) was analyzed in order to determine the best combination of regression models taking into account the multicollinearity issue (assuming a confidence level of 95%).

The correlation analysis shows that LogTotalOCR and ExpAverageRating are the variables with highest significant correlation with sales (0.402 and 0.164 respectively). Furthermore, it was determined that CreatorPopularity, Mature and All ages have not significant impact on sales and subsequently were excluded for the rest of the analysis. In general, the table shows that LogTotalOCR and ExpAverageRating are highly uncorrelated with variables such as LogPrice and Guidance Suggested. So, based on that, 6 regressions were run systematically to determine the causal relation between sales (DV), average rating (IV) and volume of ratings (IV). The collinearity analysis was made in each one of the models (Annex 10)

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Linear Regressions with inferred sales as dependent variable

Four regressions were run with the inferred sales as the DV. As Table 4.1 shows, all the models are significant at a confidence level of 95%. According to the adjusted R^2, the models represents from 16% to 29,3% of the variance in the regression's variables. The low value of the adjusted R^2 is explained by the fact that the analysis does not take into consideration important variables that influence sales such as information about consumer tastes and other companies' variables like advertisement.

As is shown in table 4.2, there is no multicollinearity in the models since the tolerance in all the cases is higher than 0.4, the VIF is less than 5 and the condition indexes shown in Annex are less than 15. In this sense, it is important to mention that the interaction terms were analysed in two different models (3 and 4) due to the multicollinearity issues (model 3 studies the impact of the interaction terms on the volume while model 4 explore the moderation effects on average rating). Nevertheless, as Bivariate Pearson Correlation analysis showed that Source and Subcategory do not have significant impact on sales, they were not included in the models to avoid multicollinearity.

Table 4.1: Regression model quality (Dependent variable LogSales) (n=498)

Model	Independent and Control Variables	Interaction terms	R	R square	Adjusted R^2	df	F-value	Sig.
1	LogTotalOCR ExpAverageRating	N/A	0.404	0.163	0.160	2	48.206	0.000
2	LogTotalOCR ExpAverageRating LogPrice (CV) Guidance (CV)	N/A	0.445	0.198	0.192	4	30.441	0.000
3	LogTotalOCR ExpAverageRating LogPrice (CV) Guidance (CV) Days.Years(CV)	Source & Subcategory score (with LogTotalOCR)	0.544	0.296	0.286	7	29.473	0.000
4	LogTotalOCR ExpAverageRating LogPrice (CV) Guidance (CV) Days.Years(CV)	Source & Subcategory score (with ExpAverageRating)	0.551	0.303	0.293	7	30.490	0.000

Table 4.2: Coefficients of regression models (Dependent variable LogSales) (n=498)

MODEL	Variable	Unstandardized Coefficients		Standardized Coefficients	Beta*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.297	.058		893.963	.000		
	LogTotalOCR	.171	.019	.388	18.621	.000	.901	1.109
	ExpAverageRating	.001	.001	.042	0.072	.328	.901	1.109
2	(Constant)	2.165	.065		771.197	.000		
	LogTotalOCR	.166	.019	.379	18.113	.000	.895	1.117
	ExpAverageRating	.001	.001	.051	0.087	.230	.898	1.113
	LogPrice	.229	.075	.124	25.710	.002	.986	1.014
	Guidance Suggested	.165	.051	.132	17.923	.001	.990	1.010
3	(Constant)	1.967	.067		614.634	.000		
	LogTotalOCR	.206	.020	.468	22.841	.000	.701	1.427
	ExpAverageRating	.000	.001	.028	0.047	.494	.875	1.143
	LogTotalOCR_Subcategory	-.046	.007	-.294	-4.512	.000	.758	1.320
	LogTotalOCR_Source	.125	.022	.272	13.259	.000	.643	1.554
	LogPrice	.132	.072	.071	14.144	.066	.955	1.047
	Days.Years	.179	.050	.172	19.570	.000	.628	1.593
	Guidance Suggested	.185	.050	.148	20.281	.000	.912	1.096
4	(Constant)	1.990	.064		631.869	.000		
	LogTotalOCR	.271	.022	.618	31.190	.000	.578	1.731
	ExpAverageRating	.003	.001	.189	0.322	.449	.560	1.786
	ExpAverageRating_Source	.006	.001	.402	0.558	.000	.449	2.228
	ExpAverageRating_Subcategory	-.002	.000	-.279	-0.179	.000	.757	1.321
	LogPrice	.106	.073	.057	11.165	.146	.919	1.088
	Days.Years	.223	.050	.215	25.003	.000	.620	1.613
	Guidance Suggested	.102	.049	.082	10.766	.039	.911	1.097

The most important results show that the average rating (ExpAverageRating) is not significant in the four models while volume (LogTotalOCR) is significant in all the cases. Furthermore, models 3 and 4 show that hedonicity and source have moderation effect on volume and average rating.

The fourth model's coefficients show that average rating impact on sales is moderated by the extent to which an app is considered utilitarian or hedonic (ExpAverageRating_Subcategory: Sig0.000< P.value 0.05, B= -0.002). It means that the more hedonic the app the fewer will be the impact of the average rating on sales. Furthermore, the platform in which the app is retailed moderate the average ratings impact on sales (Sig0.000< P.value 0.05, B= 0.006), so the average rating has higher positive impact on Amazon. By analyzing the significance level and the beta in this model, it can be concluded that the volume of ratings has statistically significant main effect on sales (Sig0.000< P.value 0.05). More specifically, taking into account that the variable was log-transformed, the parameter beta has to be converted according to the expression B*= (EXP(beta)-1)*100 to estimate the impact of the variable. In that sense, the parameter beta 0.271 of LogTotalOCR suggests that a one additional rating in a page increase in 31.19% the sales level of the app (B*=31.19).

On the other hand, the third model shows that the impact of volume of ratings is as well moderated by the platform of origin and the extent to which an app is considered hedonic or utilitarian. In the first place, the impact of volume of ratings on sales is moderated by the hedonism degree (LogTotalOCR_Subcategory: Sig0.000< P.value 0.05, B= -0.46), it means that the impact of volume of ratings on sales is less as the product is considered as more hedonic since the interaction variable is significant and negative. Additionally, the impact of volume of ratings on sales is moderated by the platform (LogTotalOCR_Source: Sig0.000< P.value 0.05, B=0.125), it seems that the impact of volume is higher in Amazon App Store.

Furthermore, both models show that the control variable Days.years depicts a positive impact on sales (Model 3: Sig0.000< P.value 0.05, B=0.179; Model 4: Sig0.000< P.value 0.05, B=0.223). It means that the apps that have been released less than one year ago sell more than older apps. Moreover, the analysis leads us to find that Guidance Suggested apps have positive impact on sales.

4.2. Hedonic degree: Further analysis

Two additional regressions were run to best describe the result of the interaction between hedonicity and OCR using dummy variables to classify the apps from strongly utilitarian to strongly hedonic. The quality of those regressions that included those dummies, with the inferred sales as the DV is assessed in table 4.3.

