Master Thesis

The influence of online product reviews on the downloading decision for mobile apps

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Abstract

The market for mobile apps has increased heavily lately, and at the same time, Internet has made it possible for consumers to share their experience of products and services to a wider public all over the world. Yet there is little understanding of how online reviews made by other consumers effect the decision to download an app. The purpose of this thesis is to study the relationship between online peer review rating scores and the number of downloads for mobile apps, and the difference between paid and free apps is studied, as well as potential differences between mobile apps within the hedonic and utilitarian category respectively. Gaming apps are used to represent hedonic products, whereas productivity apps was used to represent utilitarian products. Data on 1160 apps available on Google Play are collected and analysed using a multivariate linear regression analysis, which yielded some interesting results. We noticed that online peer ratings of use value are positively related to the number of downloads, and we saw that online peer review rating scores are more positively related to the number of downloads for free apps than paid apps. Furthermore, we could not find any statistically significant difference in the relationship between the numbers of downloads and the peer rating for apps within the hedonic and utilitarian category.
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1. Introduction

1.1. Background
Along with the growth of smart phone subscriptions and tablets usages, the market for mobile apps has grown explosively. Analysis and Growth Forecasts for the Worldwide Mobile Application Market show that apps generated an impressive USD 12 billion, 46 billion downloads in 2012, in total taking the cumulative all-time total downloads since the app game began, to 83 billion. By the end of 2017, the expected number of downloads exceed 200 billion per year, and the revenue for 2017 is predicted to reach 63.5 billion US dollars (Portio Research, 2013).

According to Kim et al. (2011), the term “App economy” has emerged, signifying the new economic landscape created by mobile apps. Along with the introduction of newer generations devices such as smart phones, tablets and wearable devices (like Apple watch for instance), the current momentum behind the app will continue, and apps for mobile shopping, social media, and contents tools (e.g. tools for editing photos, documents and videos for instance) are forecasted to further drive a capital increase. The info graph in Davidson (2014) shows that 48% of the mobile app consumers use an app on their mobile device more than ten times per day, more frequently than general grooming and eating. As mobile devices have become a necessity for a lot of people in the modern world, such population intensive customer engagement along with strong revenue grow strength, the mobile apps market attracts researchers to discover the influential factors of users’ choices of which app to download.

The current state of art in the research domain stated above (i.e. what factors that influence consumers to download an app) is mainly distributed in the following directions. Users preference under the co-existing free and non-free selling strategy approach (Liu, et al., 2012; Counsell, 2014; van der Meulen & Rivera, 2014; ABIresearch, 2012), users expectation-confirmation on perceived values (Hsu & Lin, 2015), user experiences of consumption values (Wang, et al., 2013), and of course the product usability (Nayebi, et al., 2012). However, we discover that there does not seem to be much discussion about the relation between consumers’ reviews and their downloading choice for different apps. After all, the large amount of such information like ratings, text reviews, and critics’ reviews reflect the true feedback from, and only from, real app consumers and meanwhile it is presented in the same channel as the app distribution channel (i.e. on Internet), which shall not be neglected.

1.2. Problem discussion
Internet has offered a vast platform for consumers to share their opinions, experience, and ideas about different products. Search engines make it possible for these consumers to acquaint themselves with what other consumers think about different products. Many researches have shown that consumers’ feedback on different products can influence other consumers’ purchase decision for that particular product.

Jiménez & Mendoza (2013) have stated that online product reviews have become “the most important form of electronic word-of-mouth” and they believe that the credibility of online product reviews plays an important role when customers make their purchase decision. Duan et al. (2008) have made a study to examine the importance of the awareness effect of online peer review on movies’ daily box office performance, and they conclude that people are affected by the
awareness effect. Chevalier and Mayzlin (2006) have made a comparative study on the effect of peer reviews on relative sales of books at two online bookshops, where they find that “an improvement in a book’s reviews leads to an increase in relative sales at that site”, which also addresses the influential effect on online reviews. Furthermore, Yu et al. (2014) refer to a survey from 2010 made by Channel Advisors that concluded that among holiday shoppers, 83% were influenced by the online reviews. This confirms that online reviews are also influential for holiday trip shoppers.

All the studies cited above indicate that online reviews nowadays have become an indispensable source for product information, and they bring considerable influences on consumers’ choice of products. Through our observation, such phenomenon is particularly prevailing among the products, which have their major sales channels from online stores. Then, how does it look for mobile apps? Do we get similar findings about the online reviews’ influence about app purchase choice as other products from those studies? These questions drive us to look for the studies about the influence of online product reviews in the context of mobile apps market.

The entire purchasing process for mobile apps is pure virtually cyberspace based. Mobile apps are distributed primarily through application distribution platforms, such as the Apple App Store, Google Play, Windows Phone Store and BlackBerry App World (Wang, et al., 2013) (Hsu & Lin, 2015). These distribution platforms act as virtual stores that take care of the payment transaction of the purchase and provide the channels for customer services. About the presentation and experience of the mobile app itself, it only virtually exists and exists only on the buyers’ mobile devices. Therefore, we can consider mobile apps as an extreme electronic commerce (e-commerce) product.

Researchers on consumer behaviour for e-commerce have pointed out that e-commerce involves more uncertainty and risks than traditional commerce because consumers have to deal with different transactions never faced before (Vos, et al., 2014; Kim, et al., 2008; Coker, et al., 2011; Forsythe & Shi, 2003). Therefore, consumers tend to search for additional product information and rely on other customers’ feedback of the product experience to help them in their decision-making of which product to choose, and since mobile apps are solely available online, we can assume that this holds for mobile apps as well.

We have noticed that the product information for mobile apps is rather limited, and meanwhile consumers have a high demand on the product information due to the purchasing characterises of mobiles apps as we discussed earlier. However, almost all leading mobile apps distribution platforms (Statista, 2015), like Google Play, Apple App Store, Windows Phone Store, and Amazon App store have deployed user review rating system. By observing the mobile apps in each of these stores, review rating information has taken a large portion of product information of the listed app. Not even to mention the review rating information existing on the third-party source like CNET (2015), PCMag (2015), New York Times (2015), and The Telegraph (2015) for instance. This phenomenon makes us recognize that online peer reviews are an important source of product information for mobile apps, which cannot be neglected and shall be worth to research on.

By understanding the importance of online peer reviews for mobile apps, we start looking for the research already conducted in this domain. However, we found out that there are not many
studies regarding online product reviews and its influence on consumers’ choice for mobile apps available at any greater extent so far. Is this a missing undiscovered research point for the rapid growing new market? Or is it believed as not much additional research value due to the product similarity to others, like movies, books and trip charters?

Floyd et al. (2014) have made a meta-analysis where they studied how online product reviews affected sales elasticity. In order to conduct their study, they carefully reviewed 26 articles on the topic and identified in total 446 sales elasticity. The articles they studied covered a wide variety of products, such as hotels, books, movies, and digital cameras for instance. We compare mobile app to the cluster of products that Floyd et al. (2014) have chosen for their study when making a generic meta-analysis model of the impact of online product reviews towards sales elasticity. We find we cannot really categorize mobile app similar to any of other researched product types due to the following reasons:

Firstly, the strategy of offering apps free of charge takes an indispensable weight among entire mobile apps sales. Other products may offer free samples, limited free trial but not completely free products. According to the prediction from Van der Meulen and Rivera (2014), 94.5% of all app downloads in 2017 will be for free apps. This makes mobile apps revenue construction quite different from other products. However, so far, all studies that we have come across on the influence of online product reviews is based on products where consumers must pay a certain amount of money in order to acquire. This is also the case for previous studies on mobile apps, where Hsu and Liu (2015) have made a recent study based on a survey where they conclude that app ratings have an impact on the intention to download paid apps.

With the ability to choose among paying money for a product, or getting a similar product free of charge, will the online reviews still matter to bring the influence the choice? Or will the online reviews impact differently in terms for free apps and paid apps? How large would this difference be? We will not be able to answer the questions based on existing research on online product reviews influence on product choice. This means, in order to answer these questions, we must go beyond existing literature.

There are over a billion different apps available (Statista, 2015) covering various functionalities serving various industries, although users only have a few of them on his or her devices. However, interestingly, no matter what service the mobile app provides, the physical presentation for all apps exists monotonously on a common operating platform. In that sense, we can see mobile app as one type of product that defined as the software application running on mobile operation system on a mobile device. Specifically, on one hand, no matter which operating system the user uses, the app is commonly present as a small icon on the device desktop for entry point, and users purchase and download apps to the device from app markets like Apple app market and Google Play for instance. On the other hand, from functional perspective, there is a vast variety of different types of mobile apps used for different purposes, such as games, education, news, and productivity to mention a few. Different types of mobile apps bring completely different user experience to users for different purposes.

This characteristic is unique to mobile apps compared to other products, which have relatively independent formats and focused functional aspects. The available functional variances in mobile apps have attracted users with different expectations. What kind of services do users consider as
functional or useful, and what kind of services do they regard as enjoyable and experiential? Do differences exist among users of a same group leading to classification of mobile services and user motivations? Will there be a difference also for the user experience feedback from various functional expectation acceptances? For example, do potential users care more about others’ saying when downloading a game app or a GPS app? To be able to answer the questions above, we need to discover how the online reviews’ influence act on product choice from its attributes and use motivation from consumer perspective. Mobile apps so far provide the unique opportunity for us to explore this standing out from others.

By comparing mobile apps with other products, the impact of product reviews on product choices have been studied. We find that there is a difference in the products as discussed above. Therefore, it is not clear that the findings on these products (such as movies, hotels, and books for instance) is applicable to mobile apps as well, which makes it useful to study how product reviews influence the product choice for mobile apps separately. Up until now, the research in this area is very limited.

1.3. Problem formulation
To date, we feel there is a need to study the relationship of online product reviews for consumers’ product choice in the context of mobile apps based on the discussion in the previous section. Therefore, we formulate our primary research question for this thesis stated as following:

**How do online reviews influence the downloading decision choice of mobile applications?**

To break this question into a more scalable level, we decide to make the study based on the perspectives that shows that mobile apps are different from other products, as previously discussed. We then state the following questions:

1) **How do online reviews influence the downloading decision choices of mobile applications in terms of free apps and paid apps?**

2) **How do online reviews influence the downloading decision choices of mobile applications in terms of apps own attributes and use motivation from consumer perspective?**

In order to answer the research questions above, we study the peer researchers works on online review’s influence on product choice, mobile apps characteristics, and current taxonomy for mobile apps. Based on the literature review, we propose three hypotheses, which we test through quantitative data analysis.

1.4. Purpose
The purpose of this thesis is to explore the impact of online reviews on downloading decision choices for apps from different perspectives in order to answer the research questions stated in section 1.3. Thereby, we can provide some evidence for the missing research discussion about online product review impact for mobile apps. Hopefully, this will help to extend the research work on both online product reviews and mobile apps respectively.
Specifically, we will compare our findings with what previous researchers have concluded when it comes to judging the impact of online product reviews on the purchase decision, in order to see whether earlier generic findings are applicable to mobile apps or not.

For a managerial perspective, understanding the effective relationships between online peer reviews and customers’ choice from user motivation perspective will help the business to improve the design of their products more precisely, therefore leverage the “app economy” to higher level.

1.5. Thesis outline

The remaining of this thesis is constructed as following:

The next section presents our theoretical perspective and literature review to the current research state of the art and the findings about mobile apps, product choices, functional categorisation (like games, education, and health & fitness apps for instance), and the influence of online peer previews.

Then we propose our hypotheses based on existing theory on the topic of product reviews.

After that, we will discuss different research methods and motivate our choice as well as describe how we used it in this study to design the model to test the proposed hypotheses.

We then present and analyse our results, which then is followed by a discussion of the insights gained from it. We conclude with a summary of findings, limitations and future research suggestions.
2. Literature review

2.1. Mobile apps

The term Mobile apps is the abbreviation form of mobile applications, which refers to the stand-alone software application that runs on an operating system deployed on a mobile device, such as smart phones and tablets. When the word “app” originally introduced, it referred to software mainly used for information retrieval and productivity purposes, such as weather information, calendar, and e-mail. With the technology innovation continuously refreshing in the new generations of mobile devices and platforms, it provides the possibility that mobile apps no longer only is used for simple utility usages as it was designed for in the beginning. The concept has been enlarged broadly to almost every aspects of daily life, such as games, health & fitness, education and finance tools (Hsu & Lin, 2015).

