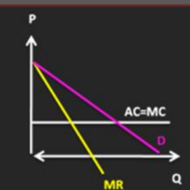

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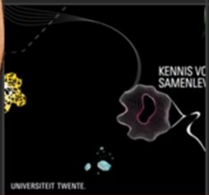

MASTER THESIS - THE MOBILE MONEYMAKER

HOW TUNING THE CONFIGURATION OF PRODUCT CHARACTERISTICS AND PRICING CAN INCREASE PROFITABILITY OF APP DEVELOPERS.

PLACE AND DATE

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KEYWORDS

Management Summary

PURPOSE – Mobile Appstores only recently attracted attention after Apple introduced their Appstore. With the tremendous increase in the number of smartphones the mobile ecosystem is to become important. With expected app revenue of 30 billion in 2013, price discrimination methods, already used in other types of markets, happen to be increasingly important. This study aims to map the mobile ecosystem and find feasible price discrimination methods, with a specific focus on virtual goods, which turns out to be a major revenue driver.

APPROACH – This study is founded on extensive literature about price discrimination and information systems aimed at the mobile ecosystem. By following a structured literature search much effort has been done to not miss important papers. Based on existing economic models, a model aimed at the virtual goods situation could be derived. Because one of the variables in the model was unknown, a survey, based on prior literature, was developed to use as a measure of correlation. To show instrument validity, conceptual validation, pretest, pilot test and statistical controls are used.

FINDINGS – This study shows that virtual goods are from both a product characteristics perspective and a price discrimination perspective the best monetization method. Furthermore, the results of the study show, that although literature suggests different, bundling, versioning and virtual goods are actually different sides of the same concept and hence one economic model could explain all three. The economic model shows that offering goods together in a bundle is always favorable regardless of the correlation between goods, although the degree to which bundling is favorable differs. Additionally seven measures, to estimate the correlation between two goods in the mobile ecosystem, are proven to indeed influence the correlation between two goods.

VALUE – This study contributes in many ways to the academic world. First it contributes to a deeper understanding of the mobile ecosystem as almost no prior literature is available. Secondly it connects two research streams, about bundling and versioning and offers a theoretical solution for combined offerings. Finally this study elaborates on the, unexplored, virtual goods territory and partly validates preliminary research about motivations to purchase virtual goods.

NEXT STEPS – To implement the findings of this study, mobile developers should reconsider their functionality offering based on the measures found in this study and aim for the most diversified (low correlation) offering. While diversification yields higher profits in general, bundling high correlated goods is relatively more favorable over the a'-la-carte offering so with an existing set of functionalities, it is recommend to bundle the highest correlated goods. Several interesting further research ideas can be derived from this study. Most importantly is how a'-la-carte pricing and bundling can be mutually used within companies and how bundling affects competition. Moreover, validation of the measures for correlation should be replicated in more reliable and representative sample populations. Lastly customized bundling i.e., variable good choice within bundles is based on unrelated literature a viable research opportunity.

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1 INTRODUCTION

1.1 Background

A range of applications stores (Chang and Yuan 2008) saw the light of day after Apple introduced the iPhone in July 2008 enabling customers to intuitively buy apps by an on device Appstore application. The number of apps quickly increased from 500 to more than 25,000 after eight months, leading to over 800 million downloads (Apple 2009). In January 2010 the number of apps in the Appstore exceeded 150,000 (Techcrunch 2010). Although a few Appstores (Getjar, Handango and Handmark) existed for many years already, Apple made it successful.

These Appstores created opportunities for app developers like eBuddy (see Appendix A for the company profile). Customers tend to be more likely to pay for software on mobile phones e.g., the web messenger of eBuddy is free and nobody wants to pay for it, while a significant percentage of the users pays for the same functionalities on the mobile phone. The total Appstore market will be important in the near future, since total sales of all Appstores combined is expected to grow to 30 billion in 2013 (Gartner 2010), hence eBuddy decided to launch products in multiple stores like the Apple App Store, Google Android Market, Nokia Ovi Store and Getjar.

In Figure 1 and Figure 2 some insight in the mobile market is given. Although the Apple App Store is way ahead of the other stores in terms of number of applications, most other stores are growing at a high pace as well, with double digit growth figures on a monthly basis.

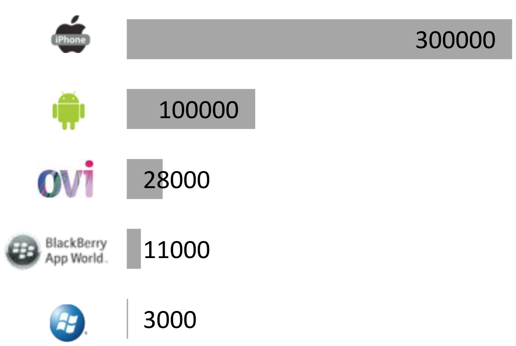


FIGURE 1, NUMBER OF APPS IN DIFFERENT UNITED STATES STORES NOVEMBER 2010, © DISTIMO

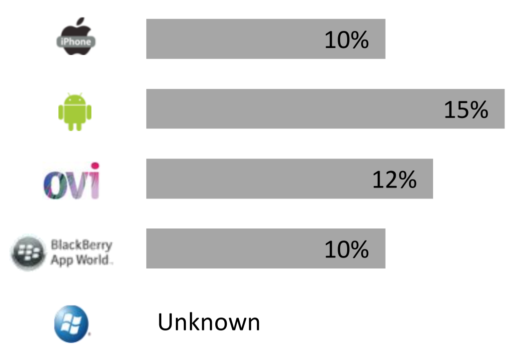


FIGURE 2, RELATIVE APPS IN STORE GROWTH NOVEMBER 2010, © DISTIMO

The Apple iPhone and iPod turned out to be the monetization strategy that made eBuddy profitable after 7 years of burning money (Wauters 2010). Before, eBuddy used an advertising-only-strategy for their web products which apparently worked out with regards to the number of users, but lacked a profitable business model. After eBuddy decided to apply the Freemium model in the Apple App Store, a significant share of users of the app have been willing to pay for premium features like themes and ad-removal.

Several different monetization methods are used in the Appstores; among the important ones are ad-driven apps like Nu.nl[1], paid-only apps like TomTom[2] and a combination of both, like the eBuddy app[3]. The eBuddy app offers a free version which is a limited version of the paid one, trying to convert free customers to paying customers. A third monetization method needs a little more explanation. Apple decided to include in-app payments, allowing developers to build in-app stores to sell premium features and virtual goods. A lot of games utilize this opportunity selling in-game credit via the Appstore, allowing customers to increase experience points (Farmville[4]), buy favor points to attack the enemy (iMobster[5]) or buy extra levels (Tap Tap Revenge[6]).

In this study pricing issues related to mobile Appstores are examined. Although many developers publishing in Appstores are profitable, no prior academic research has been done about Appstores in general and potent pricing strategies.

1.2 Research goal

This study is focused on the way that publishers can enhance their profitability in the relatively new mobile Appstores market. Therefore the overall research question is:

What configuration of product characteristics and pricing will increase profitability of mobile App developers?

Eventually the principal, eBuddy, will be taken into account and the configuration of product characteristics and pricing strategy will be specified to eBuddy.

1.3 Research approach

To answer all research questions properly a structured way of finding and assessing literature is used according to papers of Schwartz and Russo (2004), Webster and Watson (2002), and van der Linde (2004). The process and results can be found in Appendix B. In Appendix B, table 9 the concept matrix can be found, where all concepts are on both axes in order to show missing fields in the literature. Based on the concept matrix three fields of interest are defined.

- **Price elasticity** in combination with **bundling** and **versioning**
- **Network effects** in combination with **bundling** and **versioning**
- **Customer behavior** in combination with **bundling** and **versioning**

This study will discuss network effects only circuitous, because there is not sufficient relevance with the general scope of the study. Both price elasticity and customer behavior in combination with bundling and versioning will be dealt with in greater detail.

[1] http://itunes.apple.com/nl/app/nu/id294726570?mt=8
[2] http://itunes.apple.com/nl/app/tomtom-west-europa/id326075062?mt=8
[3] http://itunes.apple.com/us/app/ebuddy-messenger/id320087242?mt=8
[4] http://itunes.apple.com/us/app/farmville-by-zynga/id375562663?mt=8
[5] http://itunes.apple.com/nl/app/imobsters/id326987512?mt=8
[6] http://itunes.apple.com/us/app/tap-tap-revenge-3/id326916014?mt=8

Section 2 gives a broad introduction into the world of mobile Appstores and the characteristics of the actors. Section 3 describes all suitable pricing methods and concludes with which methods are feasible given the characteristics from Section 2. Based on these sections an economic model will be constructed in Section 4, where, without determining exact configurations, mathematically some ideal types are constructed.

The results will be interpreted and discussed in the final part of the study. First in section 5 the model is used to determine what configuration will yield the highest profit for eBuddy. Finally in section 6, the conclusions are drawn, followed by a discussion about how universal the research is, what limitations apply and what theoretical and managerial (aimed at eBuddy) implications there are.

In order to determine the optimal strategy for eBuddy, the following research questions have to be answered, with between curly brackets the type of question (Vaus 2001).

1. What price discrimination method is the most feasible given the characteristics of the mobile ecosystem?
    a. What are the characteristics of the actors in the mobile ecosystem and how do they monetize applications? (Descriptive)
    b. What kind of price discrimination methods can be distinguished and under which circumstances are they applicable? (Descriptive)
    c. Which price discrimination methods are feasible to adopt and how do they related? (Prescriptive)

2. When does price discrimination increase profits and how can we measure these conditions?
    a. How can feasible price discrimination methods be mathematically modeled? (Prescriptive)
    b. Under what conditions are price discrimination methods preferable? (Evaluative)
    c. What causal relationships are available to measure the α variable and which are statistical significant? (Evaluative)

1.4 Structure of thesis

Every section consists of several subsections, where the first subsection identifies several key definitions the reader should know before reading the section. The last subsection wraps up the content discussed in the section and draws some preliminary conclusions. Each subsection deals with a specific subject and ends with a recap of what is discussed in that subsection.

The first part of the thesis is the result of the literature research to answer the first research question. Afterwards an economic model is constructed taken into account the limitations and assumptions made in the first sections. Finally the model is used to find guidelines for the configuration of the product portfolio and theoretical and managerial implications are discussed.

The study clearly omits eBuddy in the first three sections in order to remain general, but in order to stay close to eBuddy's environment; most examples will be related to the (mobile) software industry.

2 THE MOBILE APPSTORE ECOSYSTEM

In this section the overall goal is to find the best method to generate revenue in mobile Appstores. In order to find a suitable answer, first the characteristics of Appstores and products therein are discussed. Afterwards the study digs deeper into suitable monetization models and concludes with assumptions and restrictions applicable to the remainder of the study.

2.1 Definitions

In this section various new terms will be introduced. To increase readers' convenience in this subsection, all definitions of new terms used in this section are given in alphabetical order.

APPSTORE	An online shop to purchase Smartphone software (apps).
EXPERIENCE GOOD	A product or service where product characteristics such as quality or usefulness are difficult to observe in advance, but these characteristics can be ascertained upon consumption.
HEDONIC GOOD	A product of service that pleasures the senses.
INFORMATION GOOD	A type commodity whose main market value is derived from the information it contains.
NETWORK EFFECTS	The utility that a given user derives from a good depends upon the number of other users who are in the same network.