Table 4.3: Regression model quality analysis including Hedonic classification dummies (Dependent variable LogSales) (n=498)

Model	Independent and Control Variables	Interaction terms	R	R square	Adjusted R^2	df	F-value	Sig.
5	LogTotalOCR ExpAverageRating LogPrice (CV) Guidance (CV) Days.Years(CV)	Subcategory dummies (with ExpAverageRating)	0.481	0.231	0.217	9	16.279	0.000
6	LogTotalOCR ExpAverageRating LogPrice (CV) Guidance (CV) Days.Years(CV)	Subcategory dummies (with LogTotalOCR)	0.500	0.250	0.236	9	18.034	0.000

Table 4.4: Coefficients of regression models with hedonic dummy variables (Dependent variable LogSales) (n=498)

MODEL	Variable	Unstandardized Coefficients		Standardized Coefficients	Beta*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
5	(Constant)	2.141	.065		750.725	.000		
	LogTotalOCR	.199	.021	.452	21.991	.000	.713	1.403
	ExpAverageRating	7.206E-05	.001	.004	0.007	.929	.696	1.436
	ExpAverageRating_StronglyUtilitarian	.003	.001	.145	0.272	.002	.722	1.386
	ExpAverageRating_Utilitarian	.001	.001	.057	0.107	.209	.771	1.297
	ExpAverageRating_Hedonic	-2.573E-05	.001	-.001	-0.003	.978	.827	1.209
	ExpAverageRating_StronglyHedonic	-.002	.001	-.106	-0.199	.033	.645	1.550
	Days.Years	.022	.044	.021	2.241	.612	.887	1.128
	LogPrice	.146	.077	.079	15.755	.057	.915	1.093
	Guidance Suggested	.190	.052	.152	20.967	.000	.900	1.111
6	(Constant)	2.121	.065		734.193	.000		
	LogTotalOCR	.194	.024	.441	21.383	.000	.528	1.894
	ExpAverageRating	.000	.001	.024	0.041	.568	.867	1.153
	LogTotalOCR_StronglyUtilitarian	.095	.026	.162	9.939	.000	.758	1.319
	LogTotalOCR_Utilitarian	.040	.027	.063	4.060	.143	.826	1.210
	LogTotalOCR_Hedonic	.023	.027	.038	2.360	.381	.819	1.222
	LogTotalOCR_StronglyHedonic	-.053	.021	-.141	-5.156	.012	.493	2.027
	Days.Years	.017	.043	.016	1.689	.698	.889	1.124
	LogPrice	.150	.075	.081	16.221	.047	.928	1.078
	Guidance Suggested	.228	.052	.182	25.587	.000	.892	1.122

According to table 4.4, both regressions describe that the interaction of the hedonic degree and the independent variables is significant only for the extreme cases (strongly hedonic and strongly utilitarian) and the effect on sales of both independent variables is smaller as the app is more hedonic.

In the case of the Average rating (model 5), ExpAverageRating_StronglyUtilitarian interaction is significant, it means that the strongly utilitarian apps have a positive moderator effect on the Average rating (Sig0.002< P.value 0.05, B= 0.003) while ExpAverageRating_StronglyHedonic interaction is significant as well but on the contrary it

has a negative moderation effect on the Average rating, it means that the impact of average rating is less for strongly hedonic apps (Sig0.033< P.value 0.05, B= -0.002).
On the other hand, studying the volume (model 6), LogTotalOCR_StronglyUtilitarian interaction is significant, thus the strongly utilitarian apps have a positive moderator effect on the volume of ratings (Sig0.000< P.value 0.05, B= 0.095) while LogTotalOCR_StronglyHedonic interaction is also significant so strongly hedonic apps has a negative moderation effect on the volume of ratings (Sig0.012< P.value 0.05, B= -0.053).

4.3. Discussion

In general, the results about the impact of average rating and volume were interesting. The six regressions under study, would give evidence to reject RH1 since the average rating has not significant impact on apps' sales in the models. Those outcomes differ from extant studies which have proposed that the ratings' valence matter more than volume (Chevalier & Mayzlin, 2006; Chintagunta, 2010; Sun, 2012, Ye et al., 2009; Clemons et al., 2006). In general, results showed that the relation between volume and sales is more robust than the relation between average rating's and sales.
However, by including hedonicity as interaction terms, the average rating's impact on sales became significant. This is particularly important, since it indicated that the nature of the app has moderating effect on average ratings' impact on sales.
As results shown, the more utilitarian the app, the greater will be the impact of average ratings on sales. This result was expected as the average ratings can be seen as a rational motivation to buy an app, and the purchase of utilitarian products is determined by this type of motivation (Sloot, Verhoef, & Franses, 2005). This outcome would support the acceptance of RH3 since hedonicity moderates the effect of average rating on mobile app sales.
On the other hand, the volume of ratings has positive impact on sales in all the cases. According to the B* interpretation in the models, one additional rating could represent from 20% to 30% more sales. These results are consistent with prior studies that refer that ratings' volume, rather than the valence, has explanatory power on sales (Ho-Dac, Carson, & Moore, 2013). This evidence would support the acceptance of RH2 since volume of ratings probed to have a positive impact on mobile app sales.
Additionally, according to the models' analysis, there is evidence to support the acceptance of RH4 because the effect of volume of ratings on mobile app sales is moderated by hedonicity. Again, as the volume of ratings can be seen as a rational motivation, it makes sense that the more

utilitarian the app, the greater will be the impact of volume on sales (Sloot, Verhoef, & Franses, 2005).

In general, the key finding reveals that the volume is what matter the most on sales performance for apps. However, the hedonic/utilitarian concept is a moderator for the average rating and the volume, thus the more hedonic (utilitarian) the app the fewer (greater) will be the impact of the average rating and volume on sales. This is particularly accurate for the extreme degrees, the impact of the average and volume is higher for the strongly utilitarian apps, while is lower for strongly hedonic apps. Additionally, other findings depict the apps for young people (Guidance suggested) are the ones that sell the most. Moreover, the apps with less than a year of released time have also positive correlation with sales, it means that the newest the app the most likely to have higher sales levels. Finally, regarding the two different platforms, the results showed that the effect of volume and average rating is slightly higher in Amazon App Store compared with Google Play.

CHAPTER 5: CONCLUSIONS AND IMPLICATIONS

WOM is an important variable in purchase decisions since it affects consumers' attitudes and perceptions (Brown & Reingen, 1987). Recently, due to the technological progress, consumers con share and consult information online, giving rise to the eWOM. In this regard, the importance of the online customer reviews and ratings have grown as a way to track and measure the customers' online behavior. It is therefore of great managerial interest to be able to analyze how OCRev and OCR affect the consumer decision making process influencing the products' demand. Generally speaking, however, there is still no unanimity about the true effect of OCRev/OCR on sales (Floyd, Freling, Alhoqail, Cho, & Freling, 2014); some studies show that volume has explanatory power on sales (Ho-Dac, Carson, & Moore, 2013; Liu, 2006) while others suggest that valence matter more than volume (Chevalier & Mayzlin, 2006; Chintagunta, 2010; Sun, 2012). Trying to solve this unanimity, this dissertation aims to study mainly the impact of OCR valence and OCR volume on product sales.

Besides, as product characteristics were not extensively studied in previous studies, hedonicity was incorporated in the analysis. It is referred in extant literature as an key element of online shopping attitudes (Childers, Carr, Peck, & Carson, 2002; Jones, Reynolds, & Arnold, 2006). In that sense, this dissertation aims to test as well if hedonic character of products moderates the impact of OCR on sales.

After doing the regressions analysis, results have showed that the volume has positive and significant impact on sales performance for apps. Moreover, as the hedonicity has moderation effect on valence and volume: the more hedonic (utilitarian) the app the fewer (greater) will be the impact of the average rating and volume on sales. In general, three out of four research hypotheses were confirmed:

- χ **RH1**: Average rating has a positive impact on mobile app sales.
- ✓ **RH2**: Volume of ratings has a positive impact on mobile app sales.
- ✓ **RH3**: Hedonicity moderates the effect of average rating on mobile app sales.
- ✓ **RH4**: Hedonicity moderates the effect of volume of ratings on mobile app sales.

