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The role of product characteristics on mobile app demand

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Contents

Abstract

A major innovation formed by the introduction of the mobile internet has been the widespread adoption of mobile apps. Nowadays, it is becoming easier to develop and launch a compelling mobile app and mobile app developers have increasing opportunities to monetize such an app. Mobile phones, and thus mobile apps, are becoming a medium through which people can express themselves. Since mobile phone use has been increasing, it is crucial to understand the underlying drivers of user demand for mobile apps (Ghose & Han, 2014). This thesis uses publicly available data and provides a methodology to estimate the influence of product description characteristics on mobile app demand.

An ordinal logistic regression is used to examine the collected data. The results show that overall product description characteristics have a positive effect on mobile app demand. An increase in description length, number of pictures, average rating and age will lead to an increase in app demand. Moreover, number of ratings has a significant positive effect on app downloads. Five out of the seven hypotheses of this paper have been answered.

The study sheds light to brands and marketers on how to optimally allocate resources and how to advertise the product in order to increase firm's sales and relate to customers. Moreover, managers will gain insight on consumer preference and thus discover which product characteristics can give their brand a competitive advantage.

Introduction

More than a decade ago, mobile phones were used mainly for calling and messaging. Unlike today, it was common to see groups of children playing on the streets. Active people wrote their to-do tasks in agendas and diaries, and sports people tracked their daily performance using pen and paper. However, technology has been rapidly developing over the past ten years and so has the mobile phone. It is one of the few products that has gained global acceptance in a relatively short period of time (Barnes & Scornavacca, 2004). Phones have become indispensable for many consumers. They are no longer only a communication gadget, but also extend and express individuality and personality (Sultan & Rohm, 2005; Grant & O'Donohoe, 2007). The highly personalized nature of smartphones means that individuals decide what a smartphone means for themselves (Jung, 2014). Mobile applications are a way to differentiate and modify a smartphone by the individual's activity and social life (Tossell, Kortum, Shepard, Rahmati, & Zhong, 2012).

Mobile devices are changing the way people think and function in their daily lives. A smartphone is defined as a mobile phone, which has an operating system such as Android, Apple iOS or Windows Mobile (Taylor & Levin, 2014). In 2014, 327.6 million smartphones (72% of all mobile devices) were shipped globally (Mobile hardware statistics 2014, 2015).

The Internet has been increasingly used for roughly thirty years (Tanenbaum, 1996), especially in the first decade of the new millennium. However, this trend has been surpassed by the advent of mobile applications. New markets have been created through mobile apps. The smartphone offers Internet connectivity and lets users install mobile applications (Taylor & Levin, 2014). Mobile apps now offer such activities as playing games, monitoring one's health, and reading e-books. New applications emerge constantly, while wireless networks have become more available internationally. As a result usage time of mobile phones has been increasing (Garg & Telang, 2013).

At the same time, phone companies have been increasingly competing to capture the most market share with their product. This has helped the mobile phone industry evolve into a well-developed marketplace. Today, it is hard to imagine what a smartphone does not have.

Nevertheless, the race continues: every year giants such as Samsung and Apple introduce new models featuring new characteristics and apps.

Mobile apps are very engaging which increases customer appeal. Take for example Noom Coach, a Health and Fitness app. It can be opened more than 5 times a day to write down meals, activities, and access useful health articles. The usage of an app can be affected by many of its characteristics – reviews (negative/positive), amount of reminders, etc. Customers keep and use an app because they like how it performs, but they download an app by looking at the visual cues. Well-made visuals attract users by making a great first impression (Mobile Apps: What Consumers Really Need and Want, 2012).

The number of downloads represents the demand for a given app. However, data is limited as companies such as Android and Apple, unlike Amazon, do not provide publicly available data on the exact number of downloads of their apps. Nevertheless, similar to the example about Amazon given by Telang and Garg (2011), publicly available data such as the range of downloads will be used to represent demand.

Some research examined mobile app demand and the different characteristics that have an impact on app downloads. However, what lacks from the literature is the influence of word of mouth (WOM) on demand. Word of mouth has been considered a driver for consumer demand for experience goods (Katz & Lazarsfeld, 1955). Moreover, often WOM can have such a large effect on customers' actions that they choose to ignore their own signals and fully rely on information from others (Ellison & Fudenberg, 1995). Online review and rating systems provide consumers with feedback from other users, allowing them to learn more about product quality. Thus, WOM is particularly useful for experience goods such as mobile apps (Zhu & Zhang, 2006) and it is important to examine the effect of WOM on app demand in collaboration with other app characteristics.

There are very few papers that examine the relationship between different mobile app description characteristics, especially WOM, in the Android store and their influence of the app demand (downloads). A lot of papers look at the effect of online reviews on app demand (e.g. Ghose & Han, 2014; Racherla, Furner, & Babb, 2012) and the effect of average rating on rank of app downloads (Harman, Jia, & Zhang, 2012), but very few have looked at the effect of both

average rating and number of reviews on app demand (Pagano & Maalej, 2013). However, none of these papers give a complete analysis of the overall effect of WOM on app demand. In other words, none of these papers look at the effect of both valence and volume of WOM simultaneously on app demand. Chia, Yamamoto and Asokan (2012) find that users are more likely to rate an app which they have installed, meaning that there is a correlation between volume of WOM and demand. However, it is of interest to find if volume of ratings can be a predictor for a higher app demand. This thesis fills in a literature gap by presenting a unique combination of description characteristics of a mobile app that has not been used in any other paper so far. Some attributes have been included in Ghose and Han's (2014) paper, who estimate demand for mobile applications in a new economy. However, the authors do not examine the effect of volume of ratings on the demand of mobile apps. The current dissertation adds the element word of mouth, and especially the volume of ratings, which is considered to be highly relevant regarding their influence on consumer behavior. Moreover, an ordinal logit model is used as the method for testing the hypotheses, which has not been the choice of any other research with a similar topic. Thus, the main question is formulated as follows:

What effect do product description characteristics, especially the number of ratings, have on mobile app demand?

This study is beneficial to app developers and mobile companies to understand how different characteristics of the mobile app, specifically WOM, drive consumer behavior, engagement and loyalty. Also, it allows them to further develop the presentation of apps to users and to examine users' responses to in-app purchases and ads. Furthermore, a probable outcome is higher demand, thus, higher revenues, as well as the results will shed light to brands on how to optimally allocate resources. By understanding the importance of each product characteristic as well as how they complement each other, app developers can be assured of competitive advantage. Moreover, recommendations are provided on how to evaluate the performance of a certain mobile app, how marketers can advertise in order to increase firm's sales and at the same time relate to customers.

Mobile phones are widely used and represent a huge marketing research opportunity for marketers to reach and serve users (Baruçtu, 2007; Grant & O'Donohoe, 2007; Roach, 2009).

Marketing strategies can be applied after a comprehensive understanding of why and how consumers may want to take part in mobile marketing. Smartphones also attract users because of their add-on and personalization features (Muoio, 2009; Persaud & Azhar, 2012). Knowledge of consumer preferences towards mobile app features can help app developers and designers to improve the app characteristics and optimize the consumer's experience. Moreover, marketers can gain insight into consumer preference. Furthermore, analytics enhance advertisers' abilities to predict the popularity of apps and improve their merchandising, such as in-app ads and in-app purchases (Ghose & Han, 2014).

In order to answer the research question, this paper is structured as follows. In section two, past literature will be reviewed and the hypotheses of the paper will be presented. In section three, the data, its origin and its extraction will be revealed, together with a methodology for creating two ordered logit models. In the fourth section, the results will be analyzed and the hypotheses will be tested. Last but not least, in the fifth section, a conclusion of the paper will be drawn, including limitations, implications and further research possibilities.

Literature Review, Conceptual Framework and Hypotheses

In this section the paper is going to review the concepts of product attributes and characteristics, and consumer behavior, concentrating on mobile applications, and derive the hypothesis that follow from the research question.

Product attributes

Product attributes play a big role in consumer purchasing behavior. Several studies state that physical attributes of a product such as size and color influence how customers perceive it (Wheatley & Chiu, 1977). Cox (1962) and Gardner (1970), for example, find out that different colors of ice cream and shirts affect perceptions of flavor and product quality respectively. Thus, the physical appearance of a product creates the first impression of what it might deliver when consumed.

Mehrabian and Russell (1974) come up with a framework that analyzes the effects of a given environment on people's behavior in that environment (Ha & Lennon, 2010). The authors

call this framework the Stimulus Organism Response (SOR) paradigm, which states that internal states such as pleasure, arousal, and dominance are influenced by physical stimuli of the environment such as color. The internal states serve as intermediary variables that affect consumer responses (Mehrabian & Russell, 1974). Earlier studies find out that environmental stimuli in retail stores and Web sites evoke pleasure and arousal which, on the other hand, resulted in an increase in customer satisfaction and purchase behavior (Eroglu, Machleit, & Davis, 2003; Fiore, Jin, & Kim, 2005).