2.2 Characteristics of mobile Appstores

The distribution of mobile content is changing at a high pace. However, only until a few years ago the industry could be described as hardly existing. Ringtones and applications distribution was dominated by the carriers, who tried to monetize their customers by selling games and other consumer targeted products. Besides, third-party distributors such as Jamba, sold ringtones and wallpapers while the high-end market was covered by Smartphone-focused storefronts like Handango, aimed at enterprise and productivity applications.

After the introduction of the Apple App Store all industry players were forced to innovate as well. The Apple App Store, accessible by iPhone and iPod touch users, was an immediate success. From the initial more than expected number of apps available (500) to the download behavior of customers (1 billion downloads in just 9 months). Currently, as of November 2010, the number of apps available exceeds 300,000, while the number of downloads already surpassed the 5 billion[7].

2.2.1 THE MARKET

Soon many players in the market followed Apple's lead and announced their own Appstore. However, not only the handset manufacturers tried to copy the Appstore idea, companies down- and upstream in the value chain as well. In Table 1 a hierarchical overview of all segments in the

[7] http://www.distimo.com/appstores/app-store/18-Apple_App_Store_for_iPhone

value chain is given, with an example in every segment. While aware of the 'food web' (Lin and Ye 2009) to describe the value chain, the notion exists that this web is not sufficient to fully identify all actors in the value chain. So therefore a value chain from manufacturer to end services is constructed, as can be seen in Table 1.

Value	Description	Example
Services	Online services like IM, Social Networks, Navigation, etc.	Google
Service delivery	Apps	Tapulous
Service distribution	Appstores	Getjar
Device design	Industrial design, look & feel	Apple
UI design	Design of the user interface	SPB
Core apps	Basic functions of phone, dialer, inbox, etc.	Myriad
Operating system	Software middleware and hardware interfaces	Microsoft
Hardware platform	Integrated hardware designs	RIM
Chipset IP	Design of Chipsets	HTC
Manufacturing	Component sourcing and assembly	Mediatek

TABLE 1, VALUE CHAIN OF MOBILE PHONES

When looking at the examples in Table 1, in 6 segments, players launched or at least announced an Appstore. Google was first after Apple with a market on Android, the Operating System (OS) they developed to work closely with their services. Microsoft, whose install base on new mobile phones dropped from 10% to 5% in only 1 year[8], took their losses and started from scratch with Windows Phone 7 and Windows Marketplace. RIM tried to keep momentum and leveraged their 75 million already online devices, with Blackberry Appworld. Even a typical chipset manufacturer, like Mediatek launched a pre-installed Appstore on their chipsets.

2.2.2 WHAT IS THERE TO LIKE?

All those actors putting efforts in developing and maintaining the Appstores, raises the question, what is there to like? Although no figures are known about what the costs are to maintain an Appstore, a break-down of the costs of Apple show the returns were relatively low compared to other business activities (Elmer-DeWitt 2010). Instead of being a money-maker a more suitable explanation, of all those companies jump on the bandwagon, is to take advantage of the network effects of application software (Lin and Ye 2009). A wider variety of quality applications available makes the phone more usable and increases the utility of the OS. Especially for OS developers who need to sell their OS to device manufacturers the value a customer addresses to the OS is an important issue. Device manufacturers try to produce the phones as cheap as possible, so the value of the OS to customer must exceed the implementation value of the device manufacturer.

To the device manufacturers with an own OS and operators, raising the switching costs is likely to be even more important since an average customer buys a new phone every 1.5 years. When this customer bought many useful applications which will be available on the new version of the device the customer has at that moment, but not on another platform, more customers are likely to buy a phone where their already purchased software works on. In that way creating a vendor lock-in because there are substantial switching costs i.e., the customer is dependent on the vendor.

[8] http://www.gartner.com/it/page.jsp?id=1421013

Another advantage of a platform with successful adoption by 3rd party developers is leverage. For example Apple revolutionized mobile phones by creating an app platform, and was subsequently able to leverage that success by creating the iPad and enter a whole new market. The main success factor was the wide adoption of the Appstore, so that software (utility) was already available on the iPad.

2.2.3 WHY DOES IT WORK?

So there is an incentive for companies to launch an Appstore, but why does it work? Why are people eager to access an Appstore and even pay for content they would not pay for on their computer? And why are developers willing to develop for mobile phones. Something even Apple was surprised of.[9]

Developers

According to the report of Vision Mobile (Constantinou et al. 2010), Appstores have revolutionized time to market for applications. To research exactly how radical the time to market for applications has changed since the introduction of Appstores, the survey pays attention to two parameters.

TIME TO SHELF	How long it takes from submitting an application to that application being available for purchase.
TIME TO PAYMENT	The length of time between an application being sold and the proceeds reaching the developer's bank account.

The report's findings show that Appstores have reduced the average time-to-shelf by two thirds: from 68 days across traditional channels, to 22 days via an Appstore. For developers choosing an Appstore to retail their apps, almost 60 percent get paid within a month from the sale of the application. In contrast, when using traditional channels, the time-to-payment increases substantially. On average it takes 55 days to get paid via an operator channel, 69 days when preloading an app via an operator and 168 days (5.5 months) when pre-loading an app via a handset manufacturer.

Consumers

Chen et al. (2004) studied the critical success factors of virtual stores. Their survey of 253 online consumers, indicated that there are 5 concepts that can explain and predict consumer acceptance of a store and hence the success of a store. Since in most Appstores all five concepts (product offerings, information richness, usability, service quality and trust) are better applied than in any other Appstore on the web before, consumers are more likely to start using these Appstores. In subsection 2.2.5 these concepts are discussed in more detail.

Although all players have other incentives to set-up and maintain an Appstore, the different Appstores are surprisingly equal. In the next subsection both the most important stores at the moment and promising just released stores will be discussed.

[9] http://www.cultofmac.com/apple-execs-surprised-by-app-store-success/23925

2.2.4 THE APPSTORE LANDSCAPE

Below an extensive, but not complete, overview of mobile Appstores to date is given, divided in 5 categories[10].

DEVICE MANUFACTURERS

CHIPSET MANUFACTURERS

OS DEVELOPER

OPERATORS

INDEPENDENT

As can be seen in the landscape overview, already 38 Appstores already exists while there are more to come, expected to over 100 in 2012. Although already important from a strategic point of view, the payoffs will become more important in the near future, since the total sales in all Appstores combined is expected to grow to 30 billion in 2013 (Gartner 2010). At the moment, given the

[10] http://www.appstores.info

favorable platforms by developers, see Figure 3 (Constantinou, Camilleri et al. 2010), among the most important are the Apple App Store for both iPhone and iPad, Google Android Market, Nokia Ova, Blackberry Appworld, Windows Marketplace and Getjar. In the next subsection these Appstores will be reviewed more thoroughly.

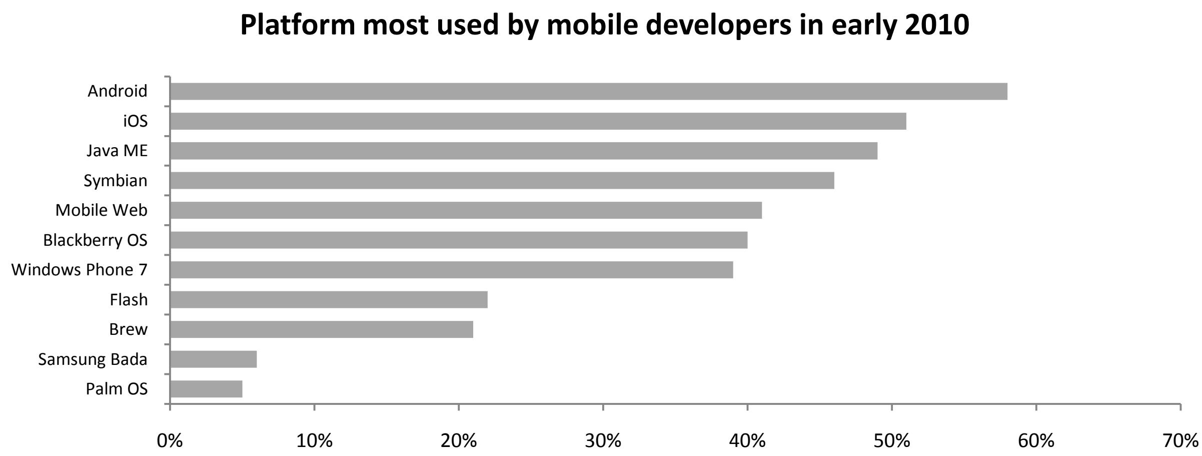


FIGURE 3, POPULARITY BY PLATFORM (CONSTANTINOU ET AL. 2010)

2.2.5 APPSTORES REVIEWED

In this subsection each Appstore will be discussed, starting with the most important one, the Apple App Store, down to the independent Getjar. To guarantee a fair comparison a few concepts are defined below on which each store is assessed. Although this study does not aim to select a winner, the concepts are retrieved from Chen et al. (2004) as discussed in subsection 2.2.3. Since the company and community behind an Appstore are of importance as well, the advantages and disadvantages are added, which give a more comprehensive overview.

PRODUCT OFFERINGS

The efficacy of product offerings is often judged by three criteria: Breadth of product selection, pricing strategies, and product retail channel fit.

INFORMATION RICHNESS

The ability of information to change understanding within a time interval". Information that enables its user to clarify ambiguity and enhance understanding of issues in a timely manner is considered rich.

USABILITY OF STOREFRONT

A poorly designed digital storefront has an adverse influence on the consumers' online shopping experience; hence interface issues related to navigation, search, and the ordering process must be given special attention.

SERVICE QUALITY

Service quality is defined as the discrepancy between what customers expect and what customers get.

- Tangibles
- Reliability

- Responsiveness
- Assurance
- Empathy

TRUST

Trust can be defined as feeling secure about relying on an entity. It has positive influence on the development of positive customer attitude, intention to purchase, and purchasing behaviors.

Key statics[11]

Owner	Apple	Google	Nokia	RIM	Microsoft	GetJar
Distribution	iTunes, Device	Device only	Web, Device	Web, Device	Web, Device	Web only
Platform	iOS	Android	Symbian, Meego, Java	Java	Windows	Java, Flash, Android, Windows ME, Palm, RIM
Scripting Language	Objective C, C	Java, C	Java, C, C++, Qt	Java	C, C#, Silverlight, XNA	NA
	Ratings, review	Ratings, review	Ratings, review	Ratings, review	Ratings, review	Ratings, review

TABLE 2, APPSTORE FUNDAMENTALS

Addressable market	~120M	~75M	+500M	~80M	-1M	+1000M
Applications	~300,000	~100,000	~30,000	~15,000	~3,000	~75,000
Downloads p/m	300M	200M	90M	50M	5M	100M
Revenue model	30% split, iAd	30% split, adMob	30% split, shelf space	30% split	30% split	30% split, shelf space

TABLE 3, APPSTORE FIGURES

Product offerings

Apple was among the first to launch its Appstore and as of today the store is the best loaded store. To date there are more than 300,000 apps in store and the store is still growing with double digit numbers. When companies decide to launch an app, most still choose the Apple App Store as the first to launch (Miller 2010). But Android market is quickly catching up with even higher growth figures as is the Nokia OVI store. Getjar, the only independent Appstore covered in this study, showed growth as well, but has also been around for quite some time now. Both Getjar and OVI have huge potential since they can leverage the enormous addressable market of feature phones with Java. Especially in less developed countries but also in western countries, the high volume phones are still feature phones.