Consequently, the popularity of apps has grown tremendously. According to the market research report from Berg Insight (2012), there were approximately 10 billion app downloads made on all mobile platform in 2010. In 2015, over 70 percent of all mobile phones shipment will be smartphones, building a large user base that will spur the number of app downloads to reach almost 100 billion during 2015. The trend with fast increasing number of downloads for mobile apps is illustrated in Figure 1. The number of app downloads per platform will gradually mimic the market share for each mobile platform.

![Figure 1 Mobile application downloads, billion downloads (World 2009-2015) (Berg Insight, 2012)](image)

It has predicted that over 268 billion apps will be downloaded in 2017 (Rivera & van der Meulen, 2013). Besides, the average smartphone users use apps 82% of the time spent on using their smartphones, and on average, they download 40 apps, and uses 15 of them frequently (Gupta, 2013).

2.1.1. Mobile apps attributes

Analysts (Anonymity, 2011) (Anonymity, 2012) have summarised six major characterises that all mobile apps have in common and those characteristics are the following:

1) Connectivity, the device continuously logs into mobile network, as the apps are constantly online. In this way, users’ particular information and notifications push to the app, as they are
accessible. This is an important characteristic of mobile application to be available anywhere. The ability of push becomes essential in growing apps on every Smartphone as this characteristic keep the app in user minds.

2) *Convenience*, an emotional design and a simple handling guarantee a high acceptance. A good app can do its job in different contexts and fast varying situations (changing environmental light and noise and unsteady movement of the device for instance.). Therefore, the information architecture and the overall usability must be planned with care to create a fitting and joyful interaction flow.

3) *Localization*, localize the info and the opportunity to provide position based information is critical feature that craft mobility stunning and practical. It works as elimination of the wheat from the chaff, thus embeds the app according to user context. The feature may not be perfect for every app but it is a good thinking to associate location with note or photo and limiting possible options and/or sorting places. The feature adds good user experience.

4) *Reachability*, reachability covers a more social attribute given by the nature of mobile applications itself. A good app can be extensively used – and more important makes sense – anywhere at any time. The core of mobile devices is to be used anywhere at any time. The same is true for Apps where reachability has become availability. Not in sense of usage, but in sense of updated information and perpetual usefulness.

5) *Security*, Security has several facets. The data transferred over the network must encrypt through the carrier network. As some Apps sync data with online, web-based applications, the storage of this data on the server must also secure. Another aspect concerns the data on the device itself. For example, user does not want anybody playing around with his or her mobile phone getting access to his or her own bank account data. Mobility is delicate, and so is the date aggregated and generated in this context.

6) *Personalization*, creating personalized content based on individual usage or context is another characteristic. It builds on all previous characteristics, as it is a kind of melting down of all of them. “I want my App fitting my needs and I want my App behaving like I want it to do.” This need covers not only personalized content but also control over data stored, shared or used for further actions. The option of turning localization on or off is true personalization. An individual background or personal categories are convenience.

In any market, there are differences among consumers in the demand for products and services. These differences are largely based on socio-demographic characteristics, product or services attributes and use motivations (Mazzoni et al. in (Ahmad, 2012)). Essentially, in the case of mobile apps, the above nature attributes incorporates both product and service attributes. According to Ahmad (2012), the developments of these attributes are made possible by continuous innovations and anticipation of consumer needs and behaviour.
2.1.2. Classification of mobile apps

With the trend of fast growing mobile market, the importance of taxonomies has been well recognized in the field of mobile commerce and mobile business researches (Lehmann & Lehner, 2002). Researchers Heinonen and Pura (2008) have given a systematic review of the research made by other fellows in order to develop a classification of mobile services and they acknowledge four main aspects of mobile services from a customer-centric perspective. These four main aspects are the *type of consumption*, the *context of use*, the *social setting*, and the *relationship between the consumer and service provider*, see Figure 2.

![Figure 2 Classification of mobile services from a customer-centric perspective (Heinonen & Pura, 2008).](image)

In the proposed conceptual model with these four factors, Heinonen and Pura (2008) suggest that the core of the mobile service represents the type of consumption related to the specific mobile service. The next consideration is the context when and where services may be used, i.e. the temporal and spatial context of use, followed by the social setting in which they may be used, and finally, the relationship between the customer and the service provider. In the case of mobile apps, as one of the typical presentation of mobile services, the classification for it fits well within this model. Since the research problem of our study is mostly interested in seeing mobile apps from use motivation perspective, we will focus on type of consumption aspect in the classification of mobile apps. Besides, studying the fundamental core of the mobile apps is believed as an efficient study approach to provide findings to future upper level studies.

Behaviour of the consumer is a result of attitudes, motives, values, and may lead into purchase and consumption behaviour. Literature on consumer behaviour suggest that consumers purchase goods and services and perform consumption behaviour because of hedonic gratification and utilitarian reasons concerned (Teller et al.; Millan, Howard; Batra, Ahtola; Holbrook, Hirschman, 1982; Millar, Tesser in (Adomaviciute, 2013)). Research has suggested that services can be classified based on the relative importance of the hedonic and utilitarian value they generated for customers (Babin, et al., 1994).

Utilitarian value refers to extrinsic motivation that is more cognitively driven, instrumental, and goal oriented and able to accomplish a functional or practical task (Strahilevitz and Myers in (Dhar & Wertenbroch, 2000)) (Babin, et al., 1994). Hedonic value means intrinsic motivation that is primarily characterized by an affective and sensory experience of aesthetic or sensual pleasure, fantasy and fun (Hirschman & Holbrook, 1982).
Similar categorization into goal oriented and experiential services have been used also in mobile field. Ahmad (2012) shows that mobile apps user interactions are impacted by the values or the benefits mobile services generate for the users. Utilitarian values of mobile services are related to functional benefits and productivity, whereas hedonic value refer to experiential and enjoyable ones. Li et al. (2012) study the influencing factors of mobile consumption experience, which also implies that emotion played a significant role in the mobile service consumption, where hedonic and utilitarian factors take impacts differently. They conclude that “hedonic factors had a positive effect on the consumption experience, while utilitarian factors had a negative effect on the consumption experience of consumers” (Li, et al., 2012). Thus, such categorization reflects the division to efficiency needs and entertainment needs.

Figure 3 shows how different mobile services can serve a utilitarian or hedonic purpose.

![Figure 3 Consumption types (Heinonen & Pura, 2008)](image)

Information based apps like weather, navigation, productivity (such as bar code scanners, notes, document-sharing drivers) and health & fitness are examples of apps that create high utilitarian values and help users to achieve a goal effectively and conveniently. Highly hedonic apps are apps that create fun experiences and are used for the sake of the experience are entertainment-oriented apps like games, music and photo & videos.

### 2.1.3. Market distribution

Digi-Capital (2014) has published a Mobile Apps Investment Review in Q1 2014, where they present the global mobile apps sector revenue from 2011 and forecast up to 2017 fall distribution based on categories; see Figure 4. The figures show the growth trend of various types of mobile apps, Games obviously taking the market lead among others. The forecast shows that mobile apps could reach more than $70 billion revenue globally, with non-games apps to double revenue share from 26% to 51% between 2013 and 2017F (2017 Fall), and the compound annual growth rate is estimated to 61.3%.
Behind such flourishing growing revenue trends of mobile apps market, it is interesting to notice that free apps are becoming domination with absolute superiority over Paid apps over years in such market (Patel, 2014). Figure 5 illustrates Free vs. Paid mobile apps downloads in percentage. This indicates that the proportion of Free apps grow in the mobile apps market does not lower the total revenue of the industry, on the contrary, Free apps seem to generate higher revenue compared to paid apps according to Figure 6.
According to Patel (2014), when the era of apps began, the app stores were filled with more than half of its proportion with paid apps. Users do not have much option as an alternative for paid apps. They were paying certain amount of money to enjoy apps. As the market for mobile devices was rising along with the innovations of mobile operation systems, many companies entered in mobile market which results into high competitions. Such competitions give rise to free apps and choices for users who will like to get the app and enjoy it without money cost. Consequently, the quantity of free apps exceeds the quantity of paid apps. Users get more attracted towards free apps as their decision focus has shifted into the preference of playing the app or not from only deciding to pay for it or not.

**Figure 6 Free vs. Paid apps Comparison in Revenue in 2013 (Patel, 2014)**

So how does app without charge generate such big revenue? The reason is the in-app purchases and in-app advertisers. According to Patel (2014), more and more business are switching to free apps as they find that they can earn a lot from in-app purchases rather than paid apps. Free apps are also great source for advertising. Users are greatly enjoying free apps and they like to pay for in-app purchases. Such mentality of users is a great benefit for business. In fact, there has been estimated that the total mobile app revenue, including pay-per-download, in-app purchase, in-app advertising, and subscriptions will grow from $8.5 million in 2011 to $46 billion in 2016 (ABIresearch, 2012).

Considering this phenomenon in the mobile app industry, evaluating consumers’ product choice only by simply calculating app sales figures is one-sided since the large amount of free apps selection also reflects consumers’ intention to download a specific app, which shall not be neglected.

**2.2. Use motivation of consumer choice**

**2.2.1. Values of consumption**

It has been argued that people use services based on different consumption values (Sheth, Newman and Gross in (Heinonen & Pura, 2008)). Different types of motivations for consumption are often divided into hedonic and utilitarian value (Hirschman & Holbrook, 1982; Babin, et al., 1994). Utilitarian value refers to extrinsic motivation that exists in goal directed service use (Babin, et al., 1994), where hedonic value means intrinsic motivation that exists in experiential, fun and enjoyable service use (Hirschman & Holbrook, 1982).
Dhar and Werthenbroch (2000) state that goods that are high on hedonic value are likely to be subject to affective preference, while the goods that are high on utilitarian value are likely to subject to cognitive preference among the consumer choice.

From a product perspective, some researches offer explanations about the difference in consumer behaviour between hedonic and utilitarian products. Adaval (2001) has examined that, for hedonic products, mood in conjunction with perceived product attribute information would generate different effects on motivation for choice. When the attribute information was evaluated consistent with participants’ mood, the positive or negative reaction projecting on choice motivation is weighted more than when evaluated inconsistent. This can be understood as the confidence raised from the confirmation of own perception deriving from external source. However, such differential weight was not evident when participants based their judgments on utilitarian products. These findings inspire the understanding of how consumers are likely to respond to reviews for hedonic versus utilitarian products. Consumers are likely to anticipate a positive mood when reading reviews for hedonic products. As a result of the affect confirmation process, they should then discount the negative information they read in the hedonic product view, as it is inconsistent with their current or anticipated mood. When reading a review for a utilitarian product, as research suggested, that affect has little effect on evaluations based on utilitarian criteria.

From consumer perspective, some researchers suggest that consumers have hedonic and utilitarian attitudes (Voss, Spangenberg, Grohmann in (Kronrod & Danziger, 2013)). Hedonic attitudes are based on emotional attachment, whereas utilitarian attitudes are a product of experience characterized by logical personal relevance. We can interpret this like the following; hedonic attitudes reflect consumers’ judgement on products more based on their perceptual knowledge compared to utilitarian attitudes, which reflect consumers’ judgement on products more based on their rational knowledge. Hedonic consumption is more “affectively rich” than utilitarian consumptions (Botti and McGill in (Kronrod & Danziger, 2013). Therefore, preferences for hedonic goods can be considered as emotionally driven, whereas utilitarian goods are more cognitively driven (Kronrod & Danziger, 2013).

Another predominant perspective in consumer behaviour is that a consumer is driven by utilitarian motives. According to Babin et.al (1994), consumers recognize consumption as a task to get something efficiently and evaluate large amount of information when making decisions. This implies differences in the decision making process for hedonic versus utilitarian products, which should also effect the perceived usefulness of reviews (Sen & Lerman, 2007). In their study, Sen and Lerman (2007) have proved that negative experiences with tangible attributes could directly impact the utility that the consumer would likely derive from the product. Because of the goal of the utility consumption, utility maximization is based on tangible and seemingly objective criteria. Consumers should feel rather comfortable relying on other consumers’ evaluations.