In this regard, in order to foster its app's sales it is clear that firms should launch campaigns to foster the users' participation in eWOM conversations. Specifically, firms can nurture the customers' participation in the app stores, for instance, by proactively asking users that have not yet provided a rating score; additionally firms can offer especial incentives or benefits for users who have already participated. According to the dissertation results, the main objective of this kind of initiatives would be obtaining the highest number of ratings because it would lead more sales (no matter the valence of the ratings).

However, one of the most important contributions of this dissertation is related with the hedonicity moderation effect that had not been studies previously in the field of OCR. The results showed that the impact of OCR volume and OCR valence on sales is moderated by the hedonicity. In general, the effect of volume and valence would be more important for utilitarian apps. It has been shown that volume and valence have greater positive effect for utilitarian apps than for hedonic ones. So, in the case of utilitarian apps, the strategic importance of increase the volume and the average rating is higher compared with hedonic apps. This confirms that OCR can be seen as a rational motivation for users.

5.1.Limitations and future research

One of the main limitations of this dissertation is about information about the real users, in other words, this study does not content any information about the consumer in terms of tastes or preferences and it relies mainly on public information about the apps. Furthermore, it also excludes other important companies´ variables such as apps advertisement which are not included in the scope of the thesis.

Moreover, the statistical analysis was focused mainly in information taken from two app stores, which is not the complete universe of existent platforms and exclude the iOS operating systems apps. Accordingly, the inferred sales were based on the rank position which was available in the top 100 bestsellers from Amazon and the top 500 for Google Play Store. Hence, most of the information treated in the statistical analysis depended on the availability of the information in the public platforms. Additionally, the analysis excluded all the free apps which compose the biggest population of apps.

Furthermore, the econometrical analysis used to calculate inferred sales from the platforms was far beyond the scope of this thesis, so the parameters used in the calculation were taken from the extant literature on the topic. On the other hand, the primary information collected in the survey where asked to friends and colleagues due to time and budget constraints.

For future research it would be interesting to analyze the benefits of eWOM in terms of firms' cost reduction. For instance by quantifying the firms' savings on customer service due to online communities, where users can post doubts and problems to be helped by other people instead of calling the company. Moreover, further analysis of the impact of OCRev on mobile app sales can incorporate different variables such as written review, information of consumers' tastes, information about free apps, other operating systems' platforms and include variance as an additional independent variable. However, in general the topic of OCR can explore different product categories and additional product variables (not only hedonicity).

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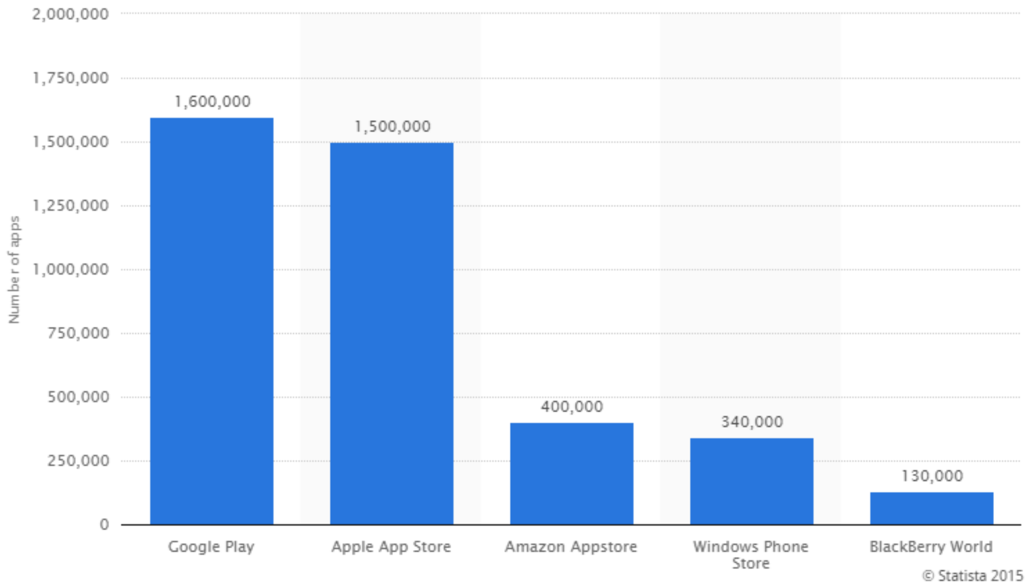
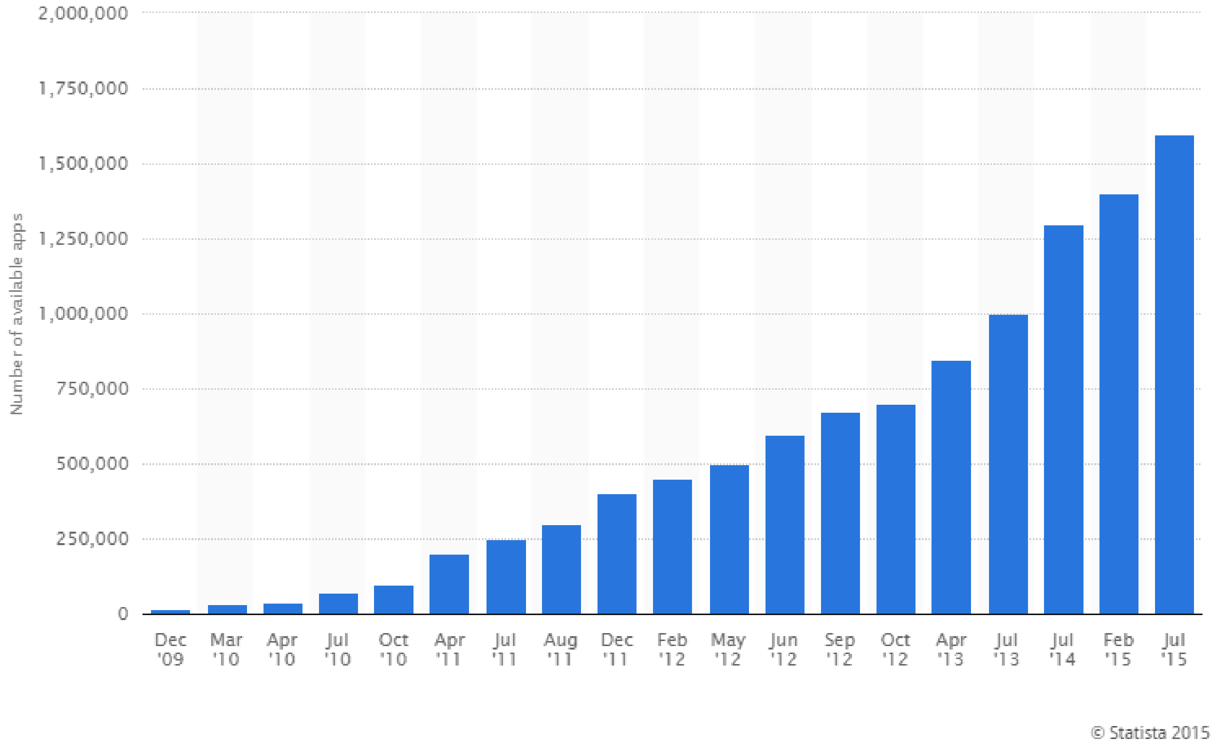
ANNEXES