Moreover, internal stimuli can be influence by the physical appearance of the product such as layout. Ampuero and Vila (2006) investigate the role of packaging on consumer perception. Packaging is important because it is the first thing that a consumer sees before making a decision to purchase the product. Moreover, in an economy where self-service is leading, manufacturers have the complicated task to make the packaging so that it captures the potential buyers' attention before brand selection (McDaniel & Baker, 1997).

Packaging may be the most essential element for communicating the product's benefits because it reaches many potential buyers who are actively engaged with it when looking for information about the product (Ampuero & Vila, 2006). Thus, it is crucial to enhance characteristics such as texts and images, communicate the right product values and achieve an appropriate visual level (Nancarrow, Tiu Wright, & Brace, 1998).

Product attributes need careful attention as they form the first impression of the consumer. Same as products in the store, mobile applications have a set of product features and characteristics that influence users' perception of the app before downloading it.

Mobile app characteristics

Information technologies and mobile devices are a growing trend. The usage of mobile phones and tablets is rapidly increasing and there is a constant battle for market share between companies. However, mobile devices become even more attractive with the addition of personalized features such as mobile applications. As Wang, Liao and Yang (2013, p.13) state, the mobile app 'is a new ICT artifact'.

Specifically in the mobile technology context, several studies have used the perceived value concept in order to research the adoption and usage of mobile technologies. For example, Kim and Han (2009) investigate what drives the adoption of mobile data services and Kim, Chan and Gupta (2007) study what motivates the adoption of mobile internet. The findings confirm that customers' perceived value has an influence on its adoption and the customers' usage behavior (Wang, Liao, & Yang, 2013).

As part of their model, Wang et al. (2013) pay attention to functional value, which includes the 'utilitarian functions and services that a product can offer'. According to Tzeng (2011), the value of a product is captured by its attributes such as features which can bring utilitarian performance. Numerous scholars empirically find that there is a positive relationship between functional value and consumers' usage behavior of information systems or mobile services (Turel, Serenko, & Bontis, 2007; Cheng, Wang, Lin, & Vivek, 2009). Moreover, Wang et al. (2013) find evidence to support their hypothesis that functional value, thus product features, has a positive effect on the behavioral intention to use mobile applications.

Ghose and Han (2014) present a theory-based structural model which examines the effect of various mobile app characteristics and different categories on consumer demand for mobile applications. The authors present the first formal model app demand estimation which is based on observing consumers' app downloading behavior. In their model, Ghose and Han (2014) include attributes such as the presence of in-app purchases, number of apps by the same developer, number of previous versions, price etc. The results of the analysis show that app demand increases with the length of the description of the app, the number of pictures in the description, the number of days since the app has been launched, and the volume and valence of user reviews. On the other hand, the results show that app demand decreases with file size (Ghose & Han, 2014). Their research comes close to what this paper aims to find out. However, this paper aims to conduct a study only on the number of downloads of free mobile apps from two categories launched in the Google Play store examining only variables in the description of the mobile app.

Description

The description is one of the most crucial elements when trying to influence and increase the buyer's likelihood to purchase a product. Consumers usually look for a specific type of information and try to find it in the descriptive text. It is of interest to see if a longer description positively affects consumer behavior or if a shorter and more concise description is a better choice. Moreover, it is intriguing to see if there is a non-linear effect of the description length on the app demand.

Some research has been done on the length of journal texts, titles and abstracts. According to White and Hernandez (1991) a tendency of longer and more complex titles of articles in journals has arisen. Yitzhaki (1992, p.436) confirms that there is a trend towards longer texts and finds that there is also a movement 'towards more 'significant' words in titles of papers' in various types of journals for the period of 1940 to 1990. Moreover, in a more recent paper, Yitzhaki (2002) hypothesizes that the higher number of words in paper titles leads to a higher number of ideas. The results show that there is a moderate positive relationship between the number of a paper and the number of words in a paper's title (Yitzhaki, 2002).

Similar to the description of a product, the title and abstract of an article give an overview of what the paper will be about. The title of a paper is an essential attribute because it draws the attention of the reader (Yitzhaki, 2002). Stremersch, Verniers and Verhoef (2007) examine the effects of domain and title length on the number of citations. On one side, the authors find that larger domains lead to more citations (King J. , 1987). On the other side, they find no significant correlation between the title length and the number of citations despite the fact that longer article titles usually hint higher informativeness (Stremersch, Verniers, & Verhoef, 2007).

Not only do longer texts suggest a higher inflow of information which is presented more efficiently, but also higher complexity. Gefen, Gefen and Carmel (2015) consider project length and project success and state that a longer project is more likely to be more exhaustively described. Moreover, a longer project is more likely to be well understood and more successful (Gefen, Gefen, & Carmel, 2015). Thus, a longer text has the potential to deliver more information in a more effective way, as well as bring more value to the customer and positively influence consumer behavior.

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Articles are only a small part of the products which text length attribute influences consumer intentions and consumer behavior. Online stores also rely on elements like text as well as visuals amongst many other. In an online environment, its layout characteristics are essential for helping consumers form an opinion. Similar to packaging, texts, such as product descriptions, and visuals, such as pictures, guide users through the process of building a first impression and making a purchase decision (Van Rompay, De Vries, & Van Venrooij, 2010).

In a time where mobile applications are shifting the use of online stores, it is of interest to explore the influence of text length on consumer behavior. Ghose and Han (2014) mention that textual information enclosed in e-commerce websites affects consumer purchase decision. For example, a study done by Decker and Trusov (2010) examines the relative effects of product attributes on the overall evaluation of the products by using text mining. The authors use length of the description of a mobile app as one of their independent variables and hypothesize there is a relationship between description length and mobile app demand (Ghose & Han, 2014).

What is more, there is little information about the quadratic relationship between description length and product demand. However, some studies have been done in a related sphere of marketing. For example, Ransbotham, Kane and Lurie (2012) examine the relationship between the number of contributors and content value. The authors find that there is a curvilinear relationship between the two variables. The most valuable collaborative user-generated content is generated at a certain number of contributors but not so much that it created information overload (Ransbotham, Kane, & Lurie, 2012). Similarly, it is expected that after a certain number of lines of the app description, the marginal utility of consumers will decrease and thus they will not download apps with descriptions longer than a given threshold.

Literature on product attributes which confines the study of product attributes to mobile applications is scarce and requires more investigation. Hence, the present study aims at filling existing gaps in literature by fully exploring the impact of mobile app characteristics on mobile app demand. Based on the existing literature on the positive and non-linear effects of text length and number of words on consumer behavior, the following hypotheses are suggested:

H1a: A longer app description has a positive effect on mobile app downloads.

H1b: A non-linear relationship exists between the app description and app downloads.

Another common characteristic that catches the consumers' attention and helps them form an opinion about the product is pictorial information.

As mentioned earlier, some scholars argue that internal states such as pleasure and arousal are likely to influence customer approach behavior and intentions induced by an online store environment (Wu, Cheng, & Yen, 2008; Ha & Lennon, 2010). Others state that in order to make a purchase decision online, consumers cannot rely on all their five senses (Finn, Wang, & Frank, 2009). Rather, they are exposed to images and text descriptions, which increase the importance of powerful web features (Koufaris, 2002).

The online store environment includes high task relevant cues such as online visual merchandising (VMD) cues. Part of the VMD cues is pictorial information that directly relates to the shopping goal of the consumer such as pictures of products in the store (Ha & Lennon, 2010). Not only are customers interested in the product features mentioned in the description, but they also want to see a visual representation of the product. Eroglu, Machliet and Davis (2001) discover a potential relationship between the high task cues such as product images and buyers' internal states, which, on the other hand, influence consumer actions.

In the online world, the two elements that best represent the offered goods and services are text and images. Through textual information, the whole description and details can be expressed and communicated in a compelling manner. Pictures complement text and fill in the gaps for those who cannot fully imagine how a product or its features look like. Moreover, pictures have an allurement of their own which can instantly capture the consumers' attention. Previous literature has found that images of hotels affect consumer decisions on hotel reservations (Ghose, Ipeirotis, & Li, 2012).

Similar to online stores, mobile apps often communicate their benefits though screenshots. A screenshot of what the app looks like when downloaded delivers useful information and insight to the consumer. It is also one of the main ways to capture the consumer's attention and influence

their decision to download the app. Ghose and Han (2014) find a relationship between the number of screenshots in the description of the mobile app and app demand.

Concluding from the existing literature, the expectation of the results is a positive correlation between the number of screenshots and app demand. Comparable to description length, the number of pictures is also thought to have a non-linear effect on app demand, since after a certain level of screenshots, users get overloaded with pictures and their marginal utility decreases, leading to less app downloads. Therefore, the second set of hypotheses of the paper are:

H2a: A higher amount of pictures has a positive effect on mobile app downloads.

H2b: A non-linear relationship exists between the number of pictures and app downloads.

WOM

Word of Mouth (WOM) is a key part for the success story of every product or brand. Scholars agree that WOM is a powerful marketing tool and that is has a great impact on consumers compared to other ways of marketing communication (Day, 1971; King, Racherla, & Bush, 2014). Bass (1969) is among the first to look at how WOM was used to spread new information about a product among non-adaptors in his diffusion model (Hu, Pavlou, & Zhang, 2006).