[11] http://www.distimo.com/appstores/

RIM's Appworld and Microsoft's marketplace lag behind the others in terms of number of apps available, but their approach is different. Both companies focus more on quality and have a focus on enterprise-related and productivity apps. Consequently the apps are on the average more expensive than all other platforms. Microsoft marketplace is latest addition to the ecosystem and while the platform has an enormous legacy of software for previous versions of the Windows mobile platform they decided to start from scratch and hence the store has the lowest number of apps available.

Some stores have one major drawback according to developers; the review process. Especially Apple is criticized about the procedures to review apps. This is not based on quality, but on some arbitrary rules[12]. These rules harm among others applications containing nudity and application copying original functions of the phone like the address book (Apple 2010). Apple does not have a consistent rejecting policy and hence developers can develop apps for months and be rejected without notice. Nokia[13], Microsoft and RIM also have (less strict) rules in place to reject apps, but their review process has not attracted any critics yet.

However, by not reviewing apps, like Google, another problem occurs. The quality of the apps can be very low, because even non-working apps are allowed. On the other hand, the absence of a reviewing process allows developers to develop just everything that enters their mind, encouraging innovation.

Information richness

Over time all stores copy best practices from each other, adopting similar functionalities. All developers can add an extensive description showed in the store with every published app. The quality of this information differs, but assuming a developer wants to sell as much apps as possible, the average quality of this information is sufficient. The on device storefronts of Apple, Android, RIM and Microsoft have limited space to show additional information, so only the description, some screenshots, the ratings and reviews are showed.

The online / offline computer storefront is available to all except for Android users and can show more information, with a *people who bought this also bought* section and the variation in ratings. For most apps there is a substitute, but it is impossible to compare apps to each other. Missing is also a function which recommends new apps on basis of the apps someone already possesses.

Usability of the storefronts

As mentioned before most stores have two store fronts, both having the same content, but aimed at a different screen size. The online / offline client needs to be downloaded or visited via the browser, while the on device store is prepackaged on the phone.

In the Apple App Store, the apps are categorized into 20 categories where the games category has an additional 20 subcategories. There are distinct top overalls for paid and free apps, showing the most popular apps in terms of download. For paid apps, the top grossing shows the most popular

[12] http://developer.apple.com/appstore/guidelines.html
[13] https://publish.ovi.com/login

apps in terms of revenue to the publisher, promoting the high quality apps (assuming higher quality apps have, on average, a higher price).

Shopping in the Appstore is just like you shop in the already familiar iTunes store for music or movies. Since customers already allowed Apple to charge their credit card, it is easy to purchase an app. Just click, enter a password and the deal is done.

As mentioned already Android Market is not as fancy as the Apple App Store, but shares almost all characteristics. All apps are categorized and there is a ranking for each category. The rankings are world-wide rankings without adjustments for downloads within a county, so an highly popular app in the U.S. pops up, although never downloaded, as a highly popular app in the Netherlands as well, given the app is made available in the Netherlands.

Ovi uses categories as well, although less than the other stores already discussed. Rankings are based on downloads per country, so each country have their own specific most popular apps listings. Appworld is categorized into 20 categories, for paid free and paid apps, available on both the handset which is prepackaged on all devices right now. Older handsets need to download the store. Not all apps are available to each RIM phone, making the web interface less usable with older phones.

Marketplace is not directly available on the device yet, which is a usability drawback. The online storefront is equal to the others, although Microsoft announced a progressive, user-friendly shopping experience that stresses improved discoverability. But it is not available yet and success has to be seen. Getjar is also web only and not directly accessible via an app on the device. The storefront is divided in 19 categories, where only apps for the selected phone are showed.

Service quality

Apple only sells the iPhone with a selected number of operators e.g., U.S.: AT&T, Europe: T-mobile, in order to get the experience right. Therefore the perceived quality to customers when using the store is higher, due to high Internet speed and no additional costs for downloading content. Since all apps are reviewed by Apple and no core apps can be installed, the phone remains fast and stable and the typical Apple look and feel is guaranteed in the core functionalities.

Google does not possess restrictions on handset manufacturers to install Android, leaving some customers with slow working phones and apps. The perceived quality can therefore be low for some customers. This problem was addressed by Google who introduced the Nexus One (Arrington 2010) to get the experience right and more recently possessed minimal requirement for the new version of Android (Coldewey 2010).

Nokia controls both the device manufacturing and the Appstore, making sure that, by their review process, only apps aimed at a specific device are made available to that device. This should enhance perceived quality of the apps. However, apps available to one Nokia device while not available to another can cause too high expectations, leading to less satisfaction and finally a low perceived quality level.

RIM provides a closed ecosystem, with one OS on all phones, just like Apple, albeit RIM has some problems with obsolete software on the older phones because RIM is active for many years. However, RIM always sold the phones in combination with Internet bundles, and reviews all apps; hence the service quality on par with Apple.

By focusing on the new Windows phone, Microsoft want to make a fresh start, allowing them to have the same advantages as Apple and only supporting one type of system, available to all phones. By opposing minimal requirement to handset manufacturers, Microsoft tries to get the experience right as well, enhancing the service quality of the store.

Getjar does not charge any costs and does not review apps before publishing, enabling developers to publish low quality apps. Next to the tremendous number of devices supported, without availability on the device itself, the perceived quality of the store is likely to be lower.

Trust

The Appstore is owned by Apple which people already found trustworthy when they bought their iPhone. Customers can shop in the Appstore after providing credentials to Apple, including credit card information to buy paid applications. Although Google is a company trusted online by many people, the payment system Google uses, Google Checkout[14] is not used by many (Reisinger 2009). Additionally, customers do not buy a Google phone, they buy a phone from one of the OEM's equipped with the Android OS. Therefore the perceived trust is lower, showed by monetization issues Android developers face (Kincaid 2009).

Nokia is an established brand – among the five best brands globally[15] - and when customers buy a Nokia phone they apparently trust Nokia. While some customer might be reluctant to provide Nokia with their credit card credentials, operator billing is available as well. RIM is a trusted brand, although not as well known as the other brands. Originally the phones were very popular among business people, but become increasingly popular among teenagers because of the free texting possibilities (Ping!). By integrating PayPal, which is a well known payment provider, as their payment service customers should trust payments in store. Microsoft and Windows are both respected brands, trusted by a lot of people, however the payment option available are by direct credit card billing, which is less trusted by customers. Carrier billing will become possible as well, making it easier for customer to buy apps. Getjar is not a known brand and therefore not trusted by default. But because payments are not supported on Getjar, this issue is less relevant.

Other characteristics

Apple already sold an estimated 120 million devices, shipping around 15 million new iPhones every quarter[16]. Developers do not need to support multiple handsets, since iPod and iPhone are similar, attracting many developers. Apple also continues to invest heavily in commercials, promoting the capabilities, ease of use and the high number of applications available. Apple also has a reputation about how to go viral. Besides, Kleiner Perkins Caufield & Byers raised a $100 million fund to seed third-party development of iPhone apps. But Apple is rather strict in who they allow into their

[14] http://checkout.google.com/
[15] http://www.interbrand.com/best_global_brands.aspx
[16] http://www.apple.com/pr/library/2010/10/18results.html

ecosystem. Developers are continuously complaining about developing in uncertainty i.e., not knowing whether the app will be approved or not, while Apple approves a host of flatulence-imitation wares. Another slightly different example is Adobe, which was banned from publishing apps developed using its Flash technology. Finally there are worries about the huge library of Apple, which can lead to discovery nightmares for consumers and monetization issues of developers.

Android recently got the lead in terms of handset in the United States. Worldwide over 200.000 android devices are activated on a daily basis[17]. Google has secured support from a broad range of players across the mobile spectrum including key operators e.g., Verizon, and handset manufacturers e.g., HTC and Motorola. Developers appreciate the open policies Google adopted, which allows them to publish and update rather quickly. Besides, Google is likely to deploy carrier billing, allowing operators to earn from apps as well. There are several issues regarding to the open character of Android, the dispersed version use (see Figure 4) and diverse handset specifications. Developers might not develop for each version / handset combination which might distract customers. Since apps are not reviewed by Google, the change for viruses and malware functionalities in apps is present.

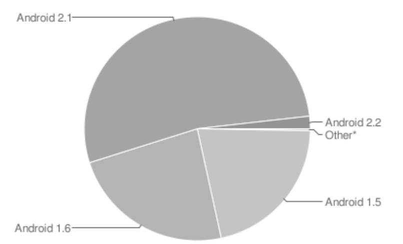


FIGURE 4, PLATFORM DISTRIBUTION, AS OF JULY 1, 2010

Nokia boasts a massive base of addressable handsets, both among smart phones and feature phones. The company has a great presence in Europe as well as in emerging markets. A key differentiator for OVI is the scope of its offerings; Nokia seeks to become not just an app retailer but a social networking provider and a cloud-based service provider, among other things. But Nokia has failed to gain much traction in North America, and its global dominance is slipping even as the overall Smartphone market grows. OVI faces a formidable task in creating an Appstore to address a wide variety of handset models and while Symbian still is the most popular Smartphone OS on the planet (300,000 activations per day[18]), it has yet to develop the kind of simple, intuitive user interface that some of Nokia's competitors have built, to remain leader.

RIM's reputation among enterprise users is iron-clad, the company is successfully expanding its audience to include lower-end business users and even consumers without a business need for a Smartphone, with their unique ping (free texting) proposition. Because RIM cuts operators out of the revenue chain, only sharing the revenue with the developers, it risks to be ignored by operators. RIM's longstanding presence in this space has produced five different SDK's, leading to a fragmented environment where developers have to choose between supporting all handsets by developing simpler apps, or building more sophisticated apps and addressing a smaller market.

While the Windows platform remains a primarily business-oriented mobile OS, it maintains a respectable market share in the Smartphone space and Microsoft has deep coffers to enter the

[17] http://mobile.venturebeat.com/2010/08/05/googles-eric-schmidt-200000-android-units-now-activated-every-day-video/
[18] http://www.gomonews.com/300000-symbian-phones-shipped-every-day/

market and compete below costs for a long time. Their new OS got good reviews at start but success is not guaranteed in this crowded place.

Getjar just received a series B funding of 11 million from Accel partners which is considered to be one of the major Venture Capital firms in the world. Because Getjar supports all devices and no strict review process is applicable they might be able to attract customers not willing to comply with the rigid policies of the others. Besides Getjar addresses the huge feature phone market, which is completely left aside except by Nokia. But the storefront is not pre-installed on any phone, there is no on-device storefront available and Getjar user base is highly dispersed.

2.2.6 WRAP UP

In this subsection an overview of the mobile Appstore landscape is given. All appstores are fundamentally like each other so therefore in the proceeding of this study the Apple App Store will be used in every analysis.

The Apple App Store is the most mature, most reliable and best documented store available right now, hence the data and knowledge about this store is more complete compared to the other mobile Appstores. As point out by Miller (2010) based on interviews, it is almost impossible for content provider to ignore the Apple App Store at this point.

Besides, at the end of 2009, the iPhone and its cousin the iPod Touch together accounted for 49-70 percent of all mobile web browsing in the US, UK, Germany and France (West and Mace 2010). This clearly supports the case of focusing on the Apple App Store, although mainly Android is rapidly catching up.

2.3 Goods in Appstores

2.3.1 POSITIONING

Apps are just another piece of software distributed in a more structured way via a closed ecosystem, the Apple App Store. Software is part of the type of goods known as digital information goods.