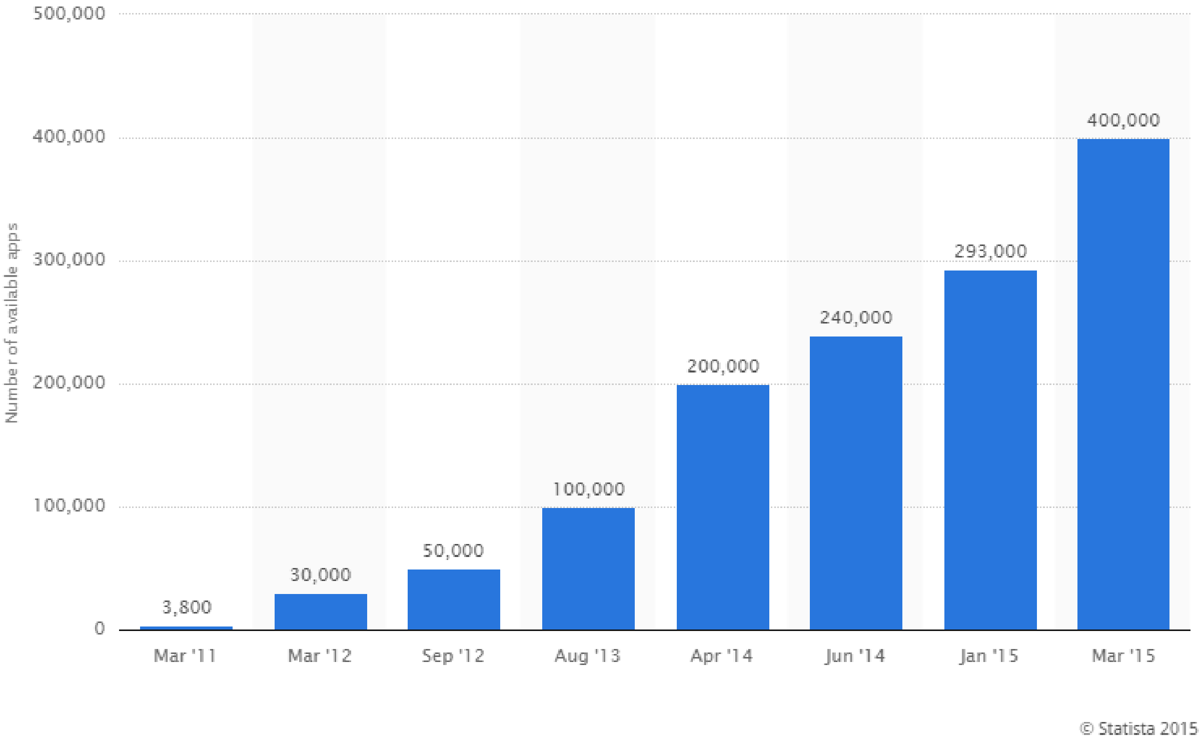
Annex 1: Most important app stores by number of apps, July 2015 (Statista, 2015a)



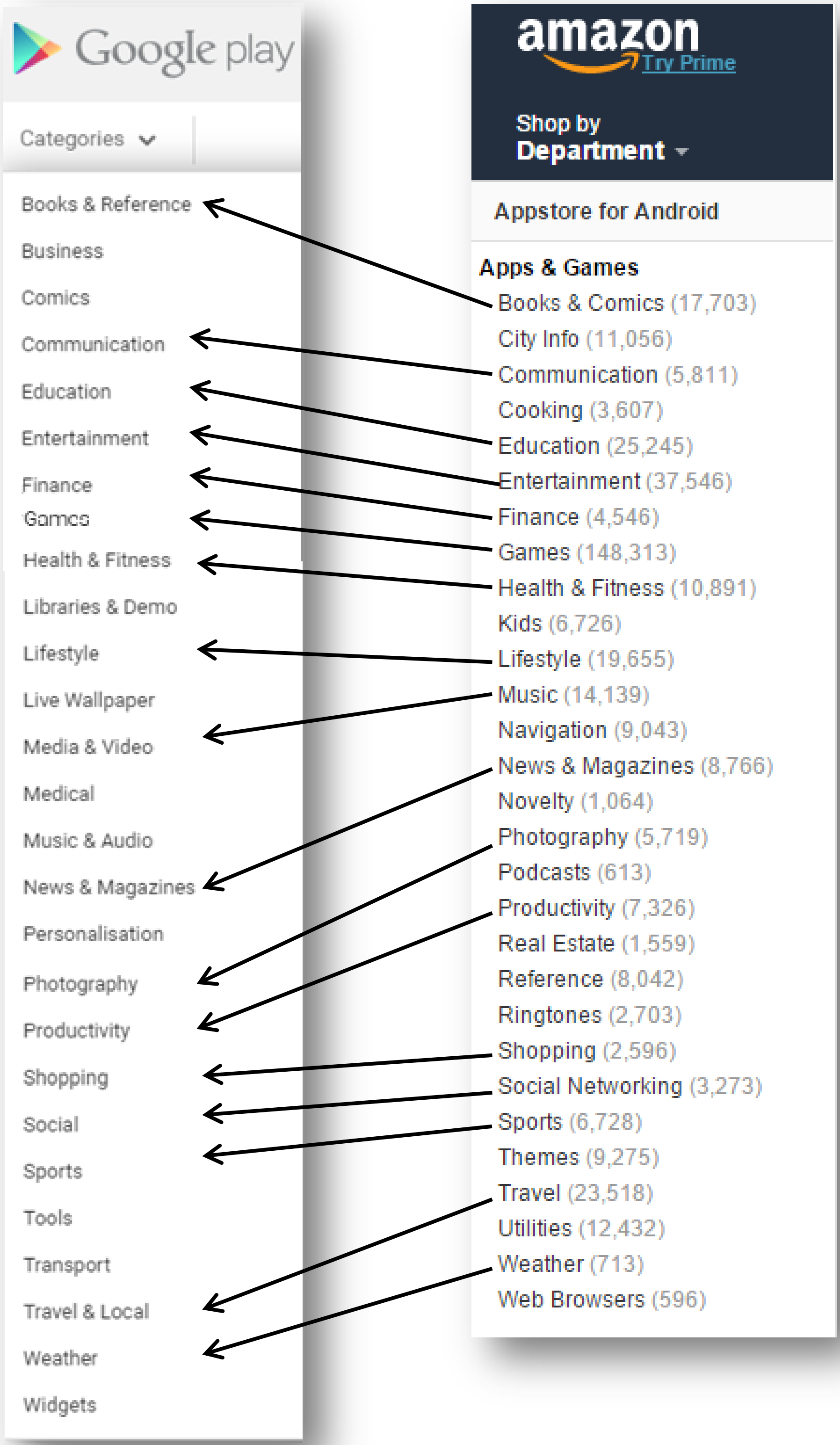
Annex 2: Evolution of total number of available apps in Google Play, July 2015 (Statista, 2015b)



Annex 3: Figure 4: Evolution of total number of apps in Amazon App Store, May 2015 (Statista, 2015c)



Annex 4: Classification of mobile app categories in the Google Play and Amazon App stores



Annex 5: Online questionnaire about consumers' hedonic vs utilitarian classifications of subcategories of mobile apps (Available also in Spanish)

Select in the upper right corner the language of your preference (English / Spanish)

This survey aims to know your opinion about the mobile apps consumption.

The survey takes no more than 8 or 9 minutes and your answers are completely confidential. Please answer as honestly as possible.

Click the >> button in the lower right corner to continue.

Thank you very much for your participation!

Are you over 16 years old?