Although it is a vigorous means of communicating information, there have been equivocal results about the impact of WOM on sales and consumers' decisions. The majority of the literature argues that word of mouth has a positive effect on consumer behavior and market outcome (Feick & Price, 1987; Bowman & Narayandas, 2001; Anderson & Salisbury, 2003; Liu, 2006; Davis & Khazanchi, 2007; Chen, Fay, & Wang, 2011). According to Katz and Lazarsfeld (1955) WOM has the highest share of importance in having an impact on purchasing behavior of household hoods and food. However, Van den Bulte and Lilien (2001) review the work of Coleman, Katz and Menzel (1966) and find that it is not WOM that plays a main role in the adoption of tetracycline among physicians, but marketing efforts are (Duan, Gu, & Whinston, 2008). Concluding from past literature, it is more likely that WOM is a driver of product sales and customer purchase behavior.

With the vast development and implementation of information and communication technologies, WOM has turned into a growing social phenomenon. With the help of the Internet,

consumers are forming communities where they share and ask for each other's experiences on different companies, products and services (Awad & Zhang, 2006). An increasing traffic is seen on message boards, forums and other online sources of customer generated media, where individuals seek communication with people outside their close circle (Dwyer, 2007). This ability to interchange 'opinions and experiences online is known as online word of mouth' (eWOM), or as others call it 'buzz' (Liu Y. , 2006) or 'word of mouse' (Dellarocas, 2003; Davis & Khazanchi, 2008, p. 130).

In an economy where self-service is leading, electronic WOM is becoming a popular and important source of information for individuals. With the growth of communication technologies, the scale and scope of WOM communication have drastically increased (Hu, Pavlou, & Zhang, 2006). The difference between digital WOM and traditional WOM is that online WOM takes place in an anonymous online environment which allows customers to easily express both their negative and positive opinions (Chatterjee, 2001). However, the advantage eWOM has is that it can reach a high amount of consumers faster than traditional WOM (Davis & Khazanchi, 2008). Digital WOM has important implications for marketers and managers because it can help firms with product development, brand awareness and customer acquisition and retention (Hu, Pavlou, & Zhang, 2006).

Online customer reviews (OCRs) are a form of online WOM and can be divided into two segments – quantitative and qualitative (Sridhar & Srinivasan, 2012). Qualitative OCRs are customer reviews which provide a text description of an experience or opinion. Quantitative OCRs are customer ratings and summarize a consumer's opinion into a single grade or rating, usually pooled together into a summary statistic (Kostyra, Reiner, Natter, & Klapper, 2015). Users are supplied with an excessive amount of product information over the Internet, which leads the assumption that eWOM can have influence on consumer purchasing behavior and thus product sales. However, there is little research on how such a relationship can be used to help firms gain business advantage (Awad & Zhang, 2006).

OCRs influence consumers in two ways. Firstly, WOM can have an impact on consumers' perception on product quality, which phenomenon is similar to the persuasive effect in advertising literature. Duan, Gu and Whinston (2009) reveal that 22% of CNET users sort products by user

ratings. Secondly, based on previous research, reviews and ratings have a positive effect on product sales (Duan, Gu, & Whinston, 2008).

Consumers highly rely on WOM and some authors suggest that it will replace traditional advertising (Awad & Zhang, 2006). Empirical evidence suggests that there is a connection between online WOM and sales (e.g. Vermeulen & Seegers, 2009; Zhu & Zhang, 2010). Numerous scholars have investigated the impact of eWOM on product sales (Chatterjee, 2001; Chen, Fay, & Wang, 2004; Dellarocas, Awad, & Zhang, 2004; Godes & Mayzlin, 2004; Liu, 2006; Duan, Gu, & Whinston, 2008; Forman, Ghose, & Wiesenfeld, 2008). However, a meta-analysis performed by Floyd, Freling, Alhoqail, Cho and Freling (2014) adquately demonstrates that the resutls are mixed. Some of the academic papers emphasize on the significant effect of WOM on product sales and consumer decision making processes (Chen, Fay, & Wang, 2004), whereas others suggest that the impact is negligible (Godes & Mayzlin, 2004; Liu, 2006; Duan, Gu, & Whinston, 2008) or context dependent (Chatterjee, 2001, Li & Hitt, 2008). Although collectively this literature provides a valuable insight within the context of online reviews and their impact, getting a better grasp of the effects of OCRs depends on investigating the variation introduced by such differences.

Volume (number of reviews and number of ratings)

According to Lui (2006), volume represents the total amount of WOM interactions, meaning the number of reviews (or comments from reviewers) and the number of ratings of a specific product or service. Three main findings occur when examining the existing literature on volume of WOM. Firstly, academics find that volume increases brand and product awareness (Awad & Zhang, 2006). Secondly, the majority of the literature also states that there is a positive relationship between volume and product sales. Last but not least, some scholars find that there is no or negligible effect of volume on sales.

The higher the number of product reviews online, the bigger the chance other consumers will become aware of the product reviewed (Awad & Zhang, 2006). Thus, more online conversations about a product lead to an increased awareness resulting in a change in sales (Dellarocas, Zhang, & Awad, 2004; Godes & Mayzlin, 2004; Alvarez, Martin, & Casielles, 2007; Davis & Khazanchi, 2008; Duan, Gu, & Whinston, 2008). For example, providing information

about a book's characteristics can push consumers towards purchasing this book. Marketing theorists, such as Keller (1993), would relate the review's informative attribute to product or brand awareness, and awareness is a key variable in the consideration set model of consumer decision making.

Consumer awareness of a firm's products contributes to the company by increasing overall sales. Volume is said to create awareness amongst users, thus it should also be connected to the increase of product sales. Over the past several years, a growing body of literature has emerged on the impact of eWOM volume on sales. Some scholars suggest that the number of comments and reviews influences the sales of a product (Godes & Mayzlin, 2004; Awad & Zhang 2006; Liu, 2006; Amblee & Bui 2007; Duan, Gu, & Whinston, 2008). Others find evidence that OCRs significantly affect sales elasticity (Floyd, Freling, Alhoqail, Cho, & Freling, 2014). Another set of academics find that purchasing decisions are highly influenced by eWOM (Mayzlin & Chevalier, 2003; Godes & Mayzlin, 2004; Bounie, Bourreau, Gensollen, & Waelbroeck, 2005; Liu 2006). In the technology and mobile sector particularly, it is interesting to examine what the relationship between digital WOM and number of downloads or app demand will be. Chia, Yamamoto, & Asokan (2012) find that there is a strong correlation between the number of ratings a mobile app has and its popularity. It is of interest for this paper to examine if digital WOM, both customer reviews and ratings, also influences app demand.

WOM can be critical for building the demand for a product (Eliashberg, Elberse, & Leenders, 2006). However, although an increase in the online reviews is highly correlated with an increase in the buzz around the product, it is not certain that all products with user comments will have increased sales (Davis & Khazanchi, 2008). There is also evidence that volume itself is insufficient (Chintagunta, Gopinath, & Venkataraman, 2010) or with little persuasive effect for movie sales (Duan, Gu, & Whinston, 2008).

Stemming from a thorough analysis of the existing literature and mixed results, it is of interest to know what impact volume of online WOM has in the mobile technology industry. More specifically, this paper focuses on mobile applications, thus the third hypothesis is as follows:

H3: A higher volume of online WOM positively affects mobile app demand.

3a: A higher number of consumer reviews has a positive effect on mobile app downloads.

3b: A higher number of consumer ratings has a positive effect on mobile app downloads.

Valence (average rating)

Valence is defined as the average rating of a product (Awad & Zhang, 2006). Ratings usually range from a score of 0 to 5. However, the scale varies across different online marketplaces. As reviewed by many, there is an emerging body of literature on the impact of valence on sales and consumer purchasing behavior (Amblee & Bui, 2007). Ratings can be seen in websites reviewing movies, games, even mobile applications. Although ratings have a straight-forward meaning, they still interrupt user behavior (Dellarocas & Narayan, 2006). Moreover, there is a similarity between the rating perception in apps and movies, as users perceive them as either very good or very bad (Girardello & Michahelles, 2010).

Similar to volume, researchers have found that there are mixed results on the impact of valence on sales. Most studies account for a significant positive effect of valence (Dellarocas, Zhang, & Awad, 2004; Chevalier & Mayzlin, 2006; Clemons, Gao, & Hitt, 2006; Li & Hitt, 2008; Dhar & Chang, 2009; Chintagunta, Gopinath, & Venkataraman, 2010; Cui, Lui, & Guo, 2012; Sun, 2012; King, Racherla, & Bush, 2014). A one point increase in online consumer ratings for video games, for example, increases video games sales by 4% (Zhu & Zhang, 2006). Kostyra, Reiner, Natter and Klapper (2015) argue that valence reflects overall product quality and thus has a positive impact on customer choice probability. Chen and Singh (2001) propose that the importance of ratings is increasing because they help the community make decisions. Some evidence suggests that out of all eWOM attributes, valence is the best predictor of sales (Dellarocas, Awad, & Zhang, 2004).