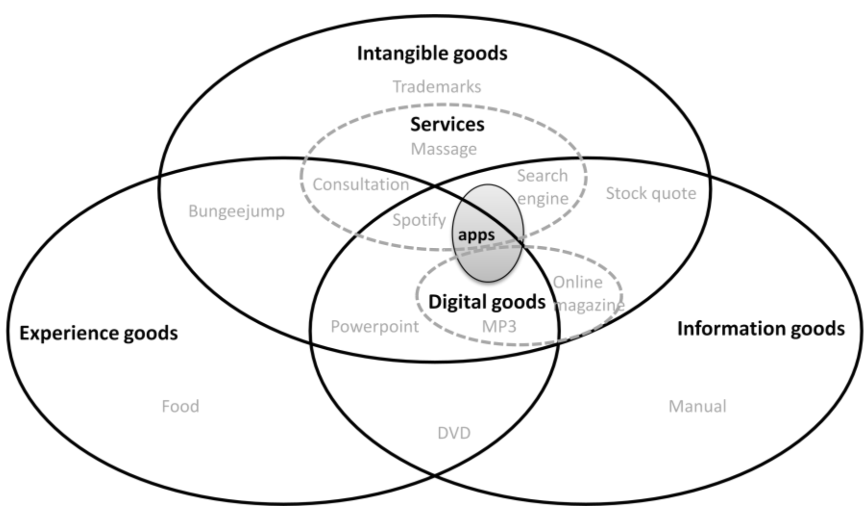


FIGURE 5, APP POSITIONING

Information goods are intangible e.g., stock quote or tangible e.g., manual and can be experience goods. Experience goods are goods consumers have to experience to determine the precise value (Chellappa and Shivendu 2005). Other examples of information goods are music, movies, or games. A digital product is content stored in a digital form and transferred via communication networks but excluding services (Viswanathan and Anandalingam 2005).

Apps share all characteristics of digital information goods i.e., development is expensive, an extra user costs almost nothing and does not harm the availability and customers are never excluded from the platform. Figure 5 shows all above discussed concepts as overlapping sets, to clarify the position of apps and an example for every category. Based on the figure, the study will from now on regard apps as digital information goods that can be experience goods. Because most apps are connected to the internet and use online services this can also be part of the app.

Digital information goods are characterized by high fixed costs and very low (zero) marginal costs. Because information goods are also public goods i.e., the consumption of one customer does not harm the availability to another customer, which is called non-rivalness. A second property of a public good is that no one can be effectively excluded from using the good; this is known as non-excludability (Viswanathan and Anandalingam 2005).

	Excludable	**Non-excludable**
Rivalrous	Private goods	Common goods
Non-rivalrous	Club goods	**Public goods**

TABLE 4, TYPES OF GOODS

When looking from the consumers' perspective, choices are driven by utilitarian and hedonic considerations (Dhar and Wertenbroch 2000). Hedonism and utilitarianism are two related dimensions, but products can score high and low on both. The hedonic dimension results from the sensations derived from the experience of using the product and the utilitarian dimension is derived from the function performed by the product (Voss, Spangenberg et al. 2003). Apps can score high on the utilitarian dimension when effective, helpful, functional, necessary and practical, which will be the case for business apps, while some Apps will be more fun, exciting, delightful, thrilling and enjoyable, scoring high on the hedonism dimension (Voss, Spangenberg et al. 2003).

2.3.2 CHARACTERISTICS

As mentioned in the last subsection, apps are just like software delivered via a closed ecosystem. However there are some differences as well, as Miller (2010) points out the characteristics are;

- They deliver a combination of content and functionality designed specifically for one or more mobile platforms.
- They are delivered as products, made available in a standardized store i.e., online environment and are offered for free or a fee managed by a centralized payment system.

- While apps may provide a simple type of content or functionality such as a ringtone or an eBook, they are distinguished from other types of content or functionality by their packaging for delivery and use via a standardized interface that sets them apart from typical web-based delivery channels.
- Many apps take advantage of the platform-provided Application programming interfaces (API) to use the features of a mobile device to add value to the app experience and/or to deliver content that can be shared with others. For example, foursquare, a mobile application that enables people to announce their "check-ins" at locations uses the geo-location services of various mobile platforms.

Concluding, an app is software designed specifically for mobile handsets which is most likely deeply integrated with the Internet in order to deliver real-time content aimed at the user's location. It differs from websites as well since the user experience is better, the control of content is more sophisticated and content providers are able to finally monetize the content (Miller 2010), where people tend to pay more easily for content (Sangani 2010), and advertisement can be better targeted.

2.3.3 Reinforcement versus Network effects

Where on the web network externalities, for most companies, are most important to become and remain successful, mobile apps face other obstacles too. The Internet exhibits what is known as positive externalities, or network effects, where the value of a good depends on the number of other people who use it. Thus, the more people joining the Internet, the more valuable an individual connection to the Internet becomes (Coiera 2000). On the Internet lots of shelf space is available via portals, search engines and social networks, to get started and maintain momentum. Not restricted by limited shelf space, storing ground, high product maintenance costs and pushed by a shift of consumers to personalization the tails of the sales distribution became fatter over the years (Kong and Lv 2008).

In a sales distribution the tails are considered 'fatter' when relatively more sales originate from low volume products. In traditional businesses however few high volume products generate the majority of the total sales. Typically 20% of the products generate 80% of the sales (Anderson 2006), this is known as the 80/20 rule. In electronic markets, like online music sales (iTunes) and movie streams (Hulu) the tails are fatter than in traditional businesses (Anderson 2006). In some cases more than 50% of the sales (both in terms of downloads and revenues) originate from the long tail (Brynjolfsson, Hu et al. 2007).

But on mobile handsets several restrictions apply, including small screens, inferior input methods and slower data connections. Research about Manga sales in Japan on mobile phones showed a deviation from the long tail where the top 12% of the Manga comics was responsible for 80% of the downloads (Sugihara, Kobayashi et al. 2009). Insufficient time and passive attitude makes customers rely on recommendation and rankings, leading to an even steeper curve than the standard 80/20 rule.

Although as showed in subsection 2.2.3 time to the shelf is greatly reduced, the war for attention intensifies on mobile. In the Apple App Store just like many other markets a Pareto (power law) distribution is applicable (Ghose and Sundararajan 2006; Brynjolfsson, Hu et al. 2007) leading to a straight line on double logarithmic axes i.e., download quantity decreases rapidly when sales rank increases. Therefore it is of utmost importance to conquer a top position in the rank listings of the Appstore and retain this ranking to keep momentum. This effect is called reinforcement effects.

So while on the Internet network effects are important, on mobile reinforcement effects are really important as well. Although these two concepts are related, it is important in the proceeding of this study to keep this in mind.

2.3.4 WRAP UP

Apps are positioned as digital information goods, often used in combination with online services. Apps can have hedonic, utilitarian or a combined nature. Apps have the promise to finally unleash the potential of virtual communities to monetize the user base.

When writing about digital information goods it is impossible to neglect the piracy issue. Many papers are written about the economic impact of piracy. However, since mobile phones and their Appstores are closed ecosystems, where piracy is very hard and uncommon, in the proceeding of this study piracy will be omitted.

2.4 Monetization strategies of publishers

The main goal of a business model is to answer the question: "*who* is offering *what* to *whom* and expects *what* in return" (Wijnhoven 2010), in other words, how does an organization deliver their products to their customers and how do a company monetizes their apps. The who, what and whom question are less relevant in this study while the what-in-return question is particularly important. The Internet world is famous for companies with unsustainable business models while receiving major funding, in search for future profits (Loebbecke and Powell 2002). However, companies active in the mobile ecosystem, are able to finally earn money for delivering online services to customers, i.e. have a sustainable monetization strategy.

ABI research (2009) conducted a survey among 235 US Smartphone users who installed applications on their devices in 2008. It revealed that 17 percent spent more than $100 on apps. That level of spending is especially significant given the low cost of most mobile applications – ranging from as little as a dollar or two in the Apple App Store (Distimo 2010) on average. Concluding, customers are likely to pay for apps on mobile, whereas for the same service on the Internet they will rather look for a free version; mobile has better ways to monetize apps, as mentioned before in subsection 2.3.2.

2.4.1 MONETIZATION STRATEGIES USED IN THE APPLE APP STORE

There is plenty of promise, but how do publishers in the Apple App Store make money? What strategies are used? First a distinction is made between supporting apps and stand alone apps. Supporting apps are left out of this study because the goal of the apps is to support an existing platform e.g., eBay has apps to make life easier for sellers on their platform. For the stand alone apps, the most used strategy in the Appstore is to offer a paid app, where around 73% of the apps was paid in June 2010 (Distimo 2010).

Although most apps are paid, the high volume apps are all free, with in the United States, the highest ranked app in Top Overall Free is downloaded 10 times more than the highest ranked paid app (Spriensma 2010). To monetize free i.e., non-monetary revenues, the most common way is to receive revenues from other sources by display advertisements. Since location, age and sometimes preferences like buying habits and personal characteristics are known the advertizing is more targeted (personalized) and therefore higher click-through rates (hence, higher revenues) are applicable (Wijnhoven and Kraaijenbrink 2008; Hung 2010).

A third way to monetize an app is by offering a basic free version and selling additional functionalities or features to increase the usability or pleasure of the consumer. Additional functionalities can be for example, selling ad-remover packages e.g., eBuddy, or adding speech recognition e.g., IM+, scoring high on the utilitarian dimension of subsection 2.3.1. Additional features, also called virtual goods will have a high score on the hedonism dimension and need some explanation, see subsection 2.4.2. This practice is, in popular literature, called freemium but is closely related to two-sided markets, were one party is subsidizing (sponsoring) the surplus of the user base (Wijnhoven 2010).

2.4.2 VIRTUAL GOODS

Virtual goods are not extensively described in the literature and there is no agreement about a precise definition yet. The best attempt so far states that virtual goods are a subset of virtual assets that can be mass-produced and as a result are frequently bought and sold like conventional consumers commodities (Lehdonvirta 2009). The properties of virtual goods are rivalrous, persistent and interconnected. In this study the rivalrous property has been discussed already in subsection 2.3.1. The use of one customer harms the availability to another customer (Viswanathan and Anandalingam 2005), which is true since a customer cannot share the items he or she bought. Of course, another person can buy the same good, but that is then another independent item. The persistent property refers to the idea the object is an asset e.g., it must exist for some time. While the interconnectedness property means that the object must not exist in isolation, others must be affected by it (Lehdonvirta 2009). Therefore, as can be derived from Table 4 virtual goods are club goods.

In order to make the virtual good concept clear a famous example from the Appstore is used; Farm Ville[19]. Farm Ville is a game, where users can build a virtual farm, and plow, plant and harvest crops in order to earn experience points (XP) and coins. With these XP and coins you can decorate or expand your farm and buy equipment like tractors. Although the game is essentially free to play and will remain free to play, when you quickly want to become a top player, having the highest crop yield, the nicest farm, etc you have to buy additional coins or farm cash, which is sold via in-app payments in bundles ranging from $4.99 to $49.99. So although a user can earn all the functionalities by simply playing Farm Ville a lot, to become successful quickly it is required to spend money. And this strategy works. The game is categorized as a simulation game in the Apple App Store. While in this category, as of 13-7-2010, the most popular paid game (U.S.) by download

[19] http://itunes.apple.com/nl/app/farmville-by-zynga/id375562663?mt=8

numbers is fishing king in the top grossing listing the app is only at spot 10. The top grossing list is dominated by free apps (rank 2 to 7), with Farm Ville on the second spot.