2.2.2. Zero price effect

The zero price effect is a phenomenon whereby the demand for a good, service, or commodity is significantly greater at a price of exactly zero compared to a price even slightly greater than zero. Studies show evidence in favour of the zero-price model (Shaman’er & Ariely, 2006). The
decisions about free products are different than simply subtracting costs from benefits, and that in fact the benefits associated with free products are perceived to be higher (Shampan’er & Ariely, 2006). When people are faced with a choice between two products, one of which is free, they “overreact” to the free product as if zero price meant not only a low cost of buying the product, but also increased consumers’ valuation of the product itself.

Several possible psychological antecedents of such effect, like Social norms, Mapping difficulty and Affect, have been discussed and tested in Shampan’er and Ariely series of experiments (2006), the results suggest Affect as the most likely cause of the effect that in favor of zero price model overwhelmingly.

Affect is the idea that options with no downside (no cost) evoke a more positive effect response than options that involve both benefits and cost. To the extent that individuals use this affective reaction as a cue for their decisions, they will choose the free option (Slovic et al. in (Shampan’er & Ariely, 2006)). The results show the attractiveness of zero cost is not limited to monetary transaction. There seems to be a general increase in attractiveness of options that do not require giving anything up.

2.3. Online peer reviews
Researchers have shown that word-of-mouth (WOM) communications in many cases play an important role when it comes to the judgement of a product (Herr, et al., 1991). Electronic word-of-mouth (eWOM) is the upgraded format of WOM which spread the words in a wider space through multiple channels like online forums, blogs, social network and review sites etc. More precisely, eWOM can be 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, et al., 2004).

In the space of Internet, online peer review is functioning as supplementary information for the product similar to advertisement, but differs from it. The discussion about the differences between online peer reviews and advertisement in Kronrod and Danziger (2013)’s work support this as following:

Firstly, it is not surprising that advertisements are often perceived as biased, persuasive attempted, and as the terms suggests, companies invest in advertisements for promoting their products in order to foster sales. On the opposite, peer reviews are generally perceived as an objective sharing of opinions.

Secondly, ads constitute professionally pre-planned mass communication. They undergo editing, restyling, and censorship. However, user-generated content is natural and spontaneous, and is usually not censored. Such difference creates communicational expectations for peer reviews that resemble the expectations of interpersonal communication, whereas communicational expectations for advertising texts are more similar to expectations for works of art (Hahn, Murken-Altrogge, Spitzer in (Kronrod & Danziger, 2013)).

Thirdly, resulted from the purpose of advertisement, ads almost always express positive information about the product, while peer reviews, on the other hand, is more evenly distributed between negative and positive opinions. Therefore, consumers may predominantly expect
superlative and praise of products in advertising, but unbiased evaluations and even criticism from peer reviews (Sen & Lerman, 2007).

Living in a world with advertising information flooded everywhere, it becomes even more difficult for users to judge the product and make choice decision. Providing and seeking peer review online help to create a different channel for broadcasting the product information from consumers’ perspective, therefore it is more trusted, easier to be accepted and even highly requested by consumers.

2.3.1. Influence of online reviews

The impacts brought by online reviews on the purchase decisions of subsequent consumers have been studied extensively in a variety of markets as we mentioned at the beginning of this thesis. Those studies generally support the idea that online reviews have become a primary reference of the consumers, and the user generated content plays an important role in the purchasing choice decisions of future potential buyers. However, as discussed in Liu et al. (2012), how online review affect consumers choice decision can differ due to a variety of factors like product types, popularity of products, quality and quantity of the reviews.

The attributes of products are some of the most significant factors moderating the effect of online reviews (Liu, et al., 2012). Comparing with that on the sales of hedonic products, the impact of online reviews on utilitarian products is relatively high due to the focus on product functionality rather than individual preferences in product evaluations (Cheema and Papatla in (Liu, et al., 2012)).

The impact of online reviews may also be influenced by the popularity of the product. In the market for mobile apps, there are billions of products competing for consumer attention and media coverage, where the products that get less attention may potentially drown among others. This consequently results in a higher degree of product uncertainty (Liu, et al., 2012). Online reviews thus become a primary source of information for consumers to reduce such uncertainty. Therefore, it is highly plausible that products less popular in the market are more significantly influenced by online reviews (Zhu & Zhang, 2010).

Furthermore, the quality and quantity of reviews also play an important role in increasing sales volume. According to Duan et al. (2008), prospective consumers tend to rely more on online reviews that are more thoroughly composed and with higher volume.

There are preferences carried in the eWOM, where positive reviews typically enhance consumers’ expected quality and attitudes toward that product, while negative reviews may involve product denigration, rumour or complaints, and often have an unfavourable impact on product attitudes (Liu in (Floyd, et al., 2014)). When assessing the influential power between positive reviews and negative reviews, many researchers also suggest that negative information is stronger, more influential, predictive, and difficult to resist than positive information (Anderson and Salisbury; Bowman and Narayandas; Chen, Wu, and Yoon; Godes and Mayzlin; Liu; Van den Bulte and Lilien;Duan, Gu, and Whinston in (Floyd, et al., 2014)).

Smith et al. (2005), mention thatpast researches have suggested that in information intensive environments, consumers seek others’ opinions as a means of managing the perceived risks
typically associated with cognitively demanding tasks, and others’ experiences is perceived to be not only easier to understand but also more trustworthy (Dowling, Stalin, Smith in (Smith, et al., 2005)).

According to Liu et al. (2012), when consumers are searching for products that they are not familiar with, they tend to rely on feedback provided by professionals or other consumers who have experienced the products to reduce uncertainty. This is especially true for experience goods. However, in the mobile app markets, available free version apps make consumers possible to test the features and functionalities before purchase, technically turning experience goods into search goods. Consequently, the influence of review rating is expected to be less significant for free apps compared to paid apps.

It has been shown that the influence of user reviews is more significant in the purchase of less attractive product and increasingly insignificant for more popular products (Duan, et al., 2008). Considering the zero price effect, it is inevitable that free apps are generally more popular than paid apps. Our researchers may imply that the impact of rating will weigh more for paid apps than free apps.

### 2.3.2. Ratings

The current available online peer reviews formats are commonly expressed as written text review and ratings. Despite there are some evidence shown that consumers tend to read the text of online reviews rather than rely solely upon summary statistics like average rating score (Chevalier & Mayzlin, 2006), most researchers for online peer reviews decided to focus on more easily quantifiable measures like product ratings rather than the written content of reviews. The reason for this is associated with costs and difficulties in measuring text reviews (Schlosser, 2011).

Ratings, as simple straight measures, visually illustrate the preference of users. In most cases, a scale of numbers is deployed for ratings. For example, apps in app markets will usually be rated from a scale of 1 to 5, where 1 indicates strongly low satisfaction and 5 represent strongly high satisfaction. The mean value of ratings usually lists separately, through which user can get an impression of how other customers think about this service or product on average. The more users who rate the app, the more trustworthy of the average values indicate real user experience feedback. Hsu et al. (2015) define app rating as “The user's overall assessment of an app” and they have concluded that a favourable rating made it more likely that a consumer would purchase that particular app.
3. Hypothesis development

3.1. Hypothesis I (H1)
From selection to usage, the entire customer engagement of mobile apps purely happens in the cyberspace. This is inevitable for customers to encounter some barriers compared shopping products offline. Research in Ahuja et al. (2003) has shown that lack of social interaction could cause people to hesitate shopping online. Social interaction here implies that opportunity to interact with a sales person and also the perception of shopping as a social activity with friends. People obtain the product information and choice confirmation from their social interaction with others during shopping. For products where there are no offline purchasing alternatives, like mobile apps, it is plausible for us to assume people have projected the expectation of feedback from their normal shopping social interaction on to others’ reviews for getting additional information about the product and the confirmation reference needed for their own choice.

Comparing with other product information available online (like advertisements for instance which we discussed in the previous chapter), it is shown that consumers have faith in rating reviews and view them as trustworthy (Aran, 2014). A 2012 Nielsen report (nielsen, 2012) survey more than 28,000 Internet users in 56 countries found that online consumer reviews are the second most trusted source of brand information only to recommendations from friends and family. According to the survey, more than two-thirds of global customers say they trust messages on the platforms (nielsen, 2012).

Through the literature studies of other peer researches about the influence of online peer reviews, it is plausible for us to assume there also exist a positive relation between online peer reviews with the downloading choice of mobile apps. With the research setting targeting on average ratings as the representing format of online reviews per say, we hereby propose a hypothesis on the relation of online peer ratings and user choice of mobile apps downloads like following:

H1: Average online peer review rating score of mobile apps is positively related to the number of downloads.

3.2. Hypothesis II (H2)
As we described in the problem discussion, mobile apps hold different characteristics than other common commerce goods in the pricing strategy. We are not only interested to find out how online peer review in general is related to the download choice, but also would like to dig into deeper to find out the effect of mobile apps peer ratings to downloading decision in terms of free apps and paid apps respectively.

As the research of the zero price effect of free products we studied from Shampan’er and Ariely (2006) shows most likely the zero price model is in favourite over non zero price model due to there is no cost evoke a more positive effect response than options that involve both benefits and cost. It can be assumed that paid apps are associated with a greater effort for the consumer than free apps since the decision to download it will cost him or her money, and therefore he or she is more careful in choosing which app to download. Hsu et al. (2015) claim that before making a purchase, the potential buyer will mentally compare different products in terms of quality. When it comes to free products on the other hand, Hsu et al. (2015) claim that "free products remove the mental transaction costs and accelerate the speed of decision making, thereby increase customer’s
willingness to give the free alternative a try”. Therefore, we may assume naturally, free apps are more popular in downloads than paid apps.

One may argue about the influence of transaction cost. In the focus of mobile apps, we can see that the transaction cost is equally distributed among free apps and paid apps. As the app purchasing process is the same for both types, that is, downloading it from certain app store, the only difference is latter one charging for actual amount of money for obtaining the app.

As we found other peer studies show that the impact of online review may be influenced by the popularity of the product. The more popular products attract more attentions, while products with less attention may potentially drown among others. As other researchers suggested it is highly plausible that products less popular in the market are more significantly influenced by online reviews (Zhu & Zhang, 2010). Therefore, we assume paid apps are more significantly influenced by online reviews compared to free apps. With this thought, we formulate our second hypothesis of this study as following:

H2: Average online peer review rating score matters more for the number of downloads of paid apps than free apps.

3.3. Hypothesis III (H3)

With the characteristics of mobile apps of functional variation among various categories, from consumer perspective, it is interesting for us also to find out how the impact of online peer reviews towards download choice in terms of user motivation.

From the consumer centric classification model of mobile services presented by Heinonen and Pura (2008) as we discussed in previous chapter, we can categorize mobile apps into hedonic and utilitarian groups based on their types in the value of consumptions.

In the literature review of use motivation of consumer choice based on value of consumptions in previous chapter, we recognize that, from a product perspective, consumers are likely to anticipate a positive mood when reading reviews for hedonic products. As a result of the affect confirmation process, they may discount the negative information they read in the hedonic product view, as it is inconsistent with their current or anticipated mood. When reading a review for a utilitarian product, as research suggests that affect has little effect on evaluations based on utilitarian criteria.

From a consumer perspective, hedonic attitudes reflect consumers’ judgement on products more based on their perceptual knowledge. Utilitarian attitudes on the other hand, reflect consumers’ judgement on products more based on their rational knowledge. Such attitude differences reflect on perceived usefulness of reviews. Sen and Lerman (2007) have proved that negative experiences with tangible attributes could directly affect the utility that the consumer will likely derive from the product. Because of the goal of the utility consumption, utility maximization is based on tangible and seemingly objective criteria. Consumers should feel rather comfortable relying on other consumers’ evaluations.

With implications above from peer researches support, we hereby propose the relation hypothesis for impact of online peer review towards user choice of downloads in terms of consumption motivation perspective, by formulating our third hypothesis like following:
H3: Average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps.

In the next chapter, we will motivate the method that we choose to do for this study and present the model that we design for testing above proposed hypothesis.
4. Research methodology

In this section, we will describe what research methodology this thesis project is based on and motivate the reason for choosing quantitative analysis of historical data as the data analysis approach in order to test the proposed hypotheses.