On the other hand, a vast amount of literature also reaches the conclusion that online consumer ratings have no or little impact on sales. For example, some studies show that valence does not have an effect on product sales (Chen, Wu, & Yoon, 2004; Amblee & Bui, 2007; Davis & Khazanchi, 2007; Amblee & Bui, 2011). Others conclude that valence has no predictive powers. Ho-Dac, Carson and Moore (2013) reveal that valence increases the sales of weak brands, but has no effect on the sales of strong brands (Ho-Dac, Carson, & Moore, 2013). Online consumer

reviews of books on Amazon.com do not affect book sales. These results imply that although consumers are influenced by the awareness effect caused by WOM, they are not affected by the persuasive effect of WOM (Duan, Gu, & Whinston, 2008).

When it comes to the mobile application marketplace, the situation can look a bit different. Previous research has analyzed the effects of valence mostly on tangible products. Mobile applications, however, differ from tangible products in two ways. First, most of the applications are either a few dollars or free, with a revenue stream based on advertisements. Second, mobile apps offer customers a free trial of the product before purchasing the whole version of the app. These two differences represent the intangible nature of the mobile application market, which can question the traditional assumptions of the effect of valence on product demand as there is little or no financial interest to protect. Hyrynsalmi, Suominen, Seppänen and Määkilä (2013) find a relationship between a high average of ratings and sales improvements. Others say that online user ratings establish consumer's net utility and willingness to pay in the mobile app market (Hao, Li, Tan, & Xu, 2011).

In another paper, Hyrynsalmi and co-authors (2012) examine the relation between average ratings and paid app downloads, as they assume that ratings are less relevant for free apps because it is easier to download them than to go through the description. The authors find a significant small negative correlation between valence and paid app downloads (Hyrynsalmi S. , Suominen, Mäkilä, & Knuutila, 2012). The view is supported by the model of Lee and Raghu (2011) where they suggest that valence is not likely to be influential to the sales performance. Similarly, Chia, Yamamoto and Asokan (2012) find a weak negative correlation between average rating and app popularity. Contradictory to the findings above, Pagano and Maalej (2013) find that higher ratings lead to higher rank in 'top lists', which further results in higher download numbers.

Despite the extended literature review, no research has been conducted on the effect of online user rating on free app download numbers. Hyrynsalmi, Suominen, Mäkilä and Knuutila (2012) review the correlation between valence and paid apps, but the results for free apps might be different because there is little financial interest to protect. This leads to the next hypothesis of this paper:

H4: A higher valence positively affects mobile app demand.

Size

Characteristics vary with products but the most common are color, size and shape. With the development of the mobile industry and the introduction of more sophisticated apps, the file size of an app tends to increase. File size can increase because the application is more complex, it conveys a higher amount of information, and graphics become more complicated and heavy. However, the larger the size of the mobile app, the more time it takes to download and thus the less comfortable it is for a consumer to download it. Nowadays, individuals use their phones because they want to be efficient and spend their time in an effective way.

Mobile app file sizes vary with the different categories of apps. Lee and Raghu (2011) examine top 300 apps in the US Apple store and they find that the average size of an app is 21.92 megabytes with a standard deviation of 71.76 megabytes.

There is little amount of research that has been conducted examining the effect of app size on consumer behavior. Some find that the file size of mobile applications is positively correlated with app sales (Lee & Raghu, 2011). Others show that there is an adverse effect between app size and consumer's app purchase decisions (Ghose & Han, 2014), and app size and bestseller rank (Carare, 2012). Results demonstrate that a 10% increase in file size lead to a 1.1% decrease in app demand, whereas a 10% increase in description length and adding one more screenshot lead to a 2.3% and 4.2% increase in app demand. Thus, app developers should consider providing enough textual and visual information to customers in order to increase app demand (Ghose & Han, 2014).

Following prior research, longer wait times negatively relate to consumer behavior. Nevertheless, it is of interest to observe what the effect of file size is on app demand, when all the above-mentioned product characteristics are included as well. Thus, the fifth hypothesis is:

H5: A larger size of the app has a negative effect on mobile app downloads.

Product age

In everyday conversations, one can learn that usually an individual perceives a more mature product (or higher product age) as a product with better quality. For example, some people identify wine vintage (age) with better wine quality (Jackson, 2008) and also higher price (María Angulo,

María Gil, Gracia, & Sánchez, 2000). Moreover, a longer stay on the market can lead to higher product awareness.

In the mobile technologies industry, the consumer's perceptions are often not that different. Whenever a new product or service comes out, sometimes consumers are hesitant in the beginning to use or purchase it because they are afraid of experiencing unnoticed by the manufacturer failures. Mobile applications are an example of a product, which age can affect consumer behavior.

App age is a product characteristic based on the number of days since the app was first launched. Some scholars state that there exists a relationship between app age and app demand. For example, Ghose and Han (2014) find a positive correlation between app age and app demand. The results show that a 10% increase in the age of an app leads to a 1.7% increase in app demand. Moreover, the authors discover that app age has a positive non-linear effect (Ghose & Han, 2014). Carare (2012) finds that an increase in app age will result in a higher bestseller rank. Interestingly, Bigné, Ruiz-Mafé and Sanz-Balz (2007) discover that age acts as a primary predictor of adoption behaviors (Taylor & Levin, 2014). A positive relationship might exist because of the increased awareness effects. Overall, results show that the maturity of apps plays an important role in consumer's app usage decisions (Ghose & Han, 2014).

However, other researchers report that age might have a negative effect on the dependent variable. One side of the research shows that product app age has a negative association with survival (Greenstein & Wade, 1998; Sorenson, 2000; Ruebeck, 2002; de Figueiredo & Kyle, 2006; Khessina & Carroll, 2008; Jung, Baek, & Lee, 2012). Another side of the research exhibits that app age has a small negative correlation with app utility (Kim, 2012).

Most of the literature researches either the effect of paid apps, or the effect of apps on utility and bestseller rank. A prospective opportunity exists to examine the effect of size of free mobile apps on the app demand, which leads to the sixth hypothesis of this paper:

H6: An older app will have more mobile app downloads than a younger app.

The characteristics of experience goods are hard to examine for customers before they have purchased the product. A type of information asymmetry occurs when a brand lacks the skills necessary to provide high quality but yet claims to possess those skills (Mishra, Heide, & Cort, 1998; Eisenhardt, 1989). One possible solution is signaling (Kirmani & Rao, 2000). Thus, firms use different kinds of signals in order to inform their potential customers about the existence, characteristics and prices of the commodities they offer (Milgrom & Roberts, 1986). Quality signals can be transferred in many different ways including advertising expenditures (Kirmani & Rao, 2000). However, the analysis does not only apply to advertising expenditures, but any kind of observable expenditure that does not directly provide information (Milgrom & Roberts, 1986).

With experience goods, Nelson (1970, 1974, 1978) explains that important elements of the product's quality are very hard to impossible to verify with the exception of actually using the product. Therefore, the customer will not be directly informed of what he/she is buying which makes the seller's claims to be offering a high quality product unverifiable before purchase. However, a key quality signal to customers is the simple fact that an experience good, such as a mobile application, is advertised. Nelson focuses to provide a linkage with repeat purchases because a high quality product is more likely to entice repeat purchases. Moreover, an initial sale is of more value to a high quality brand which is willing to spend more money on advertising or other types of enhancing the product's popularity and quality deliverable characteristics, such as provide a video, a longer description or more pictures in the case of mobile apps (Milgrom & Roberts, 1986). Customers who are rational will realize that a brand will not spend money on advertising or enhancing product characteristics unless the quality-related claims made by the firm incurring such costs are actually true (Kirmani & Rao, 2000). Thus, there may be a relationship between including an expenditure, or in otherwise providing a video in the description of an app, and the app demand, leading to the seventh hypothesis of this paper:

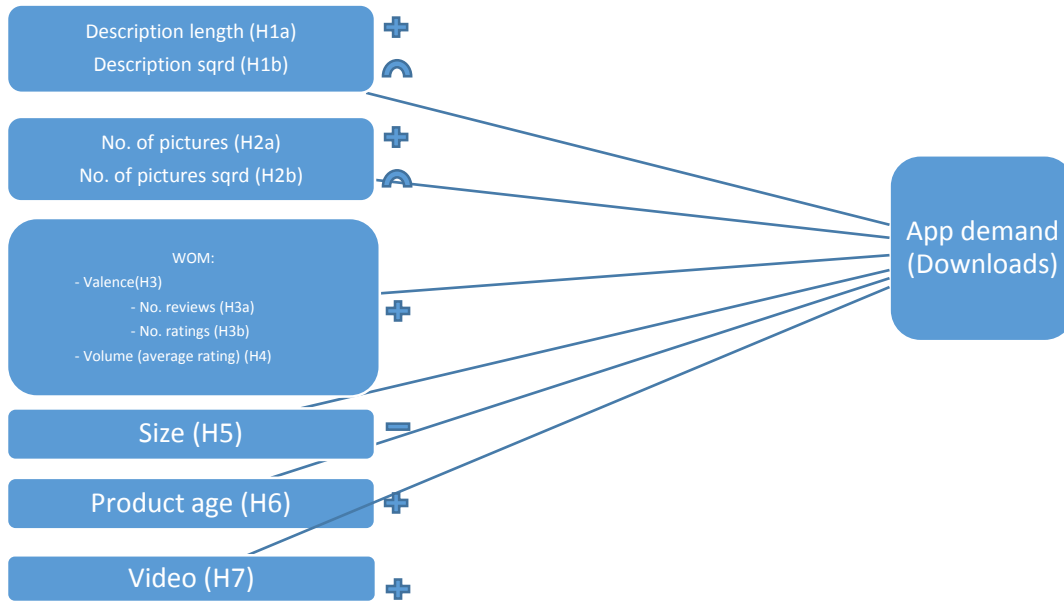*H7: The presence of a video will increase mobile app demand.*