- ❍ Yes (1)
- ❍ No (2)

If No Is selected, Go to Survey end

How often do you use mobile apps?

- ❍ Every day (1)
- ❍ 2 - 3 times a week (2)
- ❍ Once a week (3)
- ❍ 2 - 3 times a month (4)
- ❍ Once a month (5)
- ❍ Less than once a month (6)
- ❍ I have never used a mobile app (7)

If I have never... If No Is selected, Go to Gender

How often do you download mobile apps?

- ❍ Every day (1)
- ❍ 2 - 3 times a week (2)
- ❍ Once a week (3)
- ❍ 2 - 3 times a month (4)
- ❍ Once a month (5)
- ❍ Less than once a month (6)
- ❍ I have never downloaded a mobile app (7)

If I have never... If No Is selected, Go to Gender

The motivations of consumer purchasing can be hedonic, that is, because the products are related to experiences of pleasure, fantasy, fun, entertainment and sensory stimulation.

For example, someone can download a shopping app because she/he enjoys this kind of activity and she/he amuses by buying new things.

Therefore, the value of a hedonic motivation lies in the psychological, emotional or emotional gratification that produces purchase.

According to your opinion, rank the following categories of mobile applications on a scale of 1-6, where 1 means "Not hedonic at all" and 6 "Extremely hedonic".

	Not hedonic at all (1)	(2)	(3)	(4)	(5)	Extremely hedonic (6)
Action & Adventure games. For example: Need for Speed Most Wanted (1)	❍	❍	❍	❍	❍	❍
Diet & Carb-control apps. For example: My Diet Coach Pro (2)	❍	❍	❍	❍	❍	❍
Educational & Brain games. For example: Math Bingo (3)	❍	❍	❍	❍	❍	❍
Maps & GPS. For example: US Topo Maps (4)	❍	❍	❍	❍	❍	❍
Measurement Tools. For instance:	❍	❍	❍	❍	❍	❍

Speed Watcher (5)						
Media & Video. For instance: VideoShow - Video Editor (6)	❍	❍	❍	❍	❍	❍
Photography & Drawing. For instance: PhoTo Lab - Photo Editor (7)	❍	❍	❍	❍	❍	❍
Relaxation & Better sleep. For instance: iSleep: Easy sleep meditations (8)	❍	❍	❍	❍	❍	❍
Simulation & Pretend games. For instance: Farming Simulator 16 (9)	❍	❍	❍	❍	❍	❍
Transport tracking. For example: Plane Finder (10)	❍	❍	❍	❍	❍	❍
Trip planners & guides. For example: TripIt Travel Organizer (11)	❍	❍	❍	❍	❍	❍
Workout routines. For example: Daily workouts (12)	❍	❍	❍	❍	❍	❍

Only asked about 6 subcategories (Randomly assigned)

The motivations of consumer purchasing can be utilitarian, so the value of the product lies in its functionality and performance.

For example, someone can download a shopping app because it is a more practical and faster way to buy new things (compared with going directly to a store, for example).

Therefore, the value of a utilitarian motivation lies in the practical results produced by the purchase of the product (for example: satisfaction of a basic need or help in solving a problem and/or performing a particular task).

According to your opinion, rank the following categories of mobile applications on a scale of 1-6, where 1 means "Not utilitarian at all" and 6 "Extremely utilitarian".

	Not utilitarian at all (1)	(2)	(3)	(4)	(5)	Extremely utilitarian (6)

Only asked about 6 subcategories (The ones that were not taken into account in the previous question)

Please indicate your gender

- ❍ Male (1)
- ❍ Female (2)

Country of residence

- ❍ Colombia (1)
- ❍ Portugal (2)
- ❍ Venezuela (3)
- ❍ Peru (4)
- ❍ Brasil (5)
- ❍ Other (6) ____________________

Indicate your age segment

- ❍ 18 years or less (1)
- ❍ Between 19 and 25 years (2)
- ❍ Between 26 and 30 years (3)
- ❍ Between 31 and 35 years (4)
- ❍ Between 36 and 40 years (5)
- ❍ Between 41 and 45 years (6)
- ❍ Between 46 and 50 years (7)
- ❍ More than 50 years (8)

Which is your current occupation?

- ❍ Student (1)
- ❍ Self-employed (2)
- ❍ Housewife (3)
- ❍ Employed (4)
- ❍ Retired (5)
- ❍ Other (6) ____________________

Annex 6: Inferred sales: Pareto distributions' parameters used in extant literature

Pareto distribution formula used to infer sales in extant literature:

$$Sales = b * rank^{a}$$

Parameters:

a = Shape

b = Scale

Source	Product	a	b
Chevalier and Goolsbee (2003)	Books	1.199	
Chevalier and Goolsbee (2003)	Books	1.05	
Chevalier and Goolsbee (2003) Evidence from various experiments suggesting a value between 0.9 and 1.3)	Books	1.2	
Brynjolfsson et al. (2003)	Books	0.871	10,526
Ghose et al. (2006)	Books	0.952	8,532
Chevalier and Mayzlin (2006)	Books	0.78	9,610
Brynjolfsson et al. (2010)		0.613	8,046
Ghose (2014)		1.09	
Garg (2012)	iPad	0.903	13,516
Garg (2012)	iPhone	0.944	52,958
Garg (2012)	Google Play	0.985	

Data used		
Google Play	**0.985**	**33,237**
Amazon	**0.962**	**17,198**

Annex 7: Results of online questionnaire about consumers' hedonic vs utilitarian classifications of subcategories of mobile apps (n=352)

	Are you over 16 years old?	Absolut	%
1	Yes	353	98%
2	No	7	2%
	Total	**360**	**100%**

	How often do you use mobile apps?	Absolut	%
1	Every day (1)	304	86%
2	2 - 3 times a week (2)	22	6%
3	Once a week (3)	8	2%
4	2 - 3 times a month (4)	9	3%
5	Once a month (5)	3	1%
6	Less than once a month (6)	6	2%
7	I have never used a mobile app (7)	1	0%
	Total	**353**	**100%**

	How often do you download mobile apps?	Number	%
1	Every day (1)	31	9%
2	2 - 3 times a week (2)	39	11%
3	Once a week (3)	39	11%
4	2 - 3 times a month (4)	71	20%
5	Once a month (5)	86	25%
6	Less than once a month (6)	83	24%
7	I have never downloaded a mobile app (7)	2	1%
	Total	**351**	**100%**

		Not hedonic at all (1)	-2	-3	-4	-5	Extremely Hedonic (6)	Number	Average
1	Action & Adventure Games	26	16	24	19	32	58	175	4.08
2	Diet & Carb-control	31	29	22	21	25	22	150	3.31
3	Educational & Brain Games	37	18	20	24	30	29	158	3.5
4	Maps & GPS	45	19	33	19	17	16	149	2.95
5	Measurement tools	65	50	22	13	18	9	177	2.41
6	Media & Video	35	27	39	36	34	24	195	3.41
7	Photography & Drawing	19	20	36	28	33	32	168	3.79
8	Relaxation & Better Sleep	28	19	34	22	21	24	148	3.41
9	Simulation & Pretend Games	24	22	25	23	22	53	169	3.92
10	Transport Tracking	56	21	25	17	24	15	158	2.85
11	Trip planners & Guides	19	20	24	27	37	30	157	3.85
12	Workout & Routines	16	19	23	26	54	26	164	3.98