Apart from studying the relationship between online peer reviews and downloading choices of mobile apps, another major goal of this thesis project is to exercise and learn to perform a quality business science research as a business student. To achieve this goal, we decide to follow the progressive research process introduced in Saunders, Lewis and Thornhill’s book *Research Methods for Business Students* (2009). As guided in the book, the thoughts about which research approach should be taken, for example like questionnaire or interview or others, belong in the centre of the research ‘onion’, in Figure 7. In this model, it illustrates that researchers have chosen to depict the issues underlying the choice of data collection techniques and analysis procedures. Before coming to this central point, it is important to peel away outer layers of the onion.

![Figure 7 The research 'onion' (Saunders, et al., 2009)](image)

4.1. The research ‘onion’

The research ‘onion’ discussed in Saunders, Lewis and Thornhill’s book (2009, p. 108) has present the research design in layers. Starting from outmost layer, it offers a view of different research philosophies and their implications for the research design. Then the onion will be peeled back each of the subsequent layers considering the implications of methodological choices, strategy and the time horizon for design.
4.1.1. Research philosophy

Saunders, Lewis and Thornhill (2009, pp. 108-119) have addressed that how a researcher views the world, her or his assumptions about human knowledge and about the nature of the realities encountered inevitably shape how a research question is understood and the associated research design. The main influence is her or his personal view of what constitutes acceptable knowledge and the process by which this is developed. This is seen as a researcher’s philosophy.

**Positivism:** working in the tradition of the natural scientist

Researchers whose work is reflected by the philosophy of positivism usually do their research by making observations and then make predictions based on these observations, i.e. they prefer to make generalisations such as cause and effect. This is typically the case for laboratory scientists. By using what is often referred to as a scientific method, the researchers propose and test theories by using data that is structured and usually measurable, and his or her own values do not influence the research. In order to conduct this kind of research, large samples of quantitative data is usually needed, and the researcher can then test his or her hypotheses by using statistical measures. In case the data analysis does not support the theory, the theory has to be revised. (Saunders & Tosey, 2013).

**Realism:** do objects exist independently of our knowledge of their existence?

Realism is another philosophical position and it is associated with scientific enquiry. The idea behind realism is that the reality exists independent of the mind, and it is also independent of what the researcher’s sense says is the truth, although he or she will be influenced by his or her own experiences as well as his or her own world view. Realism can be further divided into direct realism and critical realism. Direct realism suggests that what the researcher can experience through his or her own senses also provides an accurate representation. Critical realism, on the other hand, suggests that what is experienced through senses will be processed subjectively by the mind. For a researcher who adopts the philosophy of critical realism, it means that not only interesting to study both what is immediately experienced but also the structures and relationships behind this. In order to perform this kind of study, either quantitative, qualitative data, or a mixture of both, can be used. (Saunders & Tosey, 2013)

**Interpretivism:** understanding differences between humans as social actors.

Interpretivism refers to the philosophical position were the researcher is less interested in providing law-like generalisations which is typical for positivism. Instead, a researcher adopting interpretivism seeks to gather rich insights into subjective meanings. This philosophical direction relates to the study of different social phenomena in their natural environment and it is used to conduct research among people instead of objects. Whereas a positivist’s own values do not influence his or her research, a researcher adopting the interpretivism philosophy thinks that research is value bond. Therefore, both data collection and analysis are likely to include qualitative data from in-depth investigations using small samples. (Saunders & Tosey, 2013).

**Pragmatism:** do you have to adopt one position?

The final research philosophy discussed by Saunders and Tosey (2013) is pragmatism, where the importance of the research lies in the practical consequences of the findings. The researchers
adopting this philosophy believe that there might be multiple realities and that no single viewpoint can give the entire picture. However, it is important to point out that this does not mean that a researcher adopting this philosophy will always use several different techniques to collect data and different procedures to analyse the data. What it means is, the research should be designed in such way, where it enables the researcher to collect credible, reliable and relevant data that support subsequent action. (Saunders & Tosey, 2013).

The comparison of the four research philosophies used in business and management research as discussed above is summarized in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Positivism</th>
<th>Realism</th>
<th>Interpretivism</th>
<th>Pragmatism</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ontology:</strong> the</td>
<td>External, objective</td>
<td>Is objective. Exists</td>
<td>Socially constructed, subjective, may change</td>
<td>External, multiple, view chosen to best enable</td>
</tr>
<tr>
<td>researcher's view of</td>
<td>and independent of social actors</td>
<td>independently of human thoughts and beliefs</td>
<td>multiple</td>
<td>answering of research question</td>
</tr>
<tr>
<td>the nature of reality</td>
<td></td>
<td>or being</td>
<td></td>
<td></td>
</tr>
<tr>
<td>or being</td>
<td></td>
<td>(realist), but is interpreted through social</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>conditioning (critical realist)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Epistemology:</strong> the</td>
<td>Only observable phenomena can provide credible</td>
<td>Observable phenomena provide credible data,</td>
<td>Subjective meanings and social phenomena</td>
<td>Either or both observable phenomena and</td>
</tr>
<tr>
<td>researcher's view</td>
<td>data, facts. Focus on causality and law like</td>
<td>facts. Insufficient data means inaccuracies</td>
<td>Focus upon the details of situation, a reality</td>
<td>subjective meanings can provide</td>
</tr>
<tr>
<td>regarding what</td>
<td>generalisations, reducing phenomena to simplest</td>
<td>in sensations (direct realism). Alternatively,</td>
<td>behind these details, subjective meanings</td>
<td>acceptable knowledge dependent upon the</td>
</tr>
<tr>
<td>constitutes</td>
<td>elements</td>
<td>phenomena create sensations which are open to</td>
<td>motivating actions</td>
<td>research question. Focus on practical</td>
</tr>
<tr>
<td>acceptable knowledge</td>
<td></td>
<td>misinterpretation</td>
<td></td>
<td>applied research, integrating different</td>
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<td></td>
<td></td>
<td>(critical realism). Focus on explaining within</td>
<td></td>
<td>perspectives to help interpret the data</td>
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<td></td>
<td></td>
<td>a context or contexts</td>
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<tr>
<td><strong>Axiology:</strong> the</td>
<td>Research is undertaken in a value-free way, the</td>
<td>Research is value laden; the researcher is</td>
<td>Research is value bound, the researcher is part</td>
<td>Values play a large role in interpreting</td>
</tr>
<tr>
<td>researcher's view of</td>
<td>researcher is independent of the data and</td>
<td>biased by world views, cultural experiences</td>
<td>of what is being researched, cannot be</td>
<td>results, the researcher adopting both objective</td>
</tr>
<tr>
<td>the role of values in</td>
<td>maintains an objective stance</td>
<td>and upbringing. These will impact on the</td>
<td>separated and so will be subjective</td>
<td>and subjective points of view</td>
</tr>
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<td>research</td>
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<td>research</td>
<td></td>
<td></td>
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<tr>
<td><strong>Data collection</strong></td>
<td>Highly structured. large samples, measurement,</td>
<td>Methods chosen must fit the subject matter,</td>
<td>Small samples, in-depth investigations,</td>
<td>Mixed or multiple method designs,</td>
</tr>
<tr>
<td>techniques most</td>
<td>quantitative, but can use qualitative</td>
<td>quantitative or qualitative</td>
<td>qualitative</td>
<td>quantitative and qualitative</td>
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<td>often used</td>
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Table 1 Comparison of four research philosophies in business and management research. (Saunders, et al., 2009)
Our research question for this thesis project is focusing on finding out *How do online reviews influence the downloading decision choice of mobile applications?* It targets a young but fast growing consumer markets, mobile apps. Through the phenomenon of mobile apps markets and their purchasing process characteristics, we want to objectively study the relation between online reviews and purchasing decision influence, and also find out the causality for the reasons behind such relationship. Based on our basic cognitive ability understanding of each research philosophy, we believe our study mostly likely fall into the category of Positivism.

4.1.2. Research approach

Saunders, Lewis and Thornhill (2009, p. 124) have addressed that it is useful to attach research approaches after defining research philosophies, where deduction owes more to positivism and induction to interpretivism.

**Induction:** build theory

Inductive approach is trying to construct theory by analysing collected data in order to be able to understand the nature of the problem better. The induction research designed would be to make sense of the data that had been collected by analysing them. The result of this analysis would be the formulation of a theory. That is, theory would follow data rather than vice versa as with deduction.

Research using an inductive approach is likely to be particularly concerned with the context in which such events were taking place. Therefore, the study of a small sample of subject might be more appropriate than a large number as with the deductive approach (Saunders, et al., 2009, p. 126).

**Deduction:** testing theory

Deduction involves the development of a theory that is subjected to a rigorous test. The dominant research approach in the natural sciences, where laws present the basics of explanation, all the anticipation of phenomena, predict their occurrence and therefore permit them to be controlled (Collis and Hussey in (Saunders, et al., 2009, p. 124)).

There are five sequential stages (Robson in (Saunders, et al., 2009, pp. 124-125)) through which deductive research will progress:

Stage 1: deducing a hypothesis from the theory;

Stage 2: expressing the hypothesis in operational terms, which propose a relationship between two specific concepts or variables;

Stage 3: testing this operational hypothesis;

Stage 4: examining the specific outcome of the inquire;

Stage 5: if necessary, modifying the theory in the light of the findings.

We have chosen deductive approach for our study, because nature of our study fits well with deduction major characteristics.
First, there is the search to explain causal relationships between variables. In our study, we wish to establish the relation between online reviews and downloading choices of mobile apps. After studying the characteristics of mobile apps characteristics and consumer consumption motivations, it occurs to us there seems to be different relationships between the online reviews and free vs. paid apps respective as well as hedonic vs. utilitarian apps respectively. Consequently, we break down our research questions in to more detailed levels and develop hypotheses that suggests that online reviews have more positively impact on downloading choice for paid apps than free apps and online reviews have more positively impact on downloading choice for utilitarian apps than hedonic apps.

Second, deduction approach is featured with quantitative data. To be able to test the proposed hypothesis, quantitative data must be collected. In our study, we collect online reviews for mobile apps based on certain categories as discussed in more detail in later sections.

Third, deduction approach is featured in using controls to allow the testing of hypothesis. These controls would help to ensure that any change in the dependent variable is a function of independent variables. In our study, we control the online review format limited only with the consideration of average rating scores from Google Play Android app market as we discuss later on.

Fourth, the concepts in deduction approach need to be operationalized in a way that enables facts to be measured quantitatively. In our study, it is possible for us to apply code-schema to map non-quantitative data to quantitative data. For instance, we use binary data to encode categorical variables like free/paid and hedonic/utilitarian.

Fifth, the principle of reductionism is being followed in deduction approach. In our study, we use Game app to reduce the complexity of defining hedonic apps and Productivity app to reduce the complexity of defining utilitarian apps. This holds that problem as a whole are better understood if they are reduced to the simplest and most straight forward possible elements.

Last but not least, the sixth characteristic of deduction is generalisation. In order to be able to generalise statistically about regularities in human social behaviour it is necessary to select samples of sufficient numerical size (Saunders, et al., 2009, p. 125). In our study, research is set on the sample data on Android apps available on Google Play. This would allow us only to make inferences about Android apps; it is arguable there might be dangerous to predict that the similar relationship online review and downloading choice also applied for Apple iOS apps.

### 4.1.3. Research strategy

Peeling away the research approach choice reveals the next layer of the onion strategy. This layer emphasises that researchers can use one or more strategies within their research design as they plan how to go about answering a research questions or addressing a research question (Saunders & Tosey, 2013). Since there are quite many different strategies, we only discuss the ones that we believe are most likely to be related to our study.
Survey

A survey could be useful for researchers in order to gather data for the study, and it has its own advantages, such as it provides data that easy to use for categorising and analysing. A survey might also enable researchers to collect data from a large amount of population in a rather short amount of time at a low cost (National Foundation for Educational Research, n.d.), (Sincero, 2012), (Kelley, et al., 2013)).

On the other hand, however, there are some disadvantages associated with survey that need to be taken into consideration. One disadvantage is that surveys are not good for open questions since interviewee generally do not want to write that much (National Foundation for Educational Research, n.d.). This means that researchers must be very specific when designing survey protocols. Another disadvantage with surveys is the fact that it can be difficult to get a high response rate (Kelley, et al., 2013), this is however crucial for getting reliable results.

In the case of our thesis project, time constraint is a bit impediment for us to carry out a survey type of study. It is difficult to get a high response rate for surveys made us looking into other means to collect the data needed to test our hypotheses. Otherwise, we might end up with too few responses meaning that we must find another way of collecting data or sending the survey to more people in hope of getting more responses. That would be too time-consuming for this short thesis project however.