Description length (H1a)
Description sqrd (H1b)

No. of pictures (H2a)
No. of pictures sqrd (H2b)

WOM:
- Valence(H3)
- No. reviews (H3a)
- No. ratings (H3b)
- Volume (average rating) (H4)

Size (H5)

Product age (H6)

Video (H7)

App demand (Downloads)

Table 1. Conceptual Framework

So far, the paper revealed the seven hypotheses that are used, in order to find an answer to the research question. The 'Literature Review, Conceptual Framework and Hypotheses' section has reviewed existing research. Literature on product attributes, consumer behavior and purchase intentions, consumer perceptions and the digital and mobile technology industry connects previous findings with the aim of the paper.

Data

This and the next sections of the paper are going to elaborate on the data and methodology that are being used in order to achieve results. An ordinal logistic regression will be conducted for two different models. The variables will be defined and explained.

Mobile technology trends

Technology has been a booming trend and has been experiencing a rapid development. Smartphones have transformed from being a simple mobile device to being an inseparable part of people's daily lives. In the smartphone and tablet industry, Android and Apple phones are the most popular among mobile phone users. In 2014, Android's global market share was 81.2%, whereas Apple had only 15% (Forrest, 2014). The global shipments of Android and Apple are 1 042.7

million and 192.7 million units respectively for 2014 (Price, 2015). For the first quarter of 2015, studies show that Android's market share has fallen to 78%, whereas Apple's global market share has risen to 18.3% (IDC, 2015). Nevertheless, Android remains a market leader when looking at market share and units sold. Therefore, the paper will concentrate on Android mobile phones.

Android's mobile application store is called Google Play and is a 'database of available apps that allows the user to discover, download and install new apps onto their device' (Wong, 2012; Magrath & McCormick, 2013, p.117). Android store is the world's largest store for mobile apps with 1.4 million applications available compared to the Apple store which has 1.2 million applications as of May 2015 (Smith, 2015). Moreover, in July 2013 Google Play exceeded the cumulate amount of 50 billion app downloads (Thornton, 2013). However, the total number of apps available in the Google Play store is almost 1.6 million up to date (Number of Android Applications, 2015). This amount of apps is achieved by 388 000 developers (Smith, 2015).

Two classes of apps exist – free and paid. Free apps are simplified versions of paid apps and most of the times they display advertisements. Some developers have a preference towards releasing free apps because they can collect profits from advertising (Carare, 2012). This paper is going to examine mobile apps which are free in the Google Play store in the Netherlands. Android's share of free apps amounts at nearly 80% compared to the 60% of the Apple store for 2013 (Forrest, 2014). Developers may be choosing to launch their applications for free on the Google Play store because Apple has a higher commission fee for every download.

Of interest are two categories of mobile apps – Games and Health and Fitness. Games was one of the largest categories in Google Play in terms of device installs as of September, 2014, resulting in 37% of all device installs in the whole store. Moreover, in the Top Overall section, nearly 50% of the applications were games, generating 92% of the revenue for Google Play (Mobile Apps in Numbers - Statistics and Trends, 2014). Thus, Games is a suitable choice for the analysis of the research question because it is a widespread category, used by a diversified crowd of people. Health and Fitness, on the other hand, is a growing category with a more narrowed set of users. Nevertheless, the mHealth apps have more than doubled in the Apple and Android stores for 2013 and 2014, reaching over 100 000 apps (research2guidance, 2014). Therefore, mHealth applications are of interest because they are a rather small market but they are rapidly expanding.

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Sample

Sample for the regression models is attained from a mobile analytics website called AppAnnie, consisting of a variety of mobile app data. The data set is collected for the two app categories mentioned above – Games and Health and Fitness. The first 300 free mobile applications on the Dutch market are examined from both categories in the Google Play store. The data set includes cross-sectional data that has been gathered over the period of 5th April 2015 until 14th May 2015 for a specific date, which is the 5th April 2015.

Variables

Dependent variable

An exhaustive list of app characteristics, which are provided to consumers when browsing the Google Play store, is captured by the regression models. Dependent variable is mobile app demand which is measured by app downloads. Since public data does not include the exact number of downloads for a given app, download ranges are used instead. The lowest range (1) varies from 100 to 500 downloads and the highest range (13) varies from 100 000 000 to 500 000 000 downloads.

Independent variables

Independent variables are the app characteristics which are observed by the consumer while looking at the app description, such as description length *(description)*, number of pictures *(pictures)*, size of the app *(size)*, number of ratings *(ratings)*, average rating *(average rating)*, number of reviews *(reviews)* and launch date of the first version of the app *(age)*. All of the variables are continuous with the exception of *average rating* and *video* which are categorical. The definition of the independent variables can be seen in Table 2. For *description* the number of lines in the text description of the app is counted as they appear in the AppAnnie website. *Number of pictures* exhibits the number of screenshots. It has been proven that information extracted from images of hotels affects consumer decisions on hotel reservations (Ghose, Ipeirotis, & Li, 2012). For both description length and number of pictures the non-linear effect is looked at, and thus two new variables arise – *description sqrd* and *pictures sqrd*. Size represents the size of the app in

megabytes (MB). Ghose and Han (2014) state that with time, apps tend to increase in size which also increases download time. The number of ratings the app has received is measured by *ratings*. In Table 5, the coefficient for *ratings* is scaled by dividing the number by 1 000 000 in order to receive an easier to review result. Moreover, the *average rating* is the score that users give to an app representing how much they like or dislike it. The rating system in Google Play is on a 5-point Likert scale, where 5 stars mean 'very good'. *Reviews* consist of the number of comments the app has received. Volume (*ratings* and *reviews*) and valence (*average rating*) control for word of mouth effects. Next, the *age* of an app is measured by the difference between the launch date of the app and the reference date – 5th April 2015. According to Ghose and Han (2014) a relationship between age and app demand may exist because of awareness effects. The last independent variable is the presence of video *(video)*. Innovative variables such as a video presentation should boost app demand (Luna-Nevarez & Hyman, 2012). Table 2 further explains each one of them.

Type of variable	Variable description
Dependent variable	
App Demand	Category of number of downloads/download range Categorical variable 1 if range in "100 – 500" 2 if range in "500 – 1 000" 3 if range in "1 000 – 5 000" 4 if range in "5 000 – 10 000" 5 if range in "10 000 – 50 000" 6 if range in "50 000 – 100 000" 7 if range in "100 000 – 500 000" 8 if range in "500 000 – 1 000 000" 9 if range in "1 000 000 – 5 000 000" 10 if range in "5 000 000 – 10 000 000" 11 if range in "10 000 000 – 50 000 000" 12 if range in "50 000 000 – 100 000 000" 13 if range in "100 000 000 – 500 000 000"
Independent variables	
Description length	Number of lines of the description of an app in AppAnnie Continuous variable Absolute number
Description squared	Number of lines of the description of an app in AppAnnie squared Continuous variable

	Absolute number	
Number of pictures	Number of pictures in the description of an app in AppAnnie Continuous variable Absolute number	
Pictures squared	Number of pictures in the description of an app in AppAnnie squared Continuous variable Absolute number	
Number of reviews	Number of comments posted for an app in the Google Play store Continuous variable Absolute number	
Number of ratings	Number of ratings an app received Continuous variable Absolute number	
Average rating	Average rating of an app Categorical variable 1-5 Likert scale, 1 if "very bad", 5 if "very good"	
Size	Size of the app in megabytes (MB) Some sizes varied across devices. In such cases, the data was extracted from an HTC One M7 with Android operating system. Continuous variable Absolute number	
Age	Number of days since it has first been released as of 14th May 2015. Continuous variable Absolute number	
Video	Is there a demo video of the app in the description? Categorical variable Dummy variable 1 if "Yes", 0 if "No"	