A recent report of Flurry[20], a company that tracks consumer behavior in apps, shows that virtual goods outpaced advertising by 4 times. Although the report is highly biased by only taking into account social network and social gaming apps, the growth of the virtual good model is clearly observed.

However in earlier literature the virtual good economy is limited to a small subsection because most of the virtual products are only decorative goods. People buy these products to dress up their avatars of decorating their houses. These products may help users to express themselves, and help others know more about the owners' styles and the roles they want to play, but there are more types of virtual goods (Shang, Chen et al. 2010). Virtual goods are, in this study, everything consumers can purchase in the app which change something (functionalities, appearance, etc.) within the app. Retailers selling real world products in-app are therefore excluded, but everything from articles in the New York Times app to digital clothes for your avatar in a virtual world app, are virtual goods.

The interconnected property is harmed by this extension but the researchers argue this property is not necessarily applicable to virtual good. A virtual good can exist in virtual world without users interacting with it i.e., no multiplayer environment, or a virtual world might have separate instances for individual users i.e., where the owner is alone and therefore not able to interact with others. Both situations would imply that when offering the same goods, the term of virtual good is not applicable anymore, which is not true, hence the assumption of the interconnected property is relaxed. A good example, that this property cannot hold, is the game TapTap Revenge, which was discussed in subsection 1.1. In this game in which most users play alone without multiplayer capabilities, it is possible to buy a wide range of goods like avatars and hit song packages. Not calling these virtual goods would not make any sense, but then the interconnected property cannot hold.

As mentioned before the top free app is downloaded 10 times as much as the top paid app and although the majority of those consumers will initially not pay for the app, in the end consumers pay anyhow. The reason why customers buy virtual goods range from advancement in status hierarchy to advantage in completive settings, keeping up with co-players, experiencing new content, customization and self-expression (Lehdonvirta 2009). This is an interesting business model since, as showed in subsection 2.3.1, the costs of every new user is (almost) zero, and overall profit is higher.

In this study has been showed before, that purchase decisions are driven by utilitarian and hedonic considerations. According to Lehdonvirta (2009) the show-off factor should be included as well, when virtual goods are discussed (this mainly relates to the interconnectedness property). This social attribute indicates the satisfaction derived from their use a marker. The good can be functionally inferior as long as the goods are exclusive and thus capable of drawing distinction.

[20] http://blog.flurry.com/bid/48418/Madison-Avenue-and-the-Land-of-Make-Believe (visited; 25/10/2010)

And while games seem to fit especially well with virtual good sales[21], other types of software adopt the business model rather successfully as well. For example Mig33, a chat and voice company, only recently started selling virtual goods and now sells around 4 million items monthly with their users[22].

Next to a solid monetization model, virtual goods can strengthen acquisition and retention. By enabling consumers to first try the product for free or at a low costs before buying the essential virtual goods to use the app can be a good acquisition strategy, especially taken into account the difference between downloads in the free and paid section. Essential in this strategy are good conversion rates. Because relevant in-app advertizing is guaranteed, since the virtual goods should be relevant to the users of the app, higher click-through rates are applicable as discussed before.

Virtual goods strengthen retention as well because for two reasons. First consumers using the app can select virtual goods to their taste and would therefore be happier customers. The app publisher can easily adopt customer feedback and offer requested new virtual goods without timely update procedures. Secondly when consumers buy virtual goods, switching costs increase, making is less likely for existing users to switch to competing apps. When customers continue using the app, they might in the future buy virtual goods again, increasing switching costs even more.

2.4.3 Wrap up

In this subsection monetization methods were discussed. In the proceeding of this study the virtual goods monetization method will be the leading strategy, since it is the most promising. Among other favorable features described before, it enables companies to leverage their already existing user base better, by offering premium features and packages.

Although virtual goods sales are an increasingly popular monetization method the model is not suited to all Appstores. A prerequisite to the successful adoption of virtual goods is the availability of in-app payments. In-app payments are available in the Apple App Store and Blackberry Appworld (just released) while announced for Android Market. Virtual goods do not necessarily need in-app payments but conversion-rates will be significantly lower, as in-app payments allow consumers to buy with a single click. Without in-app payments a difficult payment process including registration is needed, which will harm conversion rates. That virtual goods, on mobile, are only successful in the Apple App Store so far amplifies this case.

2.5 Conclusions

The aim of this section was to give insight into the mobile ecosystem and find the best way to monetize apps. Figure 6 gives a graphical summary of the mobile ecosystem.

In this mobile Appstore ecosystem the six most influential Appstores were discussed, where in Figure 6 the size of the bubble does not have any absolute value, the underlying idea is applicable

[21] http://venturebeat.com/2010/07/21/about-75-percent-of-online-users-have-bought-virtual-goods-survey-finds/

[22] http://mobile.venturebeat.com/2010/07/15/mig33s-virtual-gifts-business-grows-400-percent-in-second-quarter/

i.e., one very big store, in terms of number of apps and many small competitors. This idea is even stronger applicable to apps in general, represented by the rounded squares within the bubbles. There are a few winners, and a lot of, in terms of download, small to very small apps. The icons within the app refer to virtual goods, which are sold in some apps.

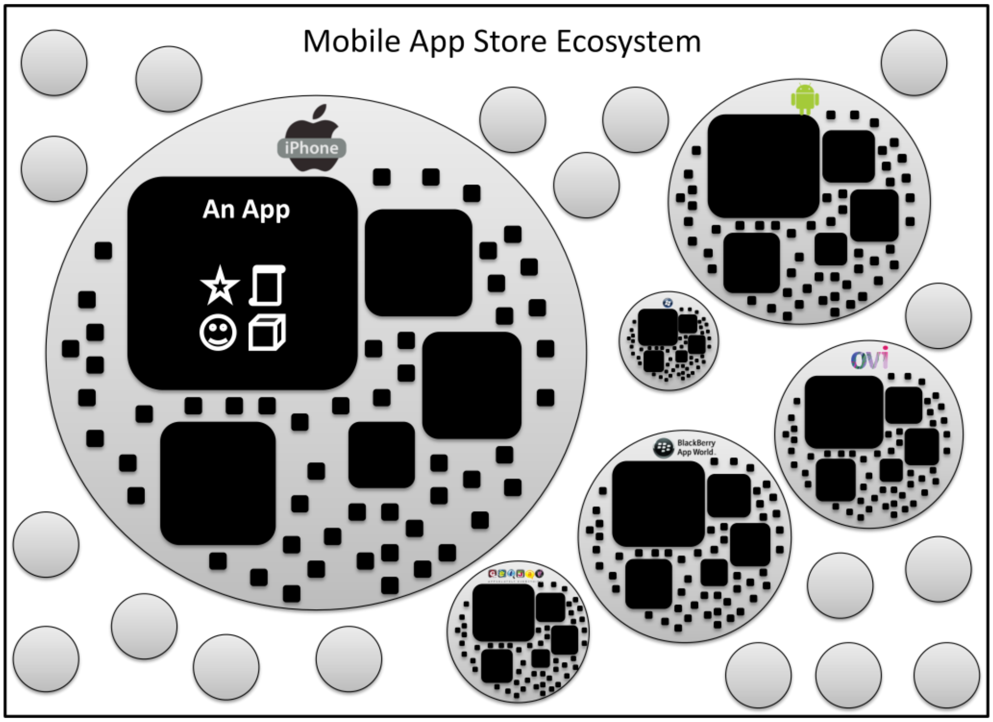


FIGURE 6, MOBILE APPSTORE ECOSYSTEM

In the remainder of this study only the Appstore of Apple will be used given the store is the most mature, most reliable and best documented store. Apps are positioned as digital information goods; often used in combination with online services where apps can have hedonic, utilitarian or a combined nature.

There is no proven best method to monetize apps, but there is indisputable a trend towards the sales of virtual goods via in-app purchases. Virtual goods seem to increase the average revenue per user (ARPU) compared to traditional monetization methods, although the 'established' brands from the traditional software studios remain using these methods. This effect is most clear in the gaming area where virtual goods adopters are frequent in the top grossing rankings. The figures are slightly biased because of the shift to social gaming which is changing the gaming landscape radically.

To give some perspective, about the shift to social gaming, the best known social gaming company, Zynga (the publisher of among others Farmville) is, by second shares, valued just below 5 billion[23] while EA, one of the biggest traditional gaming companies with a huge portfolio including Fifa, Need for Speed and the Sims, has, as of 12/08/2010, a market cap of only slightly above the 5 billion[24].

[23] http://www.secondshares.com/2010/04/06/zynga-5-billion-valuation-buy-–-early-leader-in-social-gaming-is-printing-money/
[24] http://finance.yahoo.com/q?s=ERTS

Because the turnover of Zynga is way below the turnover of EA, investors see much potential in social gaming. But even when taken this shift into account, virtual goods seem a better way to monetize app as similar effects can be observed in other types of apps.

Besides monetization effects, virtual goods have other nice properties as well. Virtual goods strengthen acquisition and retention of consumers and can leverage existing customers better. Because there is only one app which can be offered for free or at low costs, the reinforcement and network effect of subsection 2.3.3 are supported as well. Therefore in remaining of this study virtual goods are considered as the business model of the future in Appstores.

3 PRICE DISCRIMINATION IN MOBILE APPSTORES

In this section the aim is to determine the best ways of price discrimination in mobile Appstores. In order to find the answer the study starts with a general overview of non-uniform pricing methods followed by applicable methods to apply in mobile Appstores and ends by choosing a winner to be used in the proceeding of the study.

3.1 Definitions

In this section various new terms will be introduced. To increase readers' convenience in this subsection, all definitions of new terms used in this section are given in alphabetical order.

BUNDLING	*A strategy that involves offering several products for sale as one combined product.*
DEADWEIGHT LOSS	*When people who would have more marginal benefit than marginal cost are not buying the product or people who would have more marginal cost than marginal benefit are buying the product.*
PRICE DISCRIMINATION	*When sales of identical goods or services are transacted at different prices from the same provider.*
PRICE ELASTICITY OF DEMAND	*A measure to show the responsiveness of the quantity demanded of a good or service to a change in its price.*
RESERVATION PRICE	*The maximum amount a person would be willing to pay for a unit of output.*
VERSIONING	*A strategy to differentiate the products with vertically differentiated quality levels.*
WELFARE	*Sum of the consumers' and producers' surplus.*

3.2 Non-uniform pricing

Companies can, instead of setting a single price, use non-uniform pricing. A students discount is a very popular way of non-uniform pricing, where students get a discount on the price because, on average, their reservation price is lower. Ways of non-uniform pricing include two-part tariffs, tie-in sales and the most common form, price discrimination (Perloff 2008).

The example of Figure 7 will be used in the remainder of the study to explain price discrimination. Most important in this study is the producers' surplus (black box), which is the sale price minus the marginal costs (zero in the example). Consumer surplus is the surplus of the buyers (grey top) of the good. When a certain consumer has a reservation price of 2 while the actual price is 1, both the consumer and producer surplus are 1. The deadweight

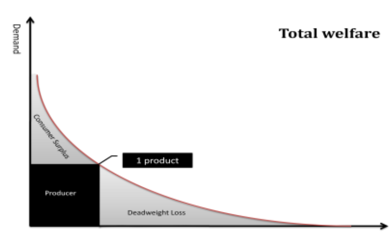


FIGURE 7, PRICE DEMAND GRAPH

loss (grey right) is the not utilized surplus, since the reservation price of those consumers did not exceed the actual price and therefore the product is not purchased.