Experiment

Experimental studies are one research method that falls under the category of quantitative research (USC Libraries, 2015) and when doing an experimental research, the researcher typically manipulates one or more variables, after which he or she controls and measures changes in other variables (Blakstad, 2008). Blakstad (2008) writes that when conducting an experiment, the independent variable is manipulated and the researcher measures changes in the dependent variable.

In our case, it could have been possible to test our hypothesis via an experiment by gathering a group of respondents and simulate how changes in online reviews would affect their willingness to download different apps. In fact, Schlosser (2011) made a similar approach when investigating whether including pros and cons can increase the helpfulness and persuasiveness of online reviews or not. For one of the studies in her paper, Schlosser (2011) let 201 undergraduates participate in an experiment where the participants read different reviews after which they completed a survey, where their attitude towards the product together purchase intention was measured. For our thesis project however, we find it less feasible to do this kind of research for different reasons. First, we find it to be quite time consuming meaning that it would be difficult to manage to conduct the study within the time frame for this thesis project. Secondly, it would be very difficult for us to find enough participants for such experiment in order to get reliable results. Schlosser (2011) for instance, let undergraduate students participate in exchange for partial completion of a course but we do not have similar opportunity to motivate people to
participate in the experiment. Therefore, based on time constraints and difficulties in getting enough participants for the experiment, we decide not to do an experiment in order to test our hypotheses.

Case study

As seen in Figure 7, case study is another kind of research strategy commonly used, and Yin (2014, p. 3) describes it as "one of the most challenging of all social science endeavours". A case study is used when one wants to study a contemporary phenomenon (which is referred to as the case) in its real-world context, especially in situations where the boundaries between phenomenon and context are not clearly evident (Yin, 2014, pp. 3-23). Saunders, Lewis and Thornhill write that this is the exact opposite of the experimental strategy where the research is conducted within a very controlled context. They also point out that the case study strategy differs from the survey strategy where the ability to explore and understand the context depends on the number of variables for which it is possible to collect data (Saunders, et al., 2009, p. 146).

Saunders, Lewis and Thornhill also emphasize that a case study often uses several different data collection techniques within the same study. As an example, a study might collect data by using semi-structured group interviews and the same study can make use of quantitative data that might have been collected using a questionnaire for instance (Saunders, et al., 2009, p. 147). For this thesis’s scope, it is feasible and sufficient to collect quantitative data with single simple approach.

Furthermore, we intend to look at the downloading of apps in a more generic level, and not only focusing on one kind of app or one company for instance, meaning that it can be argued whether a case study is really suitable for this thesis project. Yin claims that a case study might be particularly useful when the research questions require that some social phenomenon is described extensively and in-depth (2014, p. 4). In this thesis, we will investigate how online reviews affect the downloading decision for apps but we will not make an extensive research on the underlying reasons for our result. For that purpose, a case study might have been more suitable. Shuttleworth illustrates this is a good approach when he writes "...a statistical survey might show how much time people spend on talking on mobile phones, but it is case studies of a narrow group that will determine why this is so." (Shuttleworth, 2008).

In our study, we will not conduct a survey, but as described in later sections, we found that we have access to highly relevant historical data, which enables us to test different hypotheses by using statistical measures. Based on the discussion above, we intend to look for another research technique than a case study in order to conduct this study.

Archival Research

As described, several researchers have collected data from various online sources in order to study the effect of online reviews on product choice (e.g. (Chevalier & Mayzlin, 2006), (Duan, et al., 2008), (Liu, et al., 2012) and (Basuroy, et al., 2003)). Chevalier & Mayzlin (2006) for instance, gathered data on price, number of reviews, average rating scores and delivery time for different books, and then they analysed this data using regression analysis. Duan et al. (2008) made a similar approach when they collected data on movie sales and reviews, after which they used regression analysis in order to analyse the data. As many researchers have used the approach of
collecting historical data, which then has been analysed by using regression analysis, we believe this would be a suitable way for us to carry on the research as well. However, this way of conducting the research is associated with some weaknesses. In our case, we are limited by the data that is publically available, meaning that there is a risk that we might not be able to find the data we need to conduct the study. This means that what we can study partly depends on what data that is publically available.

As we will study the relationship between online peer reviews and the number of downloads for mobile apps, we need to find data on how many times certain apps have been downloaded, as well as data on the average rating score for these apps. Furthermore, as we intend to look at how online reviews affect the downloading decision for both free and paid apps respectively, we must be able to find data on whether the apps are free or paid. Finally, we need to be able to find data on hedonic and utilitarian apps respectively in order to test the third hypothesis, which suggests that *Average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps*. This means that the data available on different online sources can determine which hypothesis we can test which can be seen as a weakness. As for quantitative studies in general, it can also be difficult to quantify some of the data that might be interesting for the study (Choy, 2014). After browsing through the data available on different online sources (Google Play, App Annie, and Xyo.net), we concluded that we have access to the data we need to test our hypotheses. What data to collect and how to collect are described in more detail in later section.

At this point, we have concluded that we prefer to do our research based on historical data rather than other approaches due to the following main reasons:

1) The time constraints for this thesis project make us prefer collecting historical data, since we would otherwise risk not getting enough responses from a survey in the short amount of time. Due to time constraints and difficulties in getting enough participants, we also decide not to conduct an experiment.

2) After browsing through different online sources (Google Play, App Annie, and Xyo.net), we concluded that we can find the data we need to test our hypotheses, i.e. we have feasible access to the sufficient data we need.

3) Most papers that we have reviewed have used historical data to test the effect on online reviews on product choice (e.g. (Chevalier & Mayzlin, 2006), (Duan, et al., 2008), (Liu, et al., 2012) and (Basuroy, et al., 2003)) indicating that it is a common way to conduct this type of study.

It is worth mentioning however, that if we would like to consider socio-demographic differences when investigating the effect of online reviews on the number of downloaded apps, it is likely that we would need to use another approach to conduct the study and in that case, a survey might have been more useful. However, looking into socio-demographic differences is beyond the scope of this thesis project.

4.1.4. Research time horizon
The final layer of the research onion, before reaching the core, highlights the time horizon over which the researcher undertakes the research. Where research is undertaken to answer a question or address a problem at a particular time this ‘snapshot’ is **cross-sectional** and is likely to make
sure use of strategies such as a survey or case study (Saunders & Tosey, 2013). Conversely, where answering the question or addressing the problem necessitates data being selected for an extended period of time, the research is longitudinal, being likely to make particular use of strategies such as an experiment, action research, grounded theory and archival research (Saunders & Tosey, 2013). Our study is focusing on entire mobile apps life cycle as consumable goods, that is, the data of mobile apps is collected since the first day it launched on to the app market until the time point we fetch it. In this sense, it falls in to the category of longitudinal research.

4.1.5. Research techniques and procedures
Qualitative and quantitative research are two research techniques for data collection widely used and they differ in nature (e.g. (USC Libraries, 2015), (Choy, 2014)) as will be described.

Qualitative research
A qualitative study does not use any statistical measures and does not try to quantify anything. Instead, it helps understanding the perspectives and motivations by other people (Health Research Authority, n.d.), and it also attempts to describe, as well as interpret, human behaviour by primarily focusing on what selected individuals say (USC Libraries 2, 2015). Besides, qualitative studies often give ideas about how to formulate hypotheses, which then can be tested using other methods, and qualitative techniques are useful when the subject researched is too difficult to answer by a yes or no hypothesis (Shuttleworth2, 2008). When doing a qualitative study, several different approaches can be used, and interviews, focus groups, as well as observations are normal techniques used to collect the data needed for the study ( (Health Research Authority, n.d.), (National Foundation for Educational Research, n.d.)).

Quantitative research
Quantitative research is a common research technique used in social sciences, and it is seen as the opposite of qualitative research ( (Choy, 2014), (Shuttleworth, 2008)). A quantitative study uses statistical methods to test hypotheses (Shuttleworth, 2008) and it is used to test the relationship between an independent variable and a dependent variable (USC Libraries, 2015). This means that the data used is in form of numbers and statistics, and not in textual form (USC Libraries, 2015) as it tends to be for qualitative studies. There are different ways to collect data for a quantitative study, and surveys where people fill in a questionnaire is a common way to collect data (National Foundation for Educational Research, n.d.). There are however other ways than surveys to collect quantitative data. Chevalier et al. (2006) for instance, collected data on price, number of reviews, delivery time, and average rating score from two different online sources when they examined which impact consumer reviews had on the relative sales for books at Amazon.com and Barnesandnoble.com. Furthermore, Duan et al. (2008) collected data from three different online sources when they studied the importance of online user reviews on box office performance for movies.

Once we have described the two major techniques (qualitative and quantitative research) we need to decide which one to use in for our study. In that sense, we notice that the studies we have seen that relate online reviews to product choice have all used a quantitative approach (e.g. (Floyd, et
al., 2014), (Liu, et al., 2012), (Chevalier & Mayzlin, 2006), (Duan, et al., 2008) and (Basuroy, et al., 2003)). In chapter 3, we presented the following hypothesis:

**H1:** Average online peer review rating score of mobile apps is positively related to the number of downloads.

**H2:** Average online peer review rating score matters more for the number of downloads of paid apps than free apps.

**H3:** Average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps.

As our study aims at either proving or disproving these hypotheses, a quantitative study is suitable (Shuttleworth, 2008). As previously mentioned, a quantitative study can be used to describe the relationship between an independent variable a dependent variable (USC Libraries, 2015). In earlier chapters, we explained that we will study the relationship between the number of downloads (which can be seen as the dependent variable) and the average rating scores for different apps (which can be seen as the independent variable). Based on this, we decide to conduct a quantitative study in order to answer our research questions and test our hypotheses.

Once we have decided to do a quantitative study, we must decide how do construct the study. There are several ways of conducting a quantitative study, and surveys, where the respondents fill in a questionnaire is one way to collect data (National Foundation for Educational Research, n.d.). In their study, Hsu et al. (2015) conducted a survey when they investigated what factors that drive the purchase intention for paid mobile apps. Furthermore, Jiménez & Mendoza (2013) also conducted a survey when the investigated the relationship between online reviews and the purchase intention of search and experience goods. We notice however that other researchers (e.g. (Chevalier & Mayzlin, 2006), (Duan, et al., 2008), (Liu, et al., 2012) and (Basuroy, et al., 2003)) collected data in form of statistics from different online sources when investigating the relationship between product decision and online product reviews.

As we have decided to conduct a quantitative study based on historical data that is publically available online, we must now decide how to use this data and how we intend to analyse it. In the following sections, we describe what data to collect, and which sources we use. Thereafter, we describe how to analyse the data and which models we use. Then we test our hypothesis and discuss the results.
5. Data collection

5.1. Sample

Android, iOS, and Windows Mobile are the leading smart-phone operating system providers in the mobile app market and each of these host their own marketplace where the customers can download apps (Google Play for Android, Apple App Store for iOS and Windows Phone Store for Windows Mobile) (Hsu & Lin, 2015). Google Play is the largest market place for apps when just considering the number of apps available for download. In July 2014, Google Play had about 1.3 million apps available for downloads, whereas Apple App Store is close behind with approximately 1.2 million apps available (Statista, 2015). Then there is a big gap down to Windows Phone Store who has about 0.3 million apps available for download, showing that Google Play and Apple App Store are the major platforms when it comes to market places for downloading apps (Statista, 2015). Furthermore, analysts forecast that in 2017, 90% of the app downloads will be made from either Apple App Store or Google Play (Rivera & van der Meulen, 2013).

Since Apple App Store and Google Play are the major app stores in the market, the initial idea was to perform this study based on data from these two stores. However, Apple App Store is more conservative than Google Play when it comes to publishing product- and user-information. Furthermore, Apple is more restrict when it comes to allowing access from a third party software agent to fetch such data from their App Store. On top of that, we have access to more reliable data for Google Play than Apple App Store, which is described further in the text. Therefore, we decide to perform our study based on Android apps published on Google Play, since it allows us to collect sufficient data.