Table 2. Description of variables
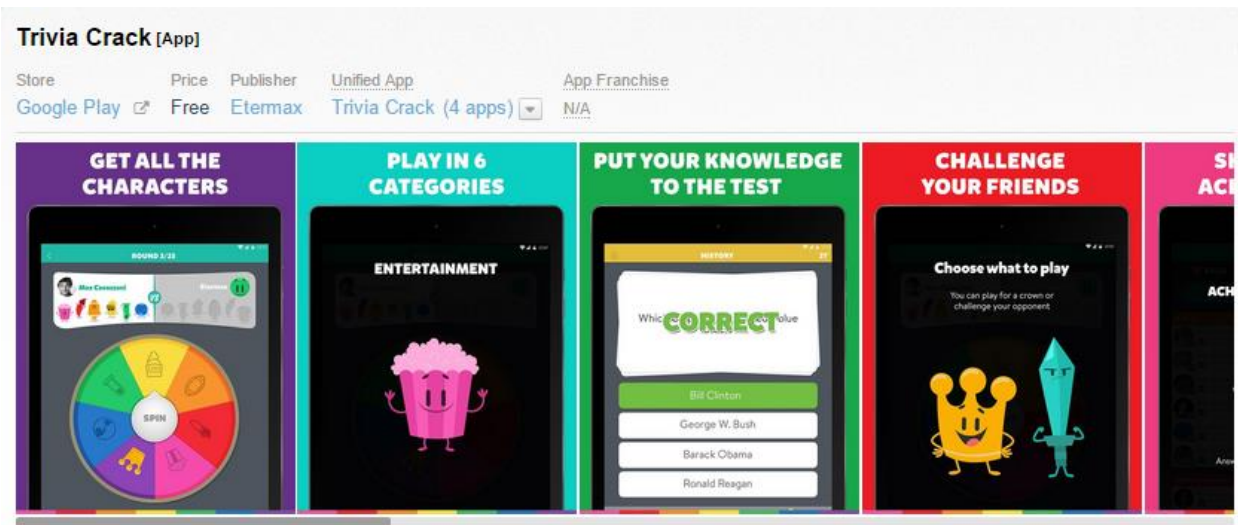
Picture 1. A screenshot of a Games app – number of pictures and presence/absence of video (AppAnnie, 2015)

Picture 2. A screenshot of a Health and Fitness app – initial release date, average ratings, number of ratings, size and downloads (AppAnnie, 2015)

Description

No.1 water app to record and remind drinking water.
More than 5 millions users' choice.
Topped 5 in 22 countries' health ranking

Do you drink enough water? Do you always forget to drink water regularly? Do
you have a fit body? This App reminds you to drink water every day and tracks
your water drinking habits.

You only need to enter your current weight and Drinking Water will help you to
determine how many water your fit body need everyday. When you have
finished drinking a cup of water, you will need to add a cup in the app. Your next
cup will be remained.

Benefits of drinking water.
* You stay in shape and keep fit, As it's calorie free
* You can clear up your skin
* You keep your skin and nails healthy

Features include:
* Reminders that will remind you the water you need to drink in the rest of the
day
* Customized cup and Imperial (oz) or Metric (ml) units
* Customized starting and ending time to drink water within a day
* Graph and logs of date record
* Stay healthy, keep fit and drink enough water!

Water Your Body is very safe software, please contact us if you have any
security question.

What's new

V3.111
* UI improvement and online bugs fix.
* Remove ads bug fixed for paid user.

Picture 3. A screenshot of a Health and Fitness app – description length (number of lines without ‘What's new' section) (AppAnnie, 2015)

The pictures above illustrate from where the data was extracted. The website used for the extraction of the data is AppAnnie. Picture 1 shows how the number of pictures and the absence or presence of a video are counted. Picture 2 reveals details such as the size of the app, the date when it was first released, the 'downloads' category it belongs to, as well as average rating and the number of ratings. Last but not least, Picture 3 is an example of how an app's description looks like on AppAnnie. The description length is measured by counting the number of lines of the text description without the section 'What's new'.
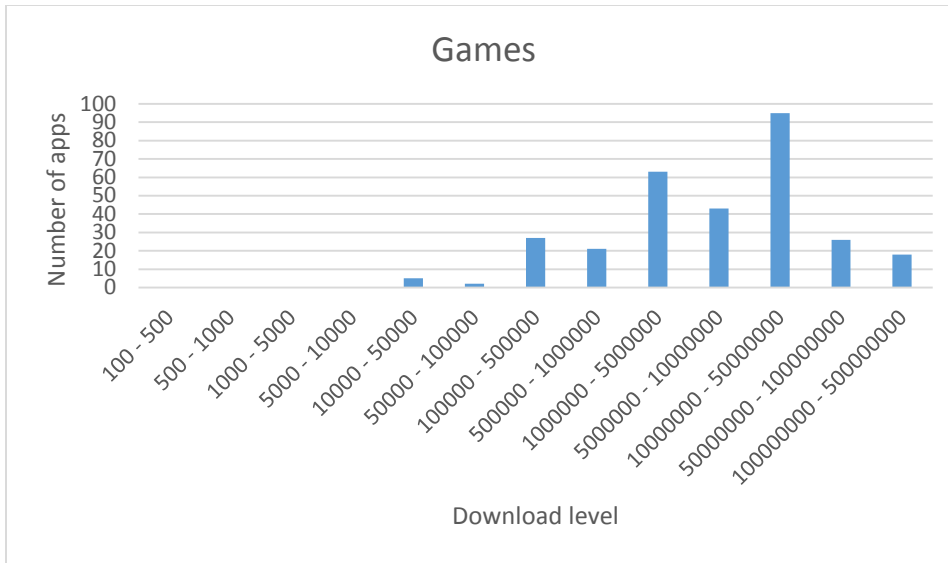
Graph 1. Games – apps per level
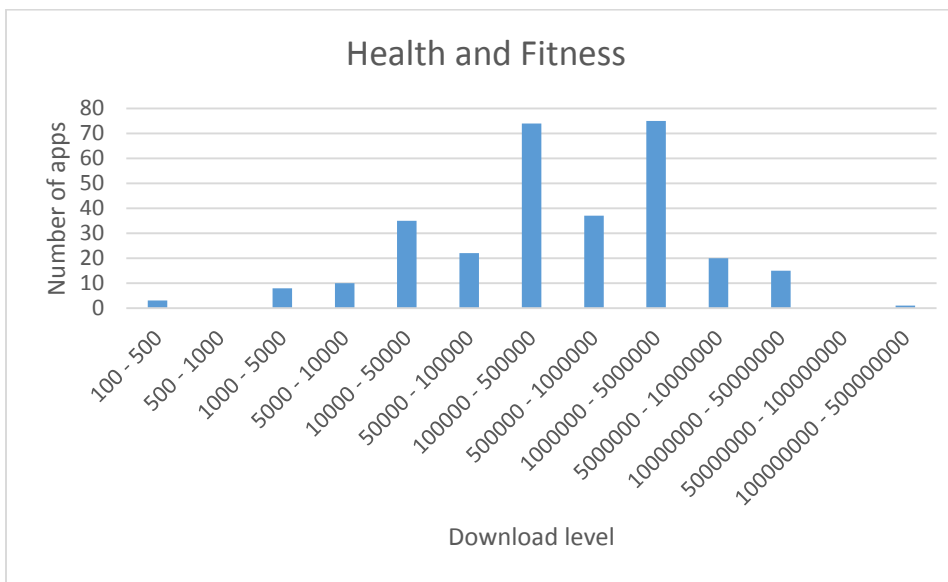
Graph 2. Health and Fitness – apps per level

Graphs 1 and 2 illustrate how many apps there are per download level in the sample used for both Games and Fitness and Health mobile app categories.

Methodology

Since the dependent variable is ordinal, a linear regression will not be a suitable way to conduct the present research. The drawback of multinomial regression model when having an ordinal categorical variable is that the ordering of the categories is ignored (Benoit, 2012). An ordinal variable is a variable which has a meaningful order, but no metric distance characteristics (Janssens, Wijnen, De Pelsmacker, & Van Kenhove, 2008). For ordinal scales, it is best to use methods that are more complex such as ordinal regression models. Thus, for testing the hypotheses an ordinal logistic regression will be applied using the statistical tool SPSS.

The ordinal logistic regression allows to draw conclusions about how app downloads are affected by the mobile app's product attributes in the description. The significance and the coefficients of the independent variables are used to estimate the effect of app description characteristics on app downloads. The regression reveals the effect of one unit increase or decrease of the independent variables on the odds of the dependent variable having a higher or lower value. The most commonly used values for a significance level in statistical research are 1%, 5% and 10% (Lavrakas, 2008). This paper will use a significance level of 5%. Coefficients significant at a 10% significance level will be said to be partially significant. The summarized results of the ordinal regression can be found in Table 7.

In the paper, two models will be used in order to test the hypotheses. The first model tests the characteristics of Games mobile applications. The second model tests the characteristics of Health and Fitness mobile applications. In order to understand how well the variables explain the models, there are three choices for a suitable fit for the models. Cox and Snell's and McFadden's R-squared are based on the log-likelihood of the model and the log-likelihood of the original model, and the sample size. However, Field (2009) states that these statistics never reach their theoretical maximum of 1. Therefore, the author introduces Nagelkerke's R-squared and thus, the interpretation of the results will be based on it as well (Field, 2009).