	Action & Adventure Games	Diet & Carb-control	Educational & Brain Games	Maps & GPS	Measurement tools	Media & Video	Photography & Drawing	Relaxation & Better Sleep	Simulation & Pretend Games	Transport Tracking	Trip planners & Guides	Workout & Routines
Min	1	1	1	1	1	1	1	1	1	1	1	1
Max	6	6	6	6	6	6	6	6	6	6	6	6
Mean	4.08	3.31	3.5	2.95	2.41	3.41	3.79	3.41	3.92	2.85	3.85	3.98
Var	3.36	3.07	3.39	2.9	2.36	2.7	2.64	2.91	3.35	3.12	2.75	2.46
Std Dev	1.83	1.75	1.84	1.7	1.54	1.64	1.62	1.71	1.83	1.77	1.66	1.57
Total	175	150	158	149	177	195	168	148	169	158	157	164

		Not utilitarian at all (1)	-2	-3	-4	-5	Extremely utilitarian (6)	Number	Average
x1	Action & Adventure Games	74	31	15	11	9	10	150	2.2
x2	Diet & Carb-control	25	27	24	49	31	19	175	3.52
x3	Educational & Brain Games	20	39	30	39	23	16	167	3.32
x4	Maps & GPS	6	3	17	20	38	94	178	5.04
x5	Measurement tools	13	16	25	24	23	46	147	4.13
x6	Media & Video	23	21	25	25	28	10	132	3.33
x7	Photography & Drawing	20	28	37	30	27	14	156	3.37
x8	Relaxation & Better Sleep	34	42	41	19	21	17	174	3.01
x9	Simulation & Pretend Games	75	37	15	14	11	3	155	2.08
x10	Transport Tracking	11	8	14	28	44	58	163	4.6
x11	Trip planners & Guides	11	8	32	33	44	40	168	4.26
x12	Workout & Routines	7	12	26	38	43	35	161	4.26

	Action & Adventure Games	Diet & Carb-control	Educational & Brain Games	Maps & GPS	Measurement tools	Media & Video	Photography & Drawing	Relaxation & Better Sleep	Simulation & Pretend Games	Transport Tracking	Trip planners & Guides	Workout & Routines
Min	1	1	1	1	1	1	1	1	1	1	1	1
Max	6	6	6	6	6	6	6	6	6	6	6	6
Mean	2.2	3.52	3.32	5.04	4.13	3.33	3.37	3.01	2.08	4.6	4.26	4.26
Var	2.47	2.43	2.27	1.72	2.81	2.48	2.26	2.51	1.9	2.24	2.13	1.93
Std Dev	1.57	1.56	1.51	1.31	1.68	1.58	1.5	1.58	1.38	1.5	1.46	1.39
Total	150	175	167	178	147	132	156	174	155	163	168	161

	Please indicate your gender	Number	%
1	Male	158	49%
2	Female	163	51%
	Total	**321**	**100%**

	Country of residence	Number	%
1	Colombia	201	63%
2	Portugal	35	11%
3	Venezuela	10	3%
4	Peru	25	8%
5	Brazil	23	7%
6	Other	27	8%
	Total	**321**	**100%**

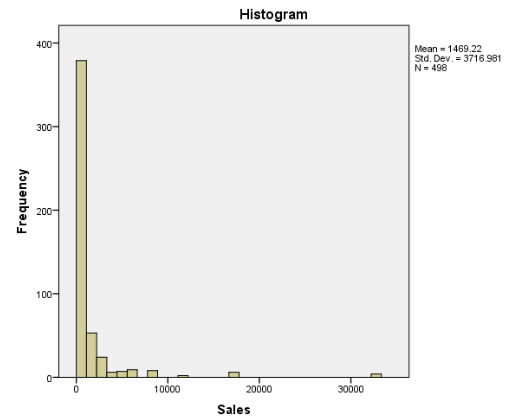
	Indicate your age segment	Number	%
1	18 years or less (1)	14	4%
2	Between 19 and 25 years (2)	197	61%
3	Between 26 and 30 years (3)	67	21%
4	Between 31 and 35 years (4)	15	5%
5	Between 36 and 40 years (5)	9	3%
6	Between 41 and 45 years (6)	5	2%
7	Between 46 and 50 years (7)	4	1%
8	More than 50 years (8)	10	3%
	Total	**321**	**100%**

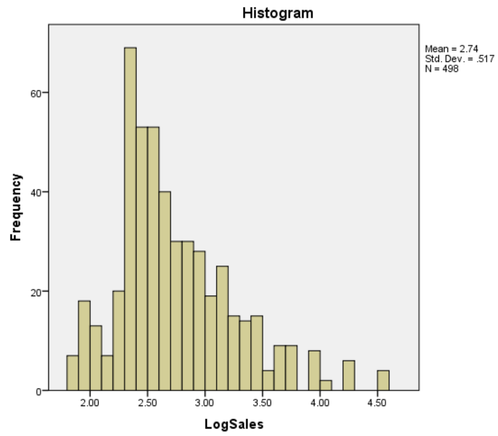
	Which is your current occupation?	Number	%
1	Student (1)	128	40%
2	Self-employed (2)	52	16%
3	Housewife (3)	8	2%
4	Employed (4)	124	39%
5	Retired (5)	4	1%
6	Other (6)	5	2%
	Total	**321**	**100%**

Annex 8: Analysis of normalized variables

Dependent variable:

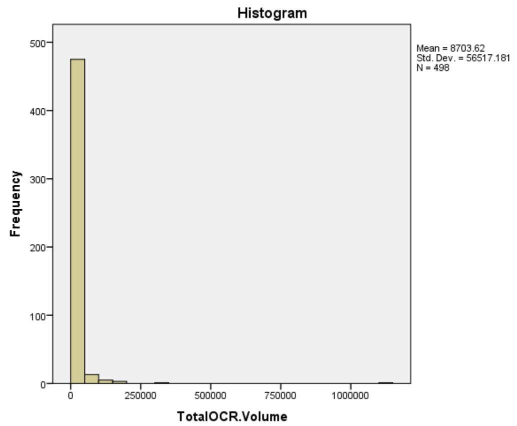
Inferred sales → Log Sales

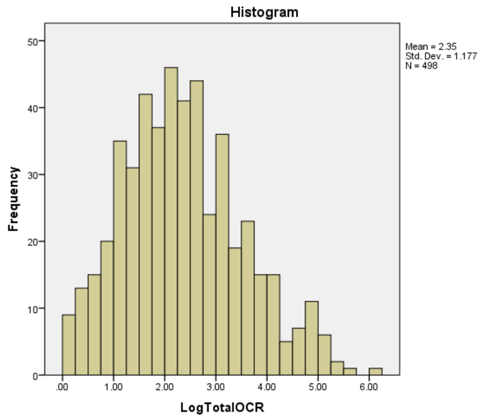




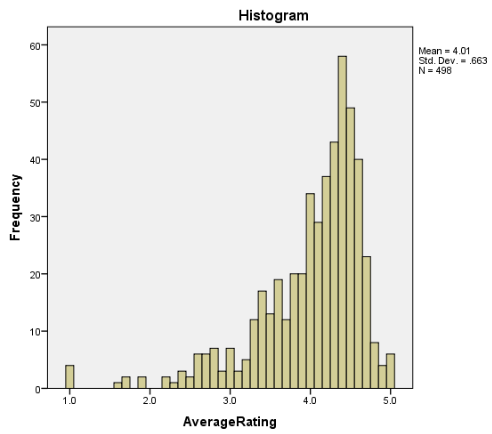
Independent Variables

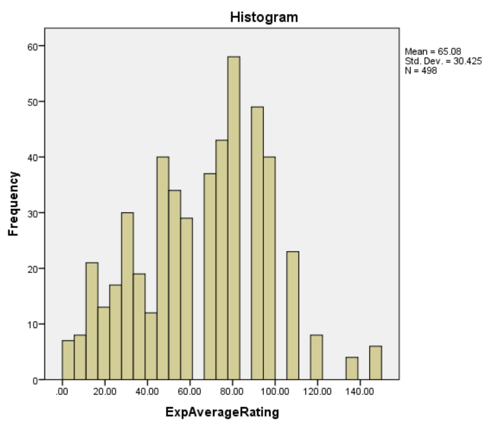
Total OCR → Log Total OCR





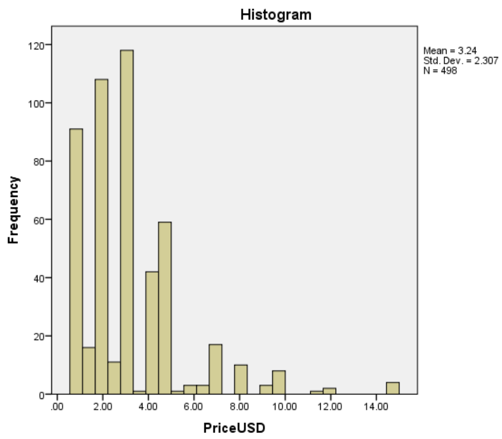
Average Ratings → Exp Average Ratings

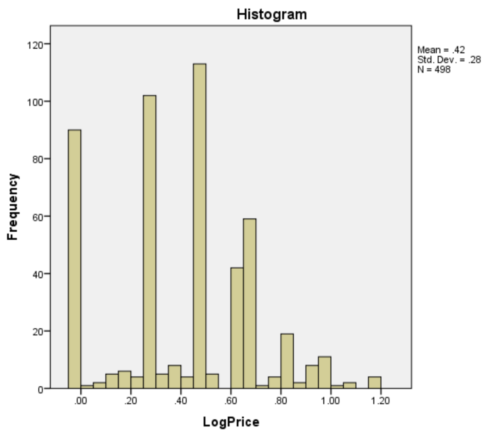




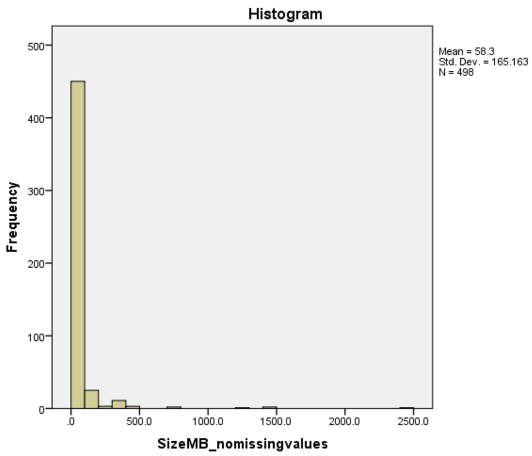
Control variables:

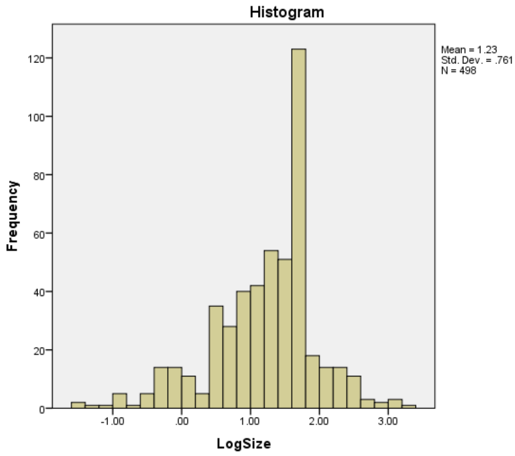
Price → Log Price





Size (without missing values) → Log Size





Annex 9: Bivariate Correlations of dependent, independent and control variables

Correlations

		LogSales	LogTotalOCR	ExpAverageRating	Source	SubcategorySurveydata	LogTotalOCR_Subcategory	LogTotalOCR_Source	ExpAverageRating_Source	ExpAverageRating_Subcategory	LogPrice	LogSize	Days.Years	Creator has more than 1 app in the bestsellers rank	Mature	Guidance Suggested	All ages
LogSales	Pearson Correlation	1	.402**	.164**	.024	-.056	-.036	.153**	.069	-.046	.168**	.135**	.120**	-.002	.018	.127**	-.047
	Sig. (2-tailed)		.000	.000	.592	.215	.425	.001	.123	.308	.000	.003	.007	.972	.690	.004	.294
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
LogTotalOCR	Pearson Correlation	.402**	1	.314**	-.444**	.317**	.392**	-.028	-.300**	.343**	.087	.353**	.265**	.093*	.155**	-.028	.003
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.536	.000	.000	.054	.000	.000	.037	.001	.534	.939
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
ExpAverageRating	Pearson Correlation	.164**	.314**	1	-.211**	-.022	.024	-.108*	.304**	.005	.022	.106*	.198**	.107*	-.065	-.064	.122**
	Sig. (2-tailed)	.000	.000		.000	.624	.586	.016	.000	.907	.617	.018	.000	.017	.149	.152	.006
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
Source	Pearson Correlation	.024	-.444**	-.211**	1	.000	-.006	.809**	.786**	.010	.011	-.095*	-.580**	-.039	.015	.257**	-.162**
	Sig. (2-tailed)	.592	.000	.000		1.000	.901	.000	.000	.827	.813	.034	.000	.390	.737	.000	.000
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
SubcategorySurveydata	Pearson Correlation	-.056	.317**	-.022	.000	1	.878**	.174**	.006	.904**	-.177**	.391**	.127**	.067	.211**	.067	-.119**
	Sig. (2-tailed)	.215	.000	.624	1.000		.000	.000	.895	.000	.000	.000	.005	.134	.000	.136	.008
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
LogTotalOCR_Subcategory	Pearson Correlation	-.036	.392**	.024	-.006	.878**	1	.141**	.019	.875**	-.100*	.335**	.088*	.096*	.261**	.185**	-.233**
	Sig. (2-tailed)	.425	.000	.586	.901	.000		.002	.671	.000	.026	.000	.049	.032	.000	.000	.000
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
LogTotalOCR_Source	Pearson Correlation	.153**	-.028	-.108*	.809**	.174**	.141**	1	.687**	.182**	.030	.080	-.544**	.026	.075	.205**	-.147**
	Sig. (2-tailed)	.001	.536	.016	.000	.000	.002		.000	.000	.502	.076	.000	.562	.093	.000	.001
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
ExpAverageRating_Source	Pearson Correlation	.069	-.300**	.304**	.786**	.006	.019	.687**	1	.014	-.018	-.035	-.474**	.058	-.027	.207**	-.121**
	Sig. (2-tailed)	.123	.000	.000	.000	.895	.671	.000		.749	.689	.432	.000	.195	.549	.000	.007
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
ExpAverageRating_Subcategory	Pearson Correlation	-.046	.343**	.005	.010	.904**	.875**	.182**	.014	1	-.195**	.326**	.099*	.051	.153**	.077	-.113*
	Sig. (2-tailed)	.308	.000	.907	.827	.000	.000	.000	.749		.000	.000	.028	.258	.001	.085	.012
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
LogPrice	Pearson Correlation	.168**	.087	.022	.011	-.177**	-.100*	.030	-.018	-.195**	1	.121**	.036	.046	.135**	.076	-.107*
	Sig. (2-tailed)	.000	.054	.617	.813	.000	.026	.502	.689	.000		.007	.424	.309	.003	.092	.017
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
LogSize	Pearson Correlation	.135**	.353**	.106*	-.095*	.391**	.335**	.080	-.035	.326**	.121**	1	.205**	.291**	.204**	-.013	.010
	Sig. (2-tailed)	.003	.000	.018	.034	.000	.000	.076	.432	.000	.007		.000	.000	.000	.766	.819
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
Days.Years	Pearson Correlation	.120**	.265**	.198**	-.580**	.127**	.088*	-.544**	-.474**	.099*	.036	.205**	1	.006	-.035	-.072	.143**
	Sig. (2-tailed)	.007	.000	.000	.000	.005	.049	.000	.000	.028	.424	.000		.902	.436	.111	.001
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
Creator has more than 1 app in the bestsellers rank	Pearson Correlation	-.002	.093*	.107*	-.039	.067	.096*	.026	.058	.051	.046	.291**	.006	1	.164**	.018	-.029
	Sig. (2-tailed)	.972	.037	.017	.390	.134	.032	.562	.195	.258	.309	.000	.902		.000	.684	.515
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
Mature	Pearson Correlation	.018	.155**	-.065	.015	.211**	.261**	.075	-.027	.153**	.135**	.204**	-.035	.164**	1	-.072	-.221**
	Sig. (2-tailed)	.690	.001	.149	.737	.000	.000	.093	.549	.001	.003	.000	.436	.000		.109	.000
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
Guidance Suggested	Pearson Correlation	.127**	-.028	-.064	.257**	.067	.185**	.205**	.207**	.077	.076	-.013	-.072	.018	-.072	1	-.864**
	Sig. (2-tailed)	.004	.534	.152	.000	.136	.000	.000	.000	.085	.092	.766	.111	.684	.109		.000
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498
All ages	Pearson Correlation	-.047	.003	.122**	-.162**	-.119**	-.233**	-.147**	-.121**	-.113*	-.107*	.010	.143**	-.029	-.221**	-.864**	1
	Sig. (2-tailed)	.294	.939	.006	.000	.008	.000	.001	.007	.012	.017	.819	.001	.515	.000	.000	
	N	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498	498