![Figure 8 Number of available apps in the leading app stores in July 2014 (Statista, 2015)](image-url)
5.2. Data source collections

5.2.1. Data source for average ratings and initial release date

As mentioned earlier, this study will be based on Android apps available on Google Play. Google Play present data on average ratings for each app, as well as an interval of how many times an app has been downloaded (e.g. 100,000-500,000 times). App Annie is an online business intelligence and analysis platform that fetches data from Google Play and presents it online. This means that App Annie also presents the average rating score and an interval on how many times an app has been downloaded (e.g. 100,000-500,000 times). However, we noticed that App Annie also presents data on when each app was initially released, and we could not find this information on Google Play. It can be assumed that the time an app has been available on the market will impact on the number of downloads. For instance, assume that an app was released on Google Play two days ago and that it has a very high average rating score. In this case, it is unlikely that it has been downloaded to any greater extent, regardless of its high average rating score, since it has been on the market for such short amount of time.

We also noticed that Google Play presents the information about the apps in a rather discrete way and there is a lack of an index of apps. Besides, Google Play refers direct to the local market based on IP address of the machine that visits the site. Since our researchers are located in Sweden, this means that when we visit Google Play from our computers, we will automatically be directed to the Swedish version of Google Play, and several of the apps listed as popular will be aiming for the Swedish market. As an example, the app *SVT Play* is listed as one of the most popular apps for entertaining, and that app enables users to watch TV-shows broadcasted by SVT (which is a Swedish television channel) online. The United States is the country with the highest number of app downloads, and in the second quarter 2014, 18% of all the app downloads in the world were made in the United States (Statista2, 2015). China was the country with the second highest number of app downloads, and they accounted for 10% of the global app downloads (Statista2, 2015). This data is based on the total amount of app downloads for all platforms, but if we only look at Google Play, we see that the United States is still the country with the highest number of app downloads (App Annie, 2015). Considering the needs of the amount of review data to perform the study, we believe the United States’ app market is more suitable for our study due to its popularity, coverage and maturity. In that sense, App Annie is well suited for our study, as it enables the user to filter for top apps on Google Play based on country, meaning that it is possible to filter for apps on the United States’ market.

Based on the discussion above, we decided to collect data on average rating from App Annie rather than Google Play. To summarize the discussion above, App Annie was chosen over Google Play for the following reasons:

1) App Annie publishes information on initial release date for each app, which Google Play does not.

2) App Annie enables us to filter for apps in the United States’ app market, which is not possible on Google Play.
5.2.2. Data source for number of downloads

In order to test the hypothesis presented in chapter 3, we do not only need data on average rating scores, but we also need data on how many times an app has been downloaded. One limitation with the free access data from App Annie (which is the same limitation as on Google Play), is that the data on how many times an app has been downloaded is only presented in a range. The game app *Dark Of The Demons* for instance, has been downloaded in the range of 100,000–500,000 times, whereas *Gold Fish Casino Slots* has been downloaded in the range of 1,000,000–5,000,000 times. Google does not review the actual number of downloads and sales revenue for the apps purchased through Google Play due to competitive reasons (Liu, et al., 2012). The large differences of download levels between different apps make us feel it is not sufficient to get accurate result by only using the range to represent actual downloading values. With the limitation of research budget, it is not an option for us to buy data on downloading numbers from various firms doing app analysis for considerable amount apps in the scope of this study. Therefore, we decide to turn for another free source (Xyo.net) to fetch apps downloads numbers, which is described further below.

Xyologic Mobile Analysis GmbH is a Germany based company providing an online platform (Xyo.net) which contains information on Android apps supplementary for Google Play, including the estimated numbers of download for particular apps. In fact, Xyo.net is the only source that we could find that presents estimated number of downloads for different apps for free. It is also worth mentioning that Tech Crunch, which is a news website focusing on IT companies, refers to the reports by Xyologic as a “treasure trove” which they recommended to people within the mobile industry (Perez, 2011). Furthermore, other researchers (e.g. (Corral, et al., 2012) and (de Pablos-Heredero, et al., 2012)) have referred to data from Xyologic which makes us believe that it is a reliable data source. Therefore, we decide to collect data on the estimated number of Android apps downloads from Xyo.net. It should also be pointed out that Xyo.net also indicates that their download estimates are better for Android (Google) than for iPhone (Apple) (Xyologic - Quality of Our App Download Estimates, 2011). In fact they write that their download estimates of individual apps are “very good” for Android, and “good” for iPhone and iPad (Xyologic - Quality of Our App Download Estimates, 2011). We will also test the reliability of the estimated number of downloads on Xyo.net, by making sure that the figure fall into the range on the number of downloads given from App Annie.

In order to apply our study to cover billions of apps on a normalized level, we think it is good to take the most representative app categories as the sample settings. As discussed in previous chapters about current taxonomy of mobile apps, the hedonic and utilitarian perspective is considered in this study for categorizing mobile apps into two groups respectively. Within each group, referring to the market share distribution, we have selected the most representative presentation of such type in the context of mobile apps type. “Game” is selected to represent hedonic group, while as “Productivity” is selected to represent utilitarian group.

5.3. Sample size and data collection process

The previous section describes that the data used for the analysis will be collected from App Annie and Xyo.net. Next step is now to decide for how many apps data shall be collected, as well as how to decide which apps to collect data for.
As discussed in previous chapters about current taxonomy of mobile apps, the hedonic and utilitarian perspective is considered in this study for categorizing mobile apps into two groups respectively. In order to conduct the study, we have selected gaming apps to represent hedonic products, and productivity apps to represent utilitarian products and this has been discussed in more detail earlier. Therefore, we need to be able to classify apps into “games” or “productivity” respectively. This is easily done using App Annie as they have (just as Google Play has) classified apps into different categories, such as games and productivity which are the important ones in our study. Therefore, we will use the same classifications as App Annie whether an app should be considered as a gaming app, or a productivity app.

Once that has been established, it must be decided which productivity and which gaming apps to use in our study. As previously mentioned, there are over a billion apps available on Google Play (Statista, 2015) and we have no way to collect and analyse data for all apps, which obviously would have been the ideal situation. Since there are so many apps available, just choosing apps randomly for our study might not be a good idea, because it is then likely that the apps have not been downloaded at all, or very few times and we might not get access to data for the apps that have been randomly chosen. Chevalier et al. (2006) made a similar reasoning when they decided also to collect data on books appearing in Publisher Weekly best-seller list. In order to handle this in our case, App Annie offers a good opportunity as it enables us to list the top 500 apps on Google Play in each category (games and productivity in this case) for the United States’ market, and it is possible to filter for free and paid apps separately. It should also be pointed out that just because an app is available on the top 500 list, does not mean that it has a high rating score, or that it has been downloaded several times. As an example, an app on place 10 in the list, might have a lower rating, and have been downloaded fewer times than an app on place 50 for instance. Therefore, to begin with, we decided to collect data on 1) 500 free Gaming apps, 2) 500 paid Gaming apps, 3) 500 free productivity apps, and 4) 500 paid productivity apps. This means that we will start by collecting data on 2,000 apps in total. We have noticed that Google Play and App Annie define free apps as apps that are free to download, regardless if they offer in-app purchases or not, and paid apps are apps where the user pay per download. Therefore, we will use the same definition when we collect the data.

In chapter 3, we presented the following hypotheses:

\( H1: \) Average online peer review rating score of mobile apps is positively related to the number of downloads.

\( H2: \) Average online peer review rating score matters more for the number of downloads of paid apps than free apps.

\( H3: \) Average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps.

In order to test these hypotheses, the following data is needed:

1) Number of downloads (collected from Xyo.net)

2) Average rating score (collected from App Annie)

3) Initial release date (collected from App Annie). This information will be used as a control variable in the analysis.
4) Interval for number of downloads on App Annie. This information will be used to assure that data on number of downloads from Xyo.net is within this interval.

5) Whether the app is a free app or a paid app (this information was collected from App Annie).

6) Information on whether it is a gaming app or a productivity app (this information was collected from App Annie).

As mentioned, we started by collecting data for 500 free Game apps, 500 paid Game apps, 500 free Productivity apps, and 500 paid Productivity apps. Next step was to compare the number of downloads obtained from Xyo.net with the download interval available on App Annie, and exclude those apps where the number of downloads was not within interval. This was made in order to increase the validity of the data used in our study. After excluding apps where the downloading number on Xyo.net was outside the interval on App Annie, 268 free gaming apps, 301 paid gaming apps, 310 free productivity apps, and 281 paid productivity apps remained, and this is illustrated in Table 1.

<table>
<thead>
<tr>
<th>Mobile Apps</th>
<th>Free</th>
<th>Paid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Game</td>
<td>268</td>
<td>301</td>
</tr>
<tr>
<td>Productivity</td>
<td>310</td>
<td>281</td>
</tr>
</tbody>
</table>
6. Data Analysis

6.1. Model design
Regression analysis is a method that is frequently used to analyse data and Keat et al. writes that “Regression analysis is perhaps the most widely used statistical tool for the analysis of empirical data in economics and business” (2014, p. 155). They also point out that regression analysis is widely used to analyse data across other academic disciplines (Keat, et al., 2014, p. 155). A regression analysis enables us to study how one variable (the dependent variable) is related to several other variables (so called independent variables) (Keat, et al., 2014, pp. 143-158). In order to test the hypotheses stated in chapter 3, we need to construct a model that relates the average rating score to the number of downloads. Since we have access to plenty of historical data, which we collected from xyo.net and appannie.com as previously described, combined with the fact that we want to study how the average rating scores affect the number of downloads, we choose to do a regression analysis to test our hypotheses.

As mentioned, we have proposed that the average rating score will influence the number of times an app has been downloaded. However, it is likely that there are other factors that affect the number of downloads, and these factors should also be included in the regression model (Keat, et al., 2014, p. 144). The zero price effect discussed earlier says that the demand for a good is much greater when the price is zero compared to when it is slightly greater than zero (Shampanier, et al., 2007). Therefore, it can be assumed that whether an app is free or paid will affect how many times it is downloaded. Furthermore, it is likely that whether the app belongs to the hedonic or utilitarian category will affect how many times it is downloaded. For instance, we have seen that gaming apps (which we have shown can be said to belong to the hedonic category) is by far the most popular app category, and in 2013, 74% of all downloaded apps was for gaming apps (Digi-Capital, 2014). It can also be assumed that the time an app has been available will influence how many times it has been downloaded as previously discussed. Based on this, we construct the following regression model to test our hypothesis, and the variables are described below:

\[
\ln(\text{numOfDownloads}) = \beta_0 + \beta_1 \times \ln(\text{avgRatingScore}) + \beta_2 \times d_{\text{Paid}} + \beta_3 \\
\times \text{paid_avgRating} + \beta_4 \times d_{\text{Hedonic}} + \beta_5 \\
\times \text{hedonic_avgRating} + \beta_6 \times \ln(\text{monthAvailable})
\] (eq. 1)

Where:

\(\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6\) = regression coefficients

\(\text{numOfDownloads}\) = How many times the app has been downloaded according to Xyo.net.

\(\text{avgRatingScore}\) = average rating scores from App Annie (takes a value between 1 and 5, where 1 is the lowest/worst, and 5 is the highest/best).

\(d_{\text{Paid}}\) = dummy variable that takes the value 1 if the app is a paid app, and 0 if the app is free. This variable is introduced as it can be assumed that whether the app is free or paid will affect how many times it has been downloaded.
**paidAvgRating** = \(d_{paid} \times \ln(\text{avgRatingScore})\); This interaction term is used to test whether the average rating scores has a different impact on the number of downloads for paid apps and free apps, i.e. to test hypothesis 2.

\(d_{\text{Hedonic}}\) = dummy variable that takes the value 1 if the app belongs to the hedonic category (which is gaming apps in this study), and the value 0 if the app belongs to the utilitarian category (which is represented by productivity apps in this study). This variable is introduced as it can be assumed that whether the app belongs to the hedonic or utilitarian category will affect how many times it has been downloaded.

**hedonicAvgRating** = \(d_{\text{Hedonic}} \times \ln(\text{avgRatingScore})\); This interaction term is used to test whether the average rating scores has a different impact on the number of downloads for hedonic apps and utilitarian apps, i.e. to test hypothesis 3.