Last but not least, in order to follow how app demand is influenced by different variables, the following equations (equation (1) and equation (2)) are worth mentioning:

$$y_i^* = \beta' x_i + \varepsilon_i \qquad\qquad\qquad (1)$$

Where $i = 1, \ldots, n$. According to Greene and Hensher (2009, p.83) the model 'is an underlying utility model or latent regression model in which the continuous latent utility or 'measure', y_i^* is observed in discrete form through a censoring mechanism;'

$$y_i = 0 \text{ if } \mu_{-1} < y_i^* \leq \mu_0$$

$$y_i = 1 \text{ if } \mu_0 < y_i^* \leq \mu_1$$

$$y_i = \cdots$$

$$y_i = J \text{ if } \mu_{J-1} < y_i^* \leq \mu_J. \qquad\qquad (2)$$

In the case of this paper, y^* is the demand of a mobile app. A particular download level is represented by y_i. All independent variables, such as number of pictures, presence of video and file size, are embodied by the symbol x.

These two sections explained the variables used in the ordinal logistic regression needed to test the seven hypotheses of the paper. Moreover, the two models of the paper were explained, together with the rationale behind using Nagelkerke's R-squared instead of Cox and Snell's and McFadden's R-squared as a model fit. Last but not least, an equation of how the logistic regression looks like was presented.

Results

In this section, the results of the two models used to test the hypotheses will be presented (Table 7).

To begin with, in order for the ordinal logistic regression to be valid, four assumptions must be satisfied. The first assumption states that the dependent variable must be measured on an ordinal level, which is the case with the download level. The second assumption is that one or more independent variables are continuous, ordinal or categorical. The second assumption is satisfied as can be seen in Table 2. Another assumption of the ordinal logit model is that there is no

multicollinearity, which happens when two or more independent variables are highly correlated with each other. This assumption will be tested further in the paper with a correlation matrix. Last but not least, the assumption of proportional odds exists, which is satisfied when each independent variable has an identical effect at each cumulative split of the dependent variable of the ordinal regression (Ordinal Regression using SPSS Statistics, 2015). The last assumption will also be tested below through the test of parallel lines in SPSS. However, the test for the proportional odds assumption has been considered anti-conservative, meaning that it nearly always results in the rejection of the assumption (Using Statistical Regression Methods in Educational Research, 2015; O'Connell, 2006). Some say it is because the number of independent variables is large (Brant, 1990) or because one of the independent variables is continuous (Allison, 1999). Others state that a reason can be large sample size (Clogg & Shihadeh, 1994).

A correlation matrix for the variables is computed and summarized in Table 3. There is one pair of variables that have a correlation higher than 0.8 which is considered to be the threshold (Field, 2009). The pair which results in a correlation of 0.912 is *number of reviews* and *number of ratings*. *Number of reviews* is a problematic variable and this paper does not examine the valence of reviews. Therefore, the variable *number of reviews* is removed from the regression and the analysis continues without it. Thus, the assumption of multicollinearity will also be satisfied. There is no strong correlation between the other independent variables.

	Description	Pictures	Nr. reviews	Nr. ratings	Avg. rating	Size	Age	Video
Description	1							
Pictures	0.277 (0.000)	1						
Nr. Reviews	0.171 (0.003)	0.122 (0.035)	1					
Nr. Ratings	0.138 (0.017)	0.119 (0.040)	0.912 (0.000)	1				
Avg. Rating	0.264 (0.000)	0.188 (0.001)	0.354 (0.000)	0.334 (0.000)	1			
Size	0.122 (0.035)	-0.002 (0.978)	0.156 (0.007)	0.087 (0.131)	0.060 (0.297)	1		
Age	0.184 (0.001)	-0.020 (0.734)	0.262 (0.000)	0.305 (0.000)	0.290 (0.000)	-0.035 (0.547)	1	
Video	0.331	0.353	0.183	0.162	0.361	-0.025	0.075	1

(0.000)   (0.000)   (0.001)   (0.005)   (0.000)   (0.672) (0.194)

Table 3. Correlation matrix

Next, Table 4 presents the model fitting information. The model fitting information is useful to know whether the model improves the ability to predict the outcome. Looking at the 2 Log Likelihood, it is important to see if there is a statistically significant improvement between using just the intercept of the model to predict which category an app falls in, and actually including the explanatory variables in the model. Both the model for Games and for Health and Fitness apps have a statistically significant final 2 Log Likelihood. Thus, it can be concluded that the models are being improved by including the explanatory variables in it.

	Model	-2 Log Likelihood	Chi-Square	Significance
Games	Intercept only	1113.348		
	Final	824.998	288.350	0.000
Health and Fitness	Intercept only	1198.571		
	Final	959.370	239.201	0.000

Table 4. Model fitting information

The Goodness-of-fit shows if the observed data are consistent with the model fitted to it. The null hypothesis is that the model is a good fit, thus the outcome should not be significant in order for the null hypotheses to not be rejected. The results in Table 5 show that both models are significant which means that the data doesn't fit the model that well. However, the test is very sensitive to missing cells and large sample size. Nevertheless, looking at the Model Fitting Information, there is enough information to suggest that there is an improvement of how well the data is predicting the outcome.

		Chi-Square	Df	Significance
Games	Pearson	1.136×10^{12}	2383	0.000
Health and Fitness	Pearson	2.573×10^{14}	2981	0.000

Table 5. Goodness-of-fit

There are three Pseudo R-squared statistics which measure the strength of the association between the dependent variable and the independent variables – Cox and Snell's R-squared, Nagelkerke R-squared and McFadden's R-squared. As discussed in the Methodology section, the paper will use the Nagelkerke R-squared for both models. Table 6 shows the results of the Pseudo R-squared

statistics. For Games, the Nagelkerke R^2 is equal to 0.633 which means that 63.3% of the variance in the outcome is explained by the explanatory variables. For Health and Fitness, the Nagelkerke R^2 is equal to 0.560, meaning that 56% of the variation of the model is explained by the predictor variables.

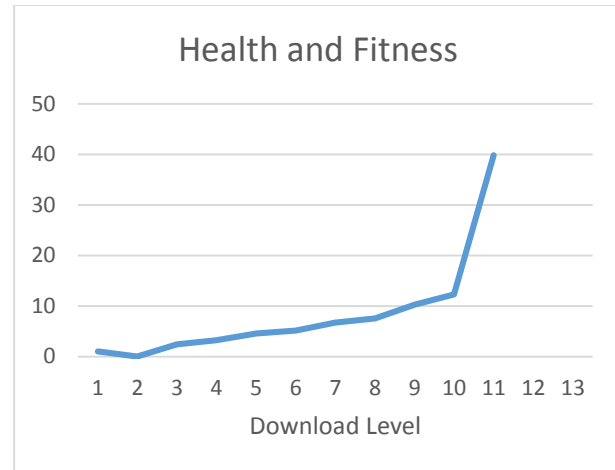|	Games	Health and Fitness
Cox and Snell	0.618	0.549
Nagelkerke	0.633	0.560
McFadden	0.259	0.200

Table 6. Pseudo R-squared

The results of the ordinal logistic regression are presented in Table 7. The threshold base line for both models is the last download level (13) which shows apps with between 100 000 000 and 500 000 000 downloads. Model 1 represents the app category 'Games' and Model 2 represents the app category 'Health and Fitness'. From the 300 apps for each category that are observed, there are none that fall into the first four download levels for the first model. More than half of the thresholds are insignificant. For Model 2, there are only two insignificant download levels. The insignificant download levels mean that after accounting for the independent variables, the apps that fall into the insignificant categories are similar to each other.

Graphs 3 and 4 show the download level differences from the ordered logistic regression. The graph for Games shows that the download level differences have a smoother distribution and are more spread out in terms of downloads than the ones for Health and Fitness. Graph 4 illustrates that the Health and Fitness apps that are downloaded heavily (levels 10 and 11) are downloaded more than the other ranges. Thus, the download level differences for Health and Fitness are more concentrated on the top downloads. However, compared to Graph 3, the one for Health and Fitness has a longer tail decreasing with the download level.
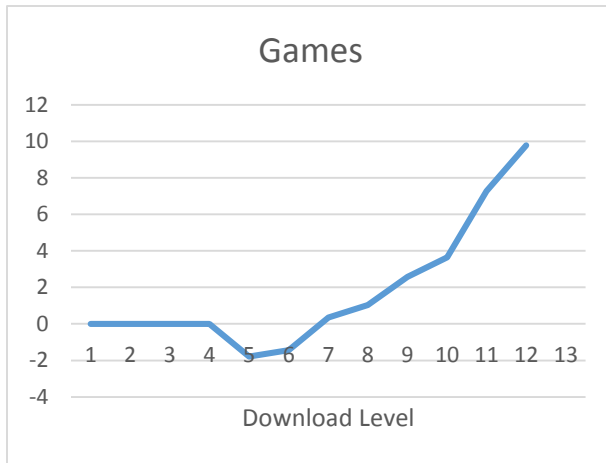
Graph 3. Games – download level differences

Graph 4. Health and Fitness – download level differences

For Model 1, two variables are significant – *ratings* and *age*, meaning that only these two variables affect consumer behavior and thus the download level. The estimate for *ratings* is 1.867×10^6 which means that one additional rating will result in a 1.867×10^6 increase in the ordered log odds of having a higher app download level. The estimate for *age* is 0.003, meaning that one additional day since the Games app was launched will result in a 0.003 increase in the ordered log odds of the app being in a higher download level.