3.2.1 PRICE DISCRIMINATION

Price discrimination refers to the situation when a firm charges consumers different prices for the same good. There are three levels of price discrimination, but at all levels they share three conditions that have to be met before any price discrimination strategy could be successful (Perloff 2008).

MARKET POWER	A firm with market power can raise prices without losing its customers to competitors. In perfectly competitive markets, market participants have no market power, so a monopoly, oligopoly or cartel has to be applicable to the firms' competitive situation, in order to have market power.
CONSUMERS MUST DIFFER IN SENSITIVITY TO PRICE	When the sensitivity differs it is possible to offer different versions of products to reach different groups of consumers.
PREVENT OR LIMIT RE-SALES	A firm must make sure the low price customers are not able to resell the products to high price customers. Else the average selling price will fall to the price offered to the low price customers.

First degree price discrimination

First degree price discrimination is also known as perfect price discrimination and is based on the idea that a company knows exactly how much every customer is willing to pay i.e., knows the reservation price of each customer. When applicable, the welfare, which is the sum of the consumers' and producers' surplus, is maximized as can be seen in Figure 8. Note that the entire surplus is gathered by the producer i.e., perfect price discrimination extracts surplus from the customers and is therefore disadvantageous for consumers. In competitive markets producers' surplus converges to zero and is therefore favorable for consumers.

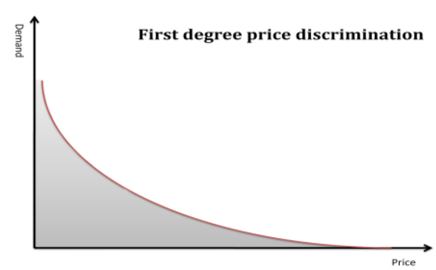


FIGURE 8, 1ST DEGREE PRICE DISCRIMINATION DEMAND CURVE

Although some firms approach perfect price discrimination, it is impossible to know, of each and every customer, the reservation price exactly and hence it is a theoretical-only form of price discrimination. Even when aiming for, the transaction costs will be too high to gather information about each customer's price sensitivity although, for Internet companies this information becomes easier (less costly) to retrieve.

Second degree price discrimination

First degree price discrimination is not suitable because of the high costs, so other ways of price discrimination are more potent strategies. Second degree price discrimination is sometimes referred to as quantity discrimination. As companies do not know the reservation prices they just sell large quantities for lower marginal fees and forgo profit, as the efficiency profits should be lower than the surplus given to the consumer, to be second degree price discrimination (Perloff 2008).

From a more general perspective this method allows consumers to differentiate themselves, by choice. But, the choice is not limited to quantity and could very well be quality or functionalities. In this way companies are able to distinguish classes of consumers. This more general view is something that is missing in (Perloff 2008), but described by multiple authors (Viswanathan and Anandalingam 2005; Lee, Yu et al. 2006). This allows the producer to set different prices to the different groups and capture a larger portion of the total welfare.

Third degree price discrimination

Third degree price discrimination is also known as multimarket price discrimination since the common method is to divide potential customers into multiple groups based on the expected reservation price. The distinction can be made on several characteristics including but not limited to income level e.g., student discount, location e.g., McDonalds and age e.g., Rollercoaster parks. Thus, the supplier sets a lower price for a specific consumer type because that consumer type has a more elastic price elasticity of demand.

3.2.2 Dynamic monotone pricing

Price discrimination focuses on a difference of elasticity of demand, and by tuning quantity, quality or characteristics tries to capture a larger portion of the surplus. When we look to market introductions of products often a price drop can be observed, where first the early adopters buy the products against fairly high prices, while when the mass adopts a product, prices significantly go down. Typically a company starts selling a new product at a relatively high price then gradually reduces the price to reach the low price elasticity segment. This practice is called price skimming (Dolgui and Proth 2010). The other way around is possible as well. For example, when network effects are strong and a product needs a critical user base, starting with low pricing and gradually increasing prices can be a potent strategy. A great example in the Apple App Store is Whatsapp[25], which is a free SMS service over IP i.e., a user can only text people for free who have Whatsapp installed on their phone as well. They offered their app for free in the first two months to accumulate a big user base while after those two months Whatsapp has been among the most downloaded paid apps for over six months in the Apple App Store. This kind of pricing is called penetration pricing (Dolgui and Proth 2010).

3.2.3 Yield Management

The types of non-uniform pricing discussed in the two preceding subsections are not mutually exclusive. Combinations of strategies can be used in order to get a larger part of the total welfare. This process is called yield management.

The goal of yield management is to anticipate customers' and competitors' behavior in order to maximize revenue (Dolgui and Proth 2010). Anticipating includes both understanding and

[25] http://www.whatsapp.com/

influencing the behavior of customers. The challenge is to sell the right resources to the right customer at the right time for the right price.

Note that, in order to maximize revenue or profits it can even be possible to ask one static price. Especially when re-sales are very easy or transactions costs to retrieve information are very high. But given the characteristics of apps from subsection 2.3.1 and 2.3.2, this study will focus on dynamic pricing and leave static pricing out.

However, price discrimination can have countervailing effects on producers' profit. For instance, one consequence of introducing a lower quality version of an existing product is the loss of profits from customers who switch from purchasing the higher quality version to purchasing the lower quality version. This effect is known as cannibalization and equals the effect when two products (old / new) compete simultaneously (Ghose and Sundararajan 2006).

3.2.4 WRAP UP

The effect of yield management can lead to perverse incentives for producers. In 2000, Amazon revealed that it used a type of dynamic pricing, explained by an example.

- a consumer ordered DVD of Julie Taymor's "Titus" at $24.49
- checks back next week and finds price is $26.24
- removes HTTP cookie with stored site preferences; price fell to $22.74

After newspaper articles (Streitfeld 2000), Amazon announced it had dropped this policy. Another known example is the airlines business. If airline companies make economy class seats as uncomfortable as possible to attract people with a larger price differential to business class they make more profit. So such a company may have substantial incentive to make economy seating more uncomfortable.

But apparently abundance creates new scarcity. For example, although the coffee is free at the office, just before the start of a typical office day, many employees buy Starbucks or Coffee Company coffee. So customers tend to pay for premium products while the inferior, but still working properly, product is free. Again this is the difference between utilitarian goods and hedonic goods, I need coffee (utilitarian) but I want a more exciting, delightful and enjoyable (hedonic) coffee.

So some strategies might be immoral ways to subtract surplus of the customer as the Amazon example showed. People want price discrimination themselves, as showed by the coffee example but also when looking to airlines. Companies like Ryan air and Easyjet, lower customer convenience in order to fly as cheap as possible, hence the low ticket prices and significant market share.

3.3 Potent pricing strategies in Mobile Appstores

Although knowing every customer's reservation price is the holy grail of firms, applying first degree price discrimination is impossible; hence this strategy will be omitted from the study. In today's world a rapid increasing number of people have a phone subscription, with 5 billion subscriptions milestone crossed and an estimated 500 million 3G users in July 2010[26]. Given the huge GDP per capita differences throughout the world, one might expect that multi-market discrimination would be a very potent strategy. While 17% of the customers in the U.S. can spend, as showed in subsection 2.4, more than 100 USD to buy apps. This 100 USD equals, according to the CIA world factbook[27], the total GDP per capita of Zimbabwe in 2009.

But, since this study only considers the Apple App Store and therefore only users of iPhones, iPods and iPads customers already tend to be in the high income class independent of which country they live in. Therefore Multi-Market price discrimination, although it might have some impact, is left out of the scope of this research.

Second degree discrimination seems to be a good alternative as Viswanathan et al. (2005) point out, the properties of ease of mix and match and modify the product for different customers of software makes customization, bundling and versioning potent strategies.

In order to apply price discrimination some conditions have to be met, as showed in subsection 3.2.1. First the price discriminating company needs to have market power and although some companies in the Appstore might have a monopoly for a while, soon after an app proved to be successful competitors will enter the market due to the properties from subsection 2.2.3.

Nevertheless there are two reasons why market power can be assumed. First the strong network and reinforcement effects of subsection 2.3.3, can result in a winner takes it all market i.e., monopoly. A good example is the app used in subsection 3.2.2, Whatsapp. A user of Whatsapp can only text for free to users of Whatsapp and so is the case for all other players (Pingchat, Textplus, etc.) therefore it is likely that in the end only one player ends-up as monopolist (at least a local winner will emerge). Another way of looking to the monopolistic situation is with regard to the item's originality (Dolgui and Proth 2010), as long as an app can be distinguished from reproductions, clones, forgeries, or derivative works, market power can be maintained.

The second property, different sensitivity to price, is assumed to be true, since it seems to be in the nature of the human being as showed in subsection 3.2.4. The last property requires that re-sales are at least limited. Apps are bonded to the owner and in no way heritable to others given the closed character of the Apple App Store, hence this property is fully met.

3.3.1 BUNDLING

Bundling allows firms that cannot directly price discriminate to charge customers different prices (Perloff 2008). Bundling is favored when combining multiple products reduces the heterogeneity of the consumers, which is the case with many information goods (Altinkemer and Bandyopadhyay 2000). This reduces the deadweight loss. With bundling the price elasticity decreases i.e., the price demand curve is flatter, so

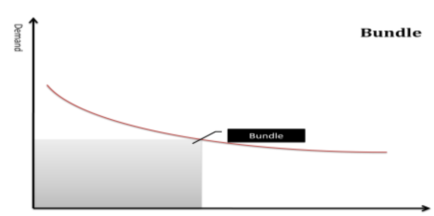


FIGURE 9, BUNDLE DEMAND CURVE

[26] http://www.ericsson.com/thecompany/press/releases/2010/07/1430616
[27] https://www.cia.gov/library/publications/the-world-factbook/index.html

it easier to determine the optimal price.

To clarify, an example of Microsoft is given. Microsoft used bundling to get a critical mass (diffusion) in the browser market, by bundling Internet Explorer as the standard browser in Windows, thereby leveraging the monopoly Microsoft had on the O.S. market by that time (Chandrashekaran, Grewal et al. 2010). But the more interesting bundling example for this study is Office. Office is Microsoft's office suite, and exists among others out of Word, Excel, Powerpoint and Access. While most people only need Word to write a letter once in a while, Microsoft only sells bundles. Table 5 shows an example with every product's reservation prices per customer type.

	Word	**Excel**	**Powerpoint**	**Bundle**
Office worker	70	20	10	100
Data analyst	25	50	25	100
Marketer	40	0	60	100

TABLE 5, RESERVATION PRICES OF DIFFERENT TYPES OF CUSTOMERS PER PRODUCT

When all three products are offered stand-alone, the maximum turnover would be only $190, Word ($80), Excel ($50) and Powerpoint ($60), while in a bundle the reservation price for the bundle equals 100, having a total turnover of $300. Note that unprofitable bundles are possible as well.

The critical success factors of bundling are (Bakos and Brynjolfsson 1999):

- There are economies of scale in production
- There are economies of scope in distribution
- Marginal costs of bundling are low
- Production set-up costs are high
- Customer acquisition costs are high
- Consumers appreciate the resulting simplification of the purchase decision and benefit from the joint performance of the combined product

As Bakos et al. (2000) showed, bundling very large numbers of unrelated information goods can be surprisingly profitable. Surprisingly because information goods share not all critical success factors, like economies of scope in distribution and high customer acquisition costs. However they showed that because it is much easier to predict valuations of customers for a bundle than for individual's goods, optimal prices can be determined and hence the overall profit is increased.