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Annex 10: Regression models' collinearity diagnostics

Collinearity Diagnostics

Model 1	Eigenvalue	Condition Index	Variance Proportions		
			(Constant)	LogTotalOCR	ExpAverageRating
1	2.780	1.000	.02	.02	.02
2	.131	4.602	.02	.80	.49
3	.088	5.605	.97	.18	.49

Collinearity Diagnostics[a]

Model 2	Eigenvalue	Condition Index	Variance Proportions				
			(Constant)	LogTotalOCR	ExpAverageRating	LogPrice	Guidance Suggested
1	3.778	1.000	.01	.01	.01	.02	.02
2	.743	2.255	.00	.01	.01	.00	.94
3	.271	3.733	.00	.07	.08	.83	.01
4	.131	5.364	.01	.79	.50	.00	.00
5	.076	7.053	.98	.12	.41	.15	.03

Collinearity Diagnostics[a]

Model 3	Eigenvalue	Condition Index	Variance Proportions							
			(Constant)	LogTotalOCR	ExpAverageRating	LogTotalOCR_Subcategory	LogTotalOCR_Source	LogPrice	Days.Years	Guidance Suggested
1	4.765	1.000	.00	.01	.01	.00	.01	.01	.01	.01
2	1.065	2.116	.00	.00	.00	.31	.06	.01	.04	.13
3	.905	2.295	.00	.00	.00	.35	.11	.01	.08	.04
4	.633	2.744	.00	.01	.00	.05	.10	.00	.04	.77
5	.259	4.289	.00	.01	.05	.08	.09	.85	.06	.01
6	.197	4.924	.00	.05	.21	.00	.48	.01	.69	.02
7	.110	6.576	.00	.81	.46	.16	.01	.03	.02	.01
8	.067	8.454	.99	.13	.27	.04	.14	.08	.06	.01

Collinearity Diagnostics[a]

Model 4	Eigenvalue	Condition Index	Variance Proportions							
			(Constant)	LogTotalOCR	ExpAverageRating	ExpAverageRating_Source	ExpAverageRating_Subcategory	LogPrice	Days.Years	Guidance Suggested
1	4.698	1.000	.00	.00	.00	.01	.00	.01	.01	.01
2	1.053	2.112	.00	.00	.00	.01	.61	.01	.01	.00
3	.965	2.206	.00	.00	.00	.09	.06	.00	.09	.22
4	.643	2.704	.00	.00	.01	.10	.03	.00	.04	.69
5	.305	3.926	.00	.02	.02	.10	.04	.43	.33	.01
6	.202	4.822	.01	.19	.03	.10	.09	.42	.29	.02
7	.077	7.797	.66	.00	.50	.03	.00	.14	.01	.04
8	.057	9.076	.32	.78	.44	.56	.18	.00	.22	.02

Collinearity Diagnostics[a]

Model 5	Eigenvalue	Condition Index	Variance Proportions									
			(Constant)	LogTotalOCR	ExpAverageRating	ExpAverageRating_StronglyUtilitarian	ExpAverageRating_Utilitarian	ExpAverageRating_Hedonic	ExpAverageRating_StronglyHedonic	Days.Years	LogPrice	Guidance Suggested
1	4.987	1.000	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01
2	1.091	2.138	.00	.00	.00	.00	.16	.08	.22	.00	.00	.10
3	1.036	2.194	.00	.00	.00	.39	.07	.04	.06	.00	.01	.01
4	1.002	2.231	.00	.00	.00	.00	.25	.46	.00	.00	.00	.00
5	.728	2.617	.00	.00	.00	.01	.07	.04	.03	.10	.00	.65
6	.403	3.519	.01	.02	.00	.03	.02	.03	.01	.73	.11	.13
7	.360	3.723	.01	.00	.01	.39	.20	.21	.41	.13	.09	.03
8	.222	4.735	.03	.08	.09	.01	.09	.08	.16	.03	.65	.01
9	.102	6.977	.04	.78	.43	.10	.11	.03	.02	.00	.01	.00
10	.069	8.524	.91	.11	.46	.06	.03	.03	.09	.00	.13	.06

Collinearity Diagnostics[a]

Model 6	Eigenvalue	Condition Index	Variance Proportions									
			(Constant)	LogTotalOCR	ExpAverageRating	LogTotalOCR_StronglyUtilitarian	LogTotalOCR_Utilitarian	LogTotalOCR_Hedonic	LogTotalOCR_StronglyHedonic	Days.Years	LogPrice	Guidance Suggested
1	4.988	1.000	.00	.00	.01	.00	.00	.00	.00	.01	.01	.01
2	1.115	2.115	.00	.00	.00	.04	.09	.07	.17	.00	.00	.13
3	1.010	2.222	.00	.00	.00	.41	.08	.16	.01	.00	.00	.00
4	1.002	2.231	.00	.00	.00	.01	.37	.35	.00	.00	.00	.00
5	.715	2.642	.00	.00	.00	.00	.03	.01	.08	.10	.00	.62
6	.407	3.499	.00	.01	.00	.00	.00	.00	.06	.81	.07	.16
7	.359	3.729	.02	.00	.04	.41	.36	.30	.21	.00	.06	.01
8	.245	4.509	.01	.03	.15	.01	.00	.01	.01	.08	.70	.01
9	.094	7.270	.15	.37	.74	.03	.03	.05	.18	.00	.05	.00
10	.064	8.813	.81	.58	.05	.07	.04	.05	.28	.00	.10	.07