Unlike Model 1, Model 2 has more significant independent variables. To begin with, the description length of an app has a positive coefficient of 0.082. A one line increase in the description length will result in 0.082 increase in the ordered log odds of the likelihood of belonging to a higher app download level. Examining if there is a non-linear effect between description length and app downloads, Table 7 shows that a one unit increase in the *description sqrd* will result in a 0.001 decrease in the ordered log odds of the likelihood of being in a higher app download level. The non-linearity means that a longer description would result in more downloads, but if the description is too lengthy, then users will not download the app as much. The number of pictures in an app have a marginally significant (using a 10% significance level) positive effect on app downloads. The coefficient for the variable *pictures* is equal to 0.149 which translates into a 0.149 increase in the ordered log odds of having a higher app download level when the number of pictures increases by one. The results show that when the number of ratings increases by one, the ordered log odds increase by 2.322×10^6. The valence of rating also has a

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significant effect on the download level. A one unit increase in the average rating results in a 0.590 increase in the ordered log odds of belonging to a higher app download level, which means that the better the rating, the more downloads the app gets. Last but not least, *age* has a small but positive effect (0.002) on the download level, meaning that a one day increase of the app age results in a 0.002 increase in the ordered log odds of the likelihood of being in a higher app download level. The independent variables *pictures sqrd, size* and *video* are insignificant, thus the data does not support the corresponding hypotheses.

		Hypotheses	**Sign**	**Model 1** **Games** *Estimates*	**Model 2** **Health and Fitness** *Estimates*
Threshold	Download level = 1				1.015
	Download level = 2				
	Download level = 3				2.424***
	Download level = 4				3.212***
	Download level = 5			-1.796	4.595***
	Download level = 6			-1.441	5.151***
	Download level = 7			0.349	6.702***
	Download level = 8			1.027	7.574***
	Download level = 9			2.575*	10.287***
	Download level = 10			3.649***	12.277***
	Download level = 11			7.280***	39.812
	Download level = 12			9.791***	
	Download level = 13				
Location	Description	H1a	+	-0.038	0.082***
	Description sqrd	H1b	∧	0.001	-0.001***
	Pictures	H2a	+	-0.037	0.149*
	Pictures sqrd	H2b	∧	0.003	-0.004
	Ratings (/1 000 000)	H3b	+	1.867***	2.322***
	Average Rating	H4	+	0.344	0.590**
	Size	H5	-	0.000	0.001
	Age	H6	+	0.003***	0.002***
	Video	H7	+	0.028	0.136

Table 7. Results of the ordered logit regression models

Significance: * for p<0.10, ** for p<0.05, and *** for p<0.01

The results above allow the hypotheses of this paper to be answered. To begin with, the first hypothesis and its sub-hypotheses are insignificant for Games and are supported by the second model. Thus, for a Health and Fitness app a longer description will result in higher app downloads

and a non-linear relationship exists between the description length and app demand. The second hypothesis and its two sub-hypotheses have interesting outcomes. Both hypotheses 2a and 2b are insignificant for the Games category. Hypothesis 2a is partially significant for the Health and Fitness category at a 10% significance level, which means that the number of pictures have a positive effect on app demand. However, this is not the case for hypothesis 2b since it is also insignificant for Health and Fitness apps.

Regarding the volume of WOM, hypothesis 3a is no longer valid since there is a high correlation between the number of reviews and the number of ratings, and *Reviews* was removed from the ordered logistic regression. Hypothesis 3b is supported for both Games and Health and Fitness categories, meaning that a higher rating will result in a higher app demand. This result is particularly important because it supports the relevance of the paper. The valence of WOM, and thus the forth hypothesis, is supported by Health and Fitness apps but is insignificant for the Games category. Therefore, a higher average rating will result in a higher app demand.

Interestingly, the fifth and seventh hypotheses regarding the size of an app and the presence of a video in the app description are insignificant for both Games and Health and Fitness, which means that the data does not support these hypotheses. Last but not least, the sixth hypothesis which states that app age has a positive impact on app downloads is supported by both Games and Health and Fitness categories.

This section presented the ordered logit regression results of the paper. The results are fully consistent with the third and sixth hypotheses for both app categories, and partially consistent with the first, second and forth hypotheses for the Health and Fitness category.

Discussion

This thesis uses publicly available level data and provides a methodology to estimate the influence of product description characteristics on mobile app demand. It fills in a literature gap by presenting a unique combination of description characteristics of a mobile app that has not been used in any other paper so far. Moreover, the research examines the effect of both valence and volume of WOM on mobile app demand, which has not been done before. In total, 600 apps were examined across two app categories – Games and Health and Fitness (top 300 each), which were

extracted for the Android Store for the Netherlands. Scholars have determined that researching popular apps, which users appear to be using, would improve the study's relevance to the field (Cowan, et al., 2012).

From the analysis, it is found that the description length, number of pictures, number of ratings, average rating and age have a positive effect on app download level for Health and Fitness apps. For Games, the results show that number of ratings and age have a significant positive effect on the app download level. An important result is that the volume of ratings has a positive significant effect on app demand for both app categories. The results from this paper are consistent with what earlier literature suggests regarding mobile apps and other products. Product description characteristics have an overall positive influence on app demand, and thus are an important factor and predictor for product demand. The findings can help firms understand how to manage and implicate advertising in mobile app platforms.

Moreover, attributes such as the description length and the number of pictures in an app can help app developers discover what levels influence consumer behavior best and thus improve the visual cues of the app description in order to provoke more app downloads. According to Racherla, Furner and Babb (2012) mobile apps that are user-centric, such as Games and Health and Fitness in this case, and ones that help consumers better navigate information, can push consumer's purchase intentions towards a certain brand more effectively. Further implications and limitations consist of improving mobile advertising as well as including another variable in order to better the analysis of the results.

Firstly, an implication for brands is that mobile apps provide a channel to promote their brand and sell their products. Mobile apps are an easy medium through which companies can reach many potential consumers. Not only reach, but also targeting, engagement, viral and transaction levels are higher than any other advertising medium (Murphy & Meeker, 2011). A specific feature that is directly connected through mobile apps is the time spent by a consumer using a given app. App developers and publishers are shifting from launching paid apps to including in-app purchases and ad-supported business models. Time spent is relevant because the more time a consumer spends using an app, the more likely he or she is to generate in-app advertising revenues and purchases. Moreover, this would present an opportunity to increase consumer engagement with

the brand through the mobile app. Thus, it would be beneficial to examine how app description characteristics in combination with time spent in mobile apps influences consumer demand.

Secondly, ratings can be used as a measure of quality and a predictor of future downloads. However, Hyrynsalmi, et al. (2013) suggest that use of ratings is more complex and that there are many different factors that can affect the final outcome. A finding of this study is that the number of reviews and the number of ratings were correlated and thus number of reviews had to be removed. It would be useful to further examine the relationship between volume and valence of reviews and app demand in collaboration with the other variables. This would be helpful because in a lot of the top ranked apps there are many negative and positive reviews which diminish the power of average rating as an indicator. Nevertheless, user reviews are still of much help to app developers as they allow for the fast gathering of feedback to improve the application (Hyrynsalmi, et al., 2013).

A limitation of the data used in this paper is the fact that app-level data does not take into account if multiple downloads of an app are derived from a single user through multiple mobile devices or whether they are from numerous users (Ghose & Han, 2014). This can be improved by having access to individual-level data and to the exact number of downloads for a certain app. Furthermore, this paper uses download level as an estimation of mobile app demand. It would be more beneficial and accurate if the actual downloads for every app are used. However, as mentioned earlier, publicly available data does not include the exact number of downloads. This is a limitation, because it makes the analysis less precise. For example, the download level 8 is considered – it includes apps with downloads from 500 000 to 1 000 000 downloads. If an app has 500 001 downloads, it will be in the same pool as an app that is downloaded 900 000 times. Thus, future research should focus and examine the effect of product description characteristics on exact number of app downloads.

Some researchers claim that ratings are averaged over multiple releases of an app (Fu, et al., 2013). However, the source used for the data extraction for the current paper does not include the number of app versions. Future research can include the number of app versions as a control variable although it is not a visual cue and thus will not be part of the app description characteristics. Moreover, it is worthy to mention as a limitation that the success of the app may

be impacted if it is featured as a highlighted app or as an 'app of the day'. Future research may include variables that include if the app has been featured either on the Google Play Home Page or only in Google Play.

Additionally, the analysis of this thesis is limited to Android apps in the Google Play store in the Netherlands. Future studies may consider performing similar analyses of apps created for other platforms such as Apple or Windows, as well as compare the current results to other countries in and outside Europe.

Last but not least, an important limitation that the analysis of this paper experiences is that there is a problem with endogeneity. Chia, Yamamoto and Asokan (2012) find that users are more likely to rate an app which they have installed, meaning that there is a correlation between volume of WOM and demand. Thus, although the current results find that ratings affect downloads, the link may be the other way around.

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