While Bakos et al. (1999) showed that bundling can enhance profits greatly, they identified that Internet clearly affects competition in many other ways as well. For instance, lower search costs, network externalities, high fixed costs, rapid market growth and changes in interactivity. As this study showed already, most of those threats are strongly applicable to the mobile ecosystem. Another assumption is the equilibrium in the market, which is in a growth market like the mobile ecosystem certainly not the case.

Finally, although as showed before, bundling might be efficient, it restricts the choice of consumers. It might provoke frustration and unhappiness, hence in customer relationship bundling might not be the right thing to do (Liebowitz and Margolis 2009).

The antithesis of bundling is called a'-la-carte pricing i.e., pay exactly what a customer consumes. A'-la-carte pricing is common in commodity markets, like people pay exactly for the amount of gasoline or electricity they use. A'-la-carte pricing seems to be fair, a perfectly homogeneous good is sold that can be purchased as narrowly as someone wish. Consumers will choose themselves whether the reservation price of a good exceeds the price set (Liebowitz and Margolis 2009).

At this moment we don´t see any viable business models in the mobile ecosystem related to bundling. Apps are originally aimed to do one specific task, but this might be changing already. For example, IM bundled with voice e.g., Nimbuzz, Fring. Although the IM and voice functionalities are complementary they are still distinct. Another example is Facebook, on the web it started as a Social Network but is expanding rapidly to become a gaming platform, a marketplace and even introduced an own currency. While these functionalities are not available on mobile yet, it is only a matter of time.

3.3.2 VERSIONING

The point of versioning is to get customers to segment themselves according to their willingness to pay. In order to do so, a company should differentiate the products with vertically differentiated quality levels. Versioning is an attractive strategy for information goods such as software, music, movies, and satellite images, because the firm can create low-quality variants at little additional cost (Bhargava and Choudhary 2008).

There are an extensive number of examples available, but this study will stick with Microsoft examples. Microsoft identified the problem of different market segments, with various valuations as well and therefore offered different versions of their Operating System e.g., Windows Starter, Home, Pro, Ultimate. While Ultimate is the flagship version, every other version disables a subset of features of the Flagship. Still Starter offers a complete O.S. suitable to most users but power users want to have professional functions like Virtual Desktop, aimed at business user. They are willing to pay extra for the functionalities.

Another form is based on releasing successive generations of the same products, with a period of time where the old and the new generations overlap. A new generation usually represents improvements, which equals the offering of related products of varying quality (Ghose and Sundararajan 2006). This strategy is used by Microsoft as well, Windows XP, the inferior OS, is still installed on cheap net books, aimed at the lower-end market, while the newer Windows Vista or Windows 7 is prepackaged on more expensive computers. This concept is also linked to price skimming, but fits better within versioning.

The most common business model in the mobile ecosystem is freemium as showed in subsection 2.4.1. Freemium is related to versioning since the basic product is free, but for extra functionalities you have to pay a premium, see Figure 10. To quantify this statement, the Top 100 Overall Free of 1 October 2010 in the United States was analyzed and for 52 out of the 100, there either was a paid version or in-app purchases available. When supported apps were omitted from the research, the

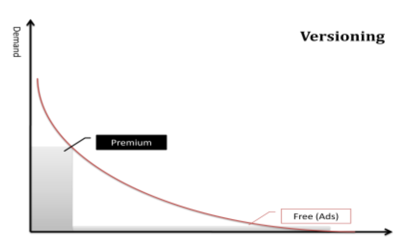


FIGURE 10, VERSIONING DEMAND GRAPH

percentage of versioning adopters increases to just over 60%. See Appendix C for an outline of the algorithm used to extract the information.

3.3.3 PRICE SKIMMING

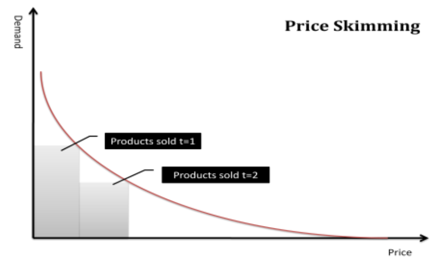


FIGURE 11, SKIMMING DEMAND GRAPH

This concept was already shortly discussed in subsection 3.2.2. In this strategy, a relatively high price is set at first, and then lowered over time. This strategy is especially useful for innovative products since its enables a publisher to reimburse huge investments made in the research and development process. Unfortunately for the companies the high prices cannot be maintained for a long time, given competitors will catch up soon. This strategy is applicable when customers are less sensitive to price e.g., Cosmetic industry or are attracted by innovations e.g., app industry (Dolgui and Proth 2010). See Figure 11 for the demand price graph.

The manufacturer could develop negative publicity if they lower the price too fast and without significant product improvements. Some early purchasers will feel they have been paid a too high price. This negative sentiment will be transferred to the brand (Dolgui and Proth 2010).

It is difficult to assess if the actual strategy of a developer is price skimming. But an estimate, to see if price skimming is common in the Apple App Store, can be made. When 100 applications that were in the top 100 Overall U.S. paid on the first of January 2010 were tracked during the year. Of the 52 still available in the Appstore 13 apps were cheaper at the first of October, while only 3 were more expensive. 33 apps were over the year at least for a certain period priced lower than the January 2010 price. In Appendix C an outline of the used algorithm is given.

3.3.4 TIE-IN SALES

A tie-in sale results from a contractual arrangement between a consumer and a producer whereby the consumer can obtain the desired good (tying good) only if he agrees also to purchase a different good (tied good) from the producer (Perloff 2008). Examples are copiers and razors, which are sold below cost, but require customers to buy specific supplies from the manufacturer in the future (cartridges / blades).

The Apple App Store is an example as well although the core products (iPod / iPhone) are not below costs. On an iPod and iPhone a customer is only allowed to buy apps via the Apple App Store, where Apple charges 30% on every purchase.

Virtual goods are related to tie-in sales; the free product enables consumers to buy virtual goods, but only from one provider (the publisher of the app). As showed in subsection 2.4.2, virtual goods sales are already observed in the Appstore. In order to see how common the tie-in practice is (with the assumption, virtual goods is the only way of tie-in sales) the top 100 Overall Free and Paid of 1 October 2010 was assessed. 42 of the 200 apps sold virtual goods via their app. An outline of the algorithm to retrieve this information can be found in Appendix C.

3.3.5 WRAP UP

In this subsection price discrimination strategies applicable to the Apple App Store were discussed. First is demonstrated that price discrimination is applicable to publishers in the Appstore given the restriction of subsection 3.2.1. Afterwards the most viable discrimination methods; bundling, versioning, skimming and tying were discussed in more detail, including information about the current use in the Apple App Store.

Earlier the decision was made to focus on virtual goods (subsection 2.4.3). As showed in this subsection, virtual goods are related to tie-in sales. In the next subsection more aspects of virtual goods as a method to price discriminate are given.

3.4 Non-uniform pricing with virtual goods

Virtual goods share certain characteristics of the non-uniform pricing methods described above but do not completely fit in one. One might argue that offering virtual goods in the app is equal to versioning, since the capabilities of the app are extended when virtual goods are bought. Even a nice colored farm, which seems useless to many people, does extend the quality of the app to a particular part of the users.

Virtual goods are also defined as mass customization, which fit within the properties from subsection 2.4.2; mass-produced and sold like conventional consumers commodities. Viswanathan et al. (2005) describe in their model highly customizable information goods with zero marginal costs and named it mass customization. Customization occurs when the customer self-selects attributes from a given menu to configure an offering that is best suited to his or her requirements (Bharadwaj, Naylor et al. 2009). An app with virtual goods can fit within this description, as the app only offers basic functionalities while the virtual goods enable the customer to tailor the product to their personal preferences. However one property of customization is not necessarily met, in customization, the information goods provider tries to understand what the consumer wants and designs and delivers a good to meet the customer's needs (Viswanathan and Anandalingam 2005).

But, this does not differ from conventional consumer behavior i.e., customers have a wide array (menu) of products they can choose from to maximize welfare. So, because the sale of virtual goods can be regarded as any other goods, standard price discrimination methods are applicable again. Something Viswanathan et al. (2005) identified as well; combining mass customization and price discrimination can enhance profit even more.

So virtual goods have the promise to lead to perfect price discrimination and subsequently extract the consumers' entire surplus as in Figure 8. This is only possible when available in infinite little pieces, which is by definition impossible. When virtual goods in combination with price discriminating methods are used, a demand graph like Figure 12 can be established, leaving some surplus to the consumers and having some, limited deadweight loss.

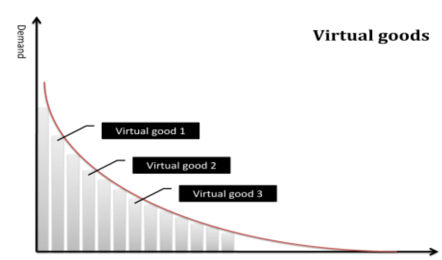


FIGURE 12, VIRTUAL GOODS DEMAND GRAPH

It is critical to understand that, in this study, information goods sales are based solely on demand; not supply and demand, since supply is infinite. While supply may not be a constraint for a virtual good seller, there is the potential to leverage supply constraints. These supply constraints can be a strategic decision to increase price and ultimately, profit. Consider luxury goods, like a diamond ring or a painting, most of the value stems from rarity. The fascinating property of these products is that even when prices increase, demand remains relatively stable i.e., price elasticity around zero, or even positive (Joosten 2007). This is closely related to the social dimension of subsection 2.4.2.

3.5 Conclusions

In section 2 the decision to proceed with the virtual goods monetization model was made. Yet in this section a broad overview of price discrimination methods is given, to keep a general perspective.

After all, the virtual good model is the most viable model from a price discriminating perspective as well since it allows a supplier to apply several forms of price discrimination within the app. The virtual goods model is similar to versioning; it allows customers to self-select the appropriate quality. Therefore the fields of interest as proposed in subsection 1.3 are still applicable as in this study virtual goods are regarded as versioning. In Figure 13 this is graphically described, where (, , ,) are additional functionalities and ( ) is the core functionality. In Figure 13, the shape of the figures illustrates functions, while the color illustrates different products.

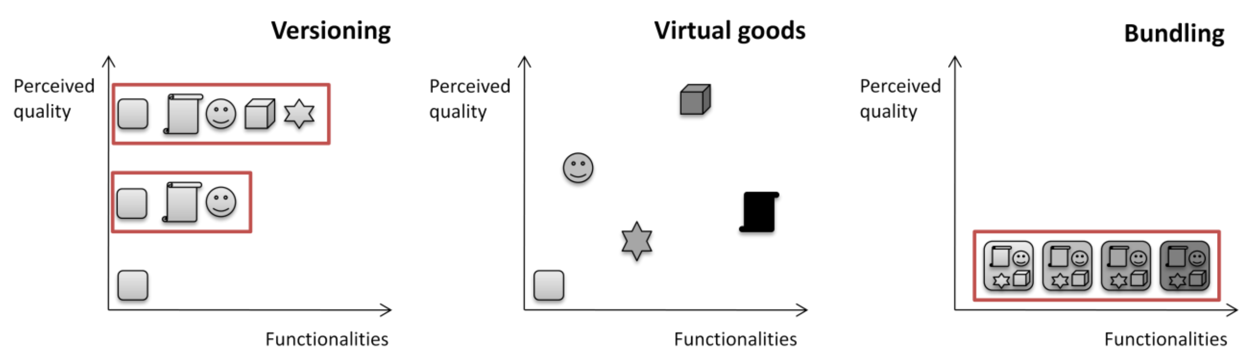


FIGURE 13, PRICE DISCRIMINATION METHODS COMPARED

In this section a clear distinction is made between bundling and versioning as proposed by the literature. Versioning is vertically price discrimination i.e., based on quality, while bundling refers to horizontal price discrimination, based on functions. From Figure 13 it is clear that virtual good is equal to versioning when the assumption, that the core functionality needs to be included in different versions, is relaxed.

However as Figure 13 further shows versioning and bundling are not distinct, actually both methods do exactly the same; combine several functionalities into one product. The difference between the two methods lies in the characteristics of the products. When looking to a typical bundling example, used before in this study, Microsoft Office, the products sold together are not related. Customers will use Excel and Word in the same setting, but the products are rather distinct.

Moreover, the two products are not substitutes at all i.e., when a customer buys Excel there can still be a need for Word.

Versioning on the other hand refers to more related products. The example used before is Microsoft Windows, where Windows Starter and Windows Ultimate are related products. A customer that bought Windows Starter will, in almost all cases, not need Windows Ultimate and vice versa, hence the products are substitutes.

Nevertheless, when looking to the additional functionalities offered in superior versions, these can be again rather distinct. For example, Windows Ultimate offers additionally encryption and multiple language support. Those functionalities, as such, are likely to most customers not related. Specific functionalities can also be referred to as virtual goods. For example the premium offering of the earlier mentioned Farmville, exists among others out of animal, trees and equipment. Rabbits are highly related and for most users substitutes to the Dutch rabbits. Trees on the other hand might be, to some users, substitutes to rabbits because they both enable to express themselves, for others the relation is non-existing. Rabbits and the tractor will probably, to almost all users, have no relation because the tractors do have a yield increasing purpose while rabbits are for decoration only. When multiple virtual goods are offered together like in TapTap Revenge it resembles bundling and versioning.

So versioning, virtual goods and bundling are conceptually the same, combining or separating multiple functionalities. The only discrepancy between the three is how the products are related. Therefore the rich line of literature available to bundling should be applicable to versioning and virtual goods as well. As will be discussed in more detail in the next section, bundling' literature is based on the assumption that products are unrelated, hence to apply the literature a measurement for relation has to be introduced. $\alpha \in [0,1]$ indicates the relation between two goods, when $\alpha = 1$, the goods are highly related, while when $\alpha = 0$ the goods are unrelated. Even though, versioning and bundling are conceptually the same, the goals are different i.e., segmentation versus heterogeneity reduction. This difference will be discussed in more detail in section 6.

Note that, so far, no explanation is given about what the α explicitly represents. Neither is any explanation given about how to measure the α. In the next section the first is discussed from a theoretical point of view, while for the latter an attempt is made in the section 5. So far the relation between two products is described by related and unrelated (following prior literature), while this only refers to a connection in general. What is meant in this study is correlation i.e., having corresponding characteristics, or a reciprocal relationship between two products. Therefore in the proceeding of this study correlated and uncorrelated is used instead of related and unrelated. Note however that uncorrelated refers to unrelated in prior literature.

4 ECONOMIC MODEL

In this section the aim is to model the mathematical implications of bundling, versioning and virtual goods. In order to model correctly the study starts with the assumptions and proceeds with adjusting just one property of the model in every subsection. To conclude the model is simulated to find when bundling is favorable.

4.1 Definitions

In this section various new terms will be introduced. To increase readers' convenience in this subsection, all definitions of new terms used in this section are given in alphabetical order.

COPULAS	*A way of formulating a multivariate distribution in such a way that various general types of dependence can be represented (Nelsen 1998).*
DISTRIBUTION	*Describes the probability of the value falling within a particular interval.*
JOINT PROBABILITY DENSITY	*Describes the joint distribution for X and Y and defines the probability of events defined in terms of both X and Y.*
LINEAR SYSTEM	*A mathematical model of a system based on the use of a linear operator.*
SIMULATION	*The imitation for scientific modeling of natural systems or human systems in order to gain insight into their functioning.*
UNIFORMLY DISTRIBUTED	*Distribution where all intervals of the same length on the distribution's support are equally probable.*
VARIANCE	*A measure of the amount of variation within the values of the variable.*

4.2 Assumptions

In the last two sections certain restrictions have been proposed that are used as boundaries of the model. In this subsection a small recap is given for the readers' convenience. First of all, only one Appstore is considered, the Apple App Store, which is the most mature store at the.

Secondly the virtual goods model is the most promising method of monetization in Appstores and interesting from a price discriminative perspective as well. Besides, up to now the study disregarded the stakeholders in all analysis in order to get an overview of the market without predefined restrictions. However since in the end the goal is to increase eBuddy´s revenues, the study will from now on focus on eBuddy's situation. eBuddy's current business model is freemium, but they want to change to a model including virtual goods. Hence virtual goods are considered in this section. As mentioned before, the line of literature available to bundling is comprehensive and hence this will be used to extend to virtual goods.

The effects of tie-in sales are applicable when selling virtual goods i.e., customers who already bought virtual goods will be less likely to use another party without those goods and users already using the app can only buy the app publishers' virtual goods. Although interesting, these effects are left out of this study and are not quantified. Besides tie-in sales, price skimming is omitted as well. It could be a very lucrative monetization model, but less suitable for a mathematical economic model and therefore not taken into account.

As discussed in subsection 2.3 the marginal costs of eBuddy are nearly zero, and hence the costs are omitted from this section. While marginal costs might not be applicable, less visible costs might be attributable to the model. These costs are not taken into consideration in the economic model, but will be discussed in subsection 4.4.4.

Note that bundling is used in two ways, stand-alone and in combination with virtual goods. From now on, bundling will refer to bundling with virtual goods as a'-la-carte pricing will refer to unbundled virtual goods. Contraire to the previous sections, products are called goods now because of the focus on virtual goods.

4.3 Model

In order to show exactly the process from the generic model to one specifically aimed at the situation, the study starts with a basic model. In every subsection the model is extended by one property.

Notations uses in the Model	
v	Valuation of the virtual good
p	The price of the virtual good
y	The demand for the virtual good
R	Revenue from selling the virtual good
i	Virtual good

TABLE 6, NOTATIONS USED IN THIS SECTION

4.3.1 A SINGLE GOOD MODEL

1. Consumers' valuation of a virtual good is assumed to be uniformly distributed at the unit of interval $\in [0,1]$, as prior literature assumed as well (Salinger 1995; Bakos and Brynjolfsson 1999).
2. Each customer has the same valuation probability distribution as the other customers and all are mutually independent (i.i.d).
3. A consumer will always buy exactly 1 virtual good if the price is lower or equal than the valuation ($p \leq v$).
4. It is not possible to re-sell goods.

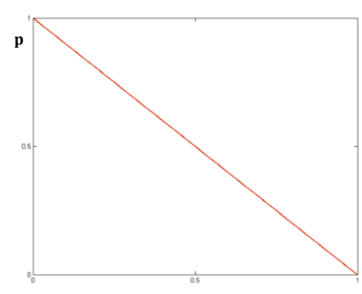


FIGURE 14, ONE GOOD DEMAND CURVE

From assumption 1, the demand of the virtual good in the first period is $y = PR(v > p) = 1 - p$. In Figure 4 the demand curve is showed, these kinds of graphs will be used throughout the whole section, where the red line will represent the demand curve of the single good. Contraire to the last section the price (demand) is presented on the vertical (horizontal) axis.

The company's revenue in each period is $R(p) = p * y = p(1 - p)$.

From the first and second order condition, the optimal price (p^*) and the optimal revenue (R^*) can be determined.

$$1^{st}\ order\ condition \qquad \frac{\partial R(p)}{\partial p} = 1 - 2p^* = 0$$

$$2^{nd}\ order\ condition \qquad \frac{\partial^2 R(p)}{\partial p^2} = -2 < 0$$

$$p^* = \frac{1}{2}, and\ R^* = \frac{1}{4}$$

4.3.2 MULTIPLE UNCORRELATED VIRTUAL GOODS

1. Consumers' valuation of each virtual good i is assumed to be uniformly distributed at the unit of interval $\in [0,1]$.
2. Each customer has for each good i the same valuation probability distribution as the other customers and all are mutually independent (i.i.d).
3. Goods are completely uncorrelated i.e., when a customer buys good i the valuation of good j does not change.

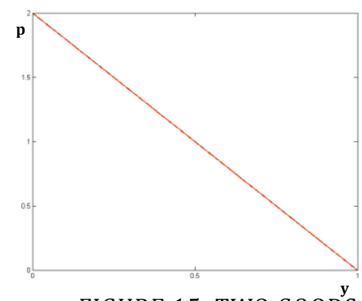


FIGURE 15, TWO GOODS DEMAND CURVE

Demand for each virtual good i equals $y_i = 1 * PR(v_i > p_i) = 1 - p_i$. From now on in this study the different goods are not explicitly named anymore, the demand and prices of all goods are written down in a vector marked by a bold $\boldsymbol{y}$ and $\boldsymbol{p}$, so the demand function is;

$$\boldsymbol{y} = (1 - \boldsymbol{p})$$

In Figure 15 the aggregated demand curve for two goods is showed, which shape does not differ from the one good curve. The company's revenue in each period is $R(\boldsymbol{p}) = \boldsymbol{p} * \boldsymbol{y} = \boldsymbol{p}(1 - \boldsymbol{p})$ and hence the revenue over infinite periods is;

$$R(\boldsymbol{p}) = \boldsymbol{p}(1 - \boldsymbol{p})$$

To determine the first order condition is more complex, because we need the partial derivative of the objective function with respect to each good.

$$1^{st}\ order\ condition \qquad \boldsymbol{D}R(\boldsymbol{p}^*) = \left(\frac{\partial R(\boldsymbol{p})}{\partial p_i}, \dots, \frac{\partial R(\boldsymbol{p})}{\partial p_k}\right) = \boldsymbol{0}$$

To check if the second order condition is negative in this multi-good situation, a Hessian matrix must be negative semidefinite.

$$Hessian\ Matrix \qquad H = \begin{pmatrix} r_{11} & r_{1i} & r_{1k} \\ r_{i1} & r_{ii} & r_{ik} \\ r_{k1} & r_{ki} & r_{kk} \end{pmatrix}$$

Where r_{ij} is $\partial^2 R/\partial p_i \partial p_j$. For a Hessian Matrix to be negative semidefinite any vector $(h_1, .., h_n)$ must satisfy;

$$2^{nd}\ order\ condition \qquad \boldsymbol{h}^T H \boldsymbol{h} \leq 0$$

In this case, since there is no relation between the goods the vector **h** has a non-zero as its first element followed by zeroes and hence the 2nd order condition is met (Varian 1992). Therefore the optimal prices ($\boldsymbol{p}^*$) and hence the optimal revenue (R^*) is;

$$\boldsymbol{p}^* = \frac{\mathbf{1}}{\mathbf{2}}, and\ R^* = \frac{k}{4}$$

4.3.3 BUNDLING UNCORRELATED VIRTUAL GOODS

To understand what is happening when multiple goods are bundled, the valuation distribution should be reconsidered. In