**monthAvailable** = the number of months the app has been on the market since the initial release. This control variable is introduced as we assume the longer an app has been on the market

As seen from eq. 1, we use the natural logarithm of each value instead of the actual value. After having collected the data, we noticed that the number of downloads had a skew distribution, and by taking the natural logarithm of the dependent variable (numOfDownloads), we noticed that the dependent variable became more normally distributed. Furthermore, by taking the natural logarithm of both sides of the equation in eq.1 it becomes easier to interpret the results. Chevalier et al. (2006) write: “The reason for the log specification rather than levels is that the log specification estimates the effect of a change in the independent variables on the percentage change in the dependent variable” (Chevalier & Mayzlin, 2006). In order to clarify this, let us assume that Y is the dependent variable, and X is the independent variable towards Y. By taking the natural logarithm of the dependent variable, and the independent variable, i.e. ln(Y) and ln(X), means that a 1% change in X, would lead in a \(\beta\)% change in Y where \(\beta\) is the regression coefficient (Kephart, 2013).

### 6.2. Model result

After collecting the data and constructing the model according to equation 1, we ran a multivariate linear regression analysis using Microsoft Excel in order to test the hypotheses stated in chapter 3. The results are presented in Table 2.

Goodness-of-Fit measures from Table 2 shows our proposed linear equation fits very well with our sample data. Firstly, the correlation coefficient Multiple R = 0.894794085 has indicated this linear relationship in the model is quite strong. Then, adjusted R square = 0.799619108 shows about 80% of the values fit the model. Last but not least, it is worth to mention that the Standard Error of Regression in this model shows that the average distance of the data points from the fitted line is about 1.38, which is quite narrow. This further confirms that the precision of adjusted R square value. From ANOVA result, since Significance F is much smaller than F value, we can conclude the entire regression is statistically significant.

As seen from the regression analysis, **hedonicAvgRating** is the only variable in the model with its coefficient not passing the t-test. Furthermore, it is also not statistically significant on 0.05 or 0.10 level. In the next section we will take further analysis on each component level.
Table 3 Regression result output

**REGRESSION RESULT OUTPUT**

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**ANOVA**

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<table>
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6.3. Model analysis

In this section, we analysis the result from each hypothesis testing, and also the potential reasons causing such results will be discussed.

6.3.1. Hypothesis I (H1) testing

We create Table 4 to map our research model together with its linear regression results. From Table 4, we can see that $\beta_1 = 4.777151693$ has passed the $t$-test and its $P$-value is statistically significant on the 0.05 level. Hereby, we can be confident that the $\ln(\text{avgRatingScore})$ truly has an impact on the dependent variable $\ln(\text{numOfDownloads})$. Since the slope of $\beta_1$ shows an up-going trend, we can get, on the nature logarithm level, average of rating score is positively linear related to the number of downloads. That is, the higher average rating score is, the more the app is downloaded. Since average of rating score in our research is the physical presentation of online peer review ratings of use value for mobile apps, we can conduct that our hypothesis $H_1$: Average online peer review rating score of mobile apps is positively related to the number of downloads is proven to be valid.

Table 4 Model mapped regression results

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model coefficients</th>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t-stat</th>
<th>p-value</th>
<th>lower 95%</th>
<th>upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>$\beta_0$</td>
<td>3.866425936</td>
<td>1.08244436</td>
<td>3.571939405</td>
<td>0.00036896</td>
<td>1.742644421</td>
<td>5.990207451</td>
</tr>
<tr>
<td>ln(avgRatingScore)</td>
<td>$\beta_1$</td>
<td>4.777151693</td>
<td>0.770223612</td>
<td>6.202291933</td>
<td>7.74129E-10</td>
<td>3.2659548</td>
<td>6.288348586</td>
</tr>
<tr>
<td>d_Paid</td>
<td>$\beta_2$</td>
<td>-2.284886654</td>
<td>1.338124355</td>
<td>-1.707529383</td>
<td>0.087992908</td>
<td>-4.910318199</td>
<td>0.340544891</td>
</tr>
<tr>
<td>paid_avgRating</td>
<td>$\beta_3$</td>
<td>-2.052486846</td>
<td>0.938044597</td>
<td>-2.188048256</td>
<td>0.02886625</td>
<td>-3.892952471</td>
<td>-0.21202122</td>
</tr>
<tr>
<td>d_Hedonic</td>
<td>$\beta_4$</td>
<td>4.165478899</td>
<td>1.385479226</td>
<td>3.0065257</td>
<td>0.002669976</td>
<td>1.447135979</td>
<td>6.883821818</td>
</tr>
<tr>
<td>hedonic_avgRating</td>
<td>$\beta_5$</td>
<td>-1.026981976</td>
<td>0.970001278</td>
<td>-1.05874291</td>
<td>0.28993863</td>
<td>-2.930147363</td>
<td>0.876183411</td>
</tr>
<tr>
<td>ln(monthsAvailable)</td>
<td>$\beta_6$</td>
<td>1.041516302</td>
<td>0.064349737</td>
<td>16.18524577</td>
<td>2.99051E-53</td>
<td>0.915260601</td>
<td>1.167772003</td>
</tr>
</tbody>
</table>
6.3.2. Hypothesis I (H1) result analysis

The result from our test of H1 shows there is a positive relation between average online peer review ratings and number of downloads for mobile apps as we can see from previous section. This shows overall users do take the average score number into account before they decide to download certain apps. This implies that relatively high rating score provide positive product information reference to attract potential consumers to become real consumers. The high rating score among high downloads numbers lift the trustworthy degree of such app. With the recommendation from the majority consumers of certain app, the new consumers more likely enjoy the experience of it as well and therefore express their satisfying experience through rating positive score.

Using the literature we have studied of past research, we can analyse the root reason behind this relationship. Past research suggested that in information intensive environment, “consumer may seek other’s opinions as a means of managing the perceived risk typically associated with cognitively demanding tasks” (Dowling & Staelin in (Smith, et al., 2005)). Among billion apps available on the mobile apps market, to find out which one is worth to download for one own purpose is like locating a sailing boat on Pacific Ocean without GPS, almost impossible. Although there are different kinds of filters provided by app store to help consumers narrowing down the selection scope, there are still quite a lot of choices within the same categories. By looking at our sample data, it is easy to find more than 500 Game apps as well as similar amount of Productivity apps. Within such massive choice available, naturally, it is reasonable for users to look for others’ opinion as reference for help. Average ratings can be seen the most straight-forward illustrated word-of-mouth format for mobile apps. Also comparing luxury consumption, product involvement for mobile apps is relatively low. This will not drive consumers to spend large amount energy checking and evaluating all possible formats of other user generated content, that is, average rating score is simple but good enough.

There are also studies showing that information provided by others is the only or predominant source of pre-purchase information use by consumers (Beatty & Smith, Olshavsky & Granbois in (Smith, et al., 2005)). As for each single app, app markets like Google Play and Apple App Store provided every simple and limited “store space” (basically one web page no matter accessed from mobile devices or PC). Consequently, this leans the available information can be present for that app is limited. Taking Candy Crash Saga from Google Play for example, in Figure 9, reviews take equality big amount of weight in presenting the product information besides Description and others. In Reviews, average rating score takes eye-catching weight.
Last but not least, as we discuss and compare word-of-mouth information and marketer-provided attribute information or advertisements in previous chapter literature discussion. It is applicable for mobile app consumers to lean to rely more on using the information provided by others experiences.
6.3.3. Hypothesis II (H2) testing

$\beta_2 = -2.28486654$ and $\beta_3 = -2.052486846$ have passed the $t$-test and the $P$-value for $\beta_2$ is statistically significant on the 0.10 level, whereas the $P$-value for $\beta_3$ is statistically significant on the 0.05 level. This shows that both free and paid apps respectively have an influence on the download numbers. The value of $\beta_2$ shows that intercept shifter of the slope of the relation between average rating score and number of downloads. The linear trend of average rating score for paid apps is generally lower related to the number of downloads compared to paid apps. This shows that the average rating score for paid app downloads is less steep compared to the average score of ratings for free apps. The value of $\beta_3$ implies that the average rating score is a weaker influential factor of mobile apps downloads numbers for paid apps than for free apps. Therefore, from this result we can tell that paid apps and free apps have variant impact on the number of downloads, and users’ average rating scores have different influential weight for paid apps download and free apps download. More precisely, user average rating scores have less positive influence on paid apps compared to free apps.

This finding shows opposite conclusion from what we proposed in $H2$: *Average online peer review rating score matters more for the number of downloads of paid apps than free apps.*

Hence, we hereby reject H2 and conclude that *average online peer review rating score is more positively related to the number of downloads for free apps than for paid apps.*

6.3.4. Hypothesis II (H2) result analysis

Normally, people would easily guess that consumers rely more on other experience feedback as evaluation reference for monetary cost goods than free ones, when making purchasing decision. For free products, it feels anyway no harm to obtain it. However, the result we got from this study in fact rejects such assumptions. The possible reasons for leading this result can be following:

Firstly, because paid apps cost money, it is likely that people who purchase them take more things into consideration before taking the purchase decision compared to the people who purchase the free apps. With such consideration, they may seek additional channel to acquire product information, like asking people in his social network, i.e. family, friends, colleague for suggestions and experience feedback, in this case, WOM from inner circle takes most valuable weight when referenced as product information input for decision making, compared to the public eWOM information.

Secondly, as we discussed the free and paid mobile apps market characteristics earlier, we have learned free apps grow rapidly and download count vice even exceed paid apps in percentage, referred to Figure 5. One of the reason for causing this is that many paid apps offered Freemium version for the same app with limited scope of offered features (Liu, et al., 2012). In this case, we can assume that many paid apps users have already tried out with the free version of wanted app and experience it by themselves before they move on deciding to pay for it. With the ability to access the product with own experience, it is likely consumers care less about overall how others’ experience about it, because he or she has the possibility to judge whether is good or not from his or her own experience.
Last but not least, although there is no monetary cost involved in purchasing a free app, the transaction cost cannot be ignored. Downloading, trying it out, deleting it and downloading another app is typically the cycle of how user getting a free app without much pre-study before performing the download. This process requires time, energy and even emotions. As in a fast-pace modern society, it is not surprising that the majority of the app users want to get an app that ultimately match their purpose even if it is free. Reviews and particular average rating scores is the easiest and simplest way to help form the quick first impression of such app. Therefore, it is worth, and in fact efficient, to refer the average rating scores when deciding to download such app or not, which most free app downloaders do invest their time on.

6.3.5. Hypothesis III (H3) testing

$\beta_4 = 4.165478899$ passes the $t$-test and is statistical significant on a 0.05 level. This shows that hedonic type and utilitarian type have different impact on the apps downloading numbers respectively. Hedonic apps are more positively related with downloads numbers than utilitarian apps, meaning that mobile users download more apps for hedonic purpose than utilitarian purpose. The value of $\beta_4$ also implies the intercept shifter of the slope of the relation between average rating score and number of downloads. The linear trend of average rating score for hedonic apps is generally higher related to the number of downloads compared to hedonic apps. This shows that the average rating score for hedonic app downloads is steeper, compared to the average score of ratings for utilitarian apps.

However, when it comes the user average rating scores’ influence on downloads on this two types respectively, the finding is exceptional. $\beta_5 = -1.026981976$ does not pass the $t$-test, and also its P-value shows the variable is not statistically significant at a 0.05 or a 0.10 level. The negative $\beta_5$ coefficient suggests that average rating scores have a greater impact on utilitarian apps than hedonic apps, but as the findings is not statistically significant, we cannot be sure that is the case. This means that although we know there is a different relation to download numbers from hedonic apps and utilitarian apps respectively, we cannot get the influential weight difference of users’ average rating scores for download numbers of hedonic apps compared to utilitarian apps. Therefore, we cannot conduct to support or reject H3.

6.3.6. Hypothesis III (H3) result analysis

One possible reason for not getting significant result for this variable that we could think of is the limitation of our sample data. We choose gaming apps to represent hedonic category and productivity apps to represent utilitarian category. It might be useful to select a few more types for hedonic and utilitarian category respectively, because with the data setting for this study, it can be argued that we do not test hedonic vs. utilitarian products, but rather just gaming apps vs. productivity apps. By choosing four app categories or even more to represent hedonic products, and equality categories to represent utilitarian products for instance, we might be able to test the influence of average rating score for hedonic vs. utilitarian respectively in a better way, as we have more apps representing each category.

Another possible (and plausible) explanation to why we do not get any statistically significant result when testing H3 might be that there is in fact no difference in how average rating score relates to the number of downloads for hedonic and utilitarian apps respectively.
Finally yet importantly, we notice that the $\beta_k$ value shows the number of month an app has been on the market is also significantly positive related to app download numbers. This means that the longer an app has been on the market, the more times it might be downloaded as we predicted earlier.

6.4. Discussion

The purpose of this study has been to investigate how online peer review rating scores affect the decision to download a mobile app, and we have considered both free and paid apps, as well as gaming apps and productivity apps, which has been chosen to represent hedonic and utilitarian products respectively. In order to carry out the research, data on 1160 apps available on Google Play was collected. More specifically, data regarding average app rating score, number of downloads, price, and initial release day was collected for apps available on the United States’ market. Based on existing literature on the topic of online product reviews, we formulated three hypotheses, and in order to test these, we ran a multivariate linear regression using Microsoft Excel, which generated interesting results as following.

Our first hypothesis suggested that the average online peer review rating score of mobile apps is positively related to the number of downloads. Our regression analysis suggests that this hypothesis is valid, i.e. a higher rating score is associated with a larger number of downloads. It is also important to mention that our finding is statistically significant. This finding is also consistent with the literature, which have studied the relationship between online reviews and the purchase decision for different products and found that higher ratings are related to higher sales. Chevalier et al. (2006) for instance who studied the impact of online reviews on book sales, concluded that higher average star rating results in higher sales, and Floyd et al. (2014) find that sales elasticity is significantly impacted by online product reviews. Furthermore, Hsu et al. (2015) concluded that app ratings had a direct impact on the intention to purchase paid apps.

Our study also shows that average rating score also impact the downloading decision for free apps. This result is interesting but not surprising, considering the fact that even if one downloads something for free, i.e. which does not cost money, it will still involve transaction cost such as time and energy. Therefore the user wants to minimize the risk of downloading an app the does not fulfil his or her needs or expectations. This means that even if the app is for free, making the downloading decision might be associated with different transaction costs. Furthermore, considering the large amount of apps available, it makes sense that the consumer uses other peoples’ opinions in order to navigate among all the apps available, before deciding which one to download. As previous studies for other products have shown that people take online peer ratings into consideration when purchasing a product (e.g. (Chevalier & Mayzlin, 2006) and (Hsu & Lin, 2015)), it can be assumed that they keep the same behaviour when deciding which free product to choose.

Our second hypothesis suggested that Average online peer review rating score matters more for the number of downloads of paid apps than free apps. Interestingly, our data analysis suggests that this is not true, i.e. that online peer ratings of use value is more positively related to the number of downloads for free apps than for paid apps which was a bit surprising to us. We have not seen much research that explores the difference in the impact of online reviews on free vs. paid products. However, Hsu et al. (2015) wrote that people are more willing to give free alternatives a try, which was one
of the main reasons to why we assumed that online peer rating scores have a greater impact on the download decision for paid apps than for free apps. One plausible reason to our finding is that people who download paid apps take more things than average rating score into consideration when downloading an app. They might have tried a free version of that particular app before for instance (if a free version is available) and then they might download the paid version in order to get some extra features. Then their choice to download is based more on personal experience. In general, it can be assumed that people care more about a product when they have to pay for it, and therefore they rely on more signals of product quality than just peer ratings before making their purchase decisions, which can be an explanation to our finding.

Furthermore, it is worth mentioning that we found evidence that people download free apps to a greater extent than paid apps, which is no surprise and it also supports the idea of the zero price effect as presented by Shampan’er and Ariely (2006). The results also reflect what Hsu et al. write, namely that people are more willing to give free alternatives a try (2015).

The last hypothesis we wanted to test was that Average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps. When we ran our regression analysis, we did not find any statistical significant results to either reject or support the hypothesis. One reason for why we do not get any statistical significant result could be the way we choose our sample data. As mentioned, we only consider two app categories, namely gaming apps and productivity apps, where we let gaming apps represent hedonic products, and productivity apps represent utilitarian apps. Even though it can be argued that these two categories represent hedonic and utilitarian products, there are also more apps that can be classified into these categories and those have not been consider. In earlier chapters for instance, we said that medical apps can also be classified as a utilitarian product for instance. In that sense, it might be fruitful to consider a few more app categories that can be classified as utilitarian or hedonic products and include them in the analysis. Another explanation to why we do not find any statistical significant proof to support or reject our hypothesis could also be that there is no general difference at all in how the number of downloads is affected by the online peer rating scores for hedonic and utilitarian apps.

Even if we do not find and statistical significant difference in how peer review rating scores affect the number of downloads, our regression analysis shows that hedonic apps are downloaded to a greater extent than utilitarian apps. This finding is not surprising since we have seen that gaming apps (which belongs to the hedonic category) is by far the most popular app category in terms of revenue (Digi-Capital, 2014) which makes it highly likely that it is the app category with the highest number of downloads.
7. Conclusions

This thesis has studied the impact of peer review rating scores on the number of downloads for mobile apps available on Google Play. In order to conduct the study, we started to review several scientific articles that studied the relationship between online reviews and product choice, and we studied the market for mobile apps as well. This helped us formulating the following research question:

**How do online reviews influence the downloading decision choice of mobile applications?**

we then divided this question into the following two research questions:

1) **How do online reviews influence the downloading decision choices of mobile applications in terms of free apps and paid apps?**

2) **How do online reviews influence the downloading decision choices of mobile applications in terms of apps own attributes and use motivation from consumer perspective?**

In order to be able to answer these research questions, we proposed the following three hypotheses based on the literature review:

**H1:** Average online peer review rating score of mobile apps is positively related to the number of downloads

**H2:** Average online peer review rating score matters more for the number of downloads of paid apps than free apps.

**H3:** Average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps.

After collecting data on 1160 apps belonging to the gaming and productivity category, we ran a multivariate linear regression in order to test our hypotheses. In this study, gaming apps was used to represent the hedonic category, whereas productivity apps represented the utilitarian category.

When analysing our regression result, we found that online peer review rating scores are positively related to the number of downloads (i.e. higher ratings leads to more downloads), and this was true for both free and paid apps. This means that the first hypothesis proved to be true. This finding is consistent with previous research that has studied the relationship between peer reviews and product choice which found that there is a positive relationship between the good reviews and the product choice (e.g. (Chevalier & Mayzlin, 2006), (Floyd, et al., 2014) and (Hsu & Lin, 2015)).

Furthermore, our regression analysis showed that online peer review ratings have a greater impact on the number of downloads for free apps than for paid apps which was surprising to us. This means that the second hypothesis proved to be false. A possible reason to this finding could be that when people have to give up money for an app they might tend to rely on more signals of product quality than just peer rating scores.

Finally, we did not manage to find any statistically significant evidence that online peer review ratings matter more for utilitarian apps than for hedonic apps, i.e. we could neither support, nor
reject the third hypothesis. One possible reason for this could be related to one of our research limitations which is the fact that we only use one app category to represent hedonic apps (gaming apps) and one app category to represent utilitarian apps (productivity apps). This issue is discussed further in section 5.2.

7.1. Practical implications
Our findings gives an understanding of how online peer review ratings affect the number of downloads for both free and paid mobile apps. This is interesting since it relates to how product reviews affect the product decision for free products, which is something contributed into such research domain. It shows that it is actually worth to study mobile apps particularly for the impact of online reviews on product choice since there are numerous free apps available. Our study also shows that there is a difference in how much influence that peer ratings has on free and paid apps respectively, where the result suggests that online peer ratings is more influential for the downloading decision for free apps than for paid apps.

7.2. Theoretical implications
On the theoretical level, our research suggests that online reviews have an influence on consumers’ product choice for free products. This extends the discussion about zero price effect. Although previous studies show that consumers may overreact on zero price product, our results show consumers do not just take it for granted. That is, price is not the one and only judgement condition for consumers to for their choice decision making; instead, reference from other consumption experience is taken into account.

Furthermore, the results from our study aligns with previous studies that have shown that online reviews have a positive impact on the purchase decision (e.g. (Chevalier & Mayzlin, 2006), (Floyd, et al., 2014) and (Hsu & Lin, 2015)). Interestingly however is that our study suggests that online reviews have a greater impact on free products than paid products. Additionally, we support that rating is a tangible resource to use for researching online reviews’ influence.

Last but not least, our study shows that hedonic apps are more positively related with downloads numbers than utilitarian apps, meaning that mobile users download more apps for hedonic purpose than utilitarian purpose. This provides a field evidence in mobile apps market about user preference motivation of consumption choice. It implies that the contemporary consumers of mobile apps have shifted their usage purpose gradually from utilitarian-centric over to more hedonic centric.

For managers and app developers, our findings show that there is a positive relationship between the average rating score and the number of downloads for apps, both for free and paid versions. Therefore, app developers shall encourage current and satisfied users to rate the app, and they could also use eventual positive ratings in their advertising.

7.3. Limitations
In this section, there are some limitations associated with our study will be discussed here. Firstly, due to limited access to data from some platforms, our study is solely based on Android apps available on Google Play, which means that we have excluded apps from Apple App Store, another major player in mobile app market. This means that the study does not cover all platforms for app downloads. It has been predicted that 90% of the app downloads in 2017 will
be made from either Google Play or Apple App Store (Rivera & van der Meulen, 2013). In that sense, it would be interesting for future researchers to study how online rating scores effect the number of downloads for iOS available on Apple App Store in order to get a more generic result. Including Apple App Store in the analysis would also be useful in order to discover potential differences between the influence of online reviews on the number of downloads for apps available on Google Play and Apple App Store respectively.

Secondly, the sample data collection we have chosen is limited within Game and Productivity type of apps. One may argue how well representative each of these categories stand for hedonic and utilitarian apps. Such limitation may potentially results insignificant result from our study about the evidence whether average online peer review rating score matters more for the number of downloads of utilitarian apps than hedonic apps, or the other way around, or if there is no difference.

Thirdly, as mention in data collection chapter, the researchable data of mobile apps with free access is quite limited. We collected data from the top 500 lists on Appannie.com, which might be a limitation to the data sample, as it might not allow for enough variance among the apps chosen for the study. It is important to notice however, that the data of apps on the top 500 list is still valid for studying. The top ranking apps are neither the most downloaded apps, nor the apps with the highest ratings. It is worth to mention there are outstanding other researchers also to use ranked list. For example, Chevalier et al. (2006) partly use books from the best-seller list in their study.

7.4. Future research suggestions
In our study, we have focused solely on online peer rating scores, apart from it, there are exiting other formats of review for mobile apps as well. One of the major alternative formats is the text review written by peers. The findings by Chevalier & Mayzlin (2006) suggest that customer read written reviews and not solely rely on rating scores for instance when making their purchase decision for books. With such inspiration, it would be interesting to discover how the written text reviews affect influence the downloading decision for apps. The suggestion for future researches here is to study the impact of written reviews on the downloading decision for mobile apps, and then study its importance compared to rating scores.

Except for peer reviews where reviews written by other consumers, there are also so called expert reviews where reviews made by a critic instead of a peer. Basuoy et al. (2003) made a study on the effect of critics’ reviews on box office performance for movies and they concluded that critics’ reviews could influence box office performance. When we did our study however, we noticed that it was not much critic reviews for mobile apps compared to other products, like movies. It will be interesting for future researchers to make a more thorough investigation of the source of critics’ reviews for mobile apps and their impact of on purchase decision.

Another interesting aspect on online reviews which thesis study can be extended to, is how socio-demographic differences influence the product choice. It would be interesting to see if there is a difference in how people value online reviews depending on age, gender, educational level, and country for instance. As an example, teens might take less consideration in online reviews than senior citizens, and future research can investigate if that is the case or not.
Additionally, throughout this thesis, our study scope focused on average rating scores. There are also data available for each level of consumers’ preferences. For example, on Google Play, besides the average rating, there are also data present separately for the ones has been rated 1 star, 2 star, 3 star, 4 star, and 5 star respectively. To look into different satisfaction levels reflected from this data, it will be interesting for future researchers to find out if there are any different impact of different level of ratings for mobile apps. Previous research has suggested that one-star reviews have a greater impact than five-star reviews on the purchase decision for books (Chevalier & Mayzlin, 2006), and it could be interesting to see if this holds for mobile apps as well.

Last but not least, it is worth to mention that our study is based on the fundamental level of mobile services, i.e. type of consumption, in the classification model proposed by Heinonen and Pura’s (2008). It will be interesting for future researchers to continue following this direction to explore how the online ratings or reviews impact on consumers’ download decision based on upper layer classification concept, that is, from different perspectives to categorize mobile apps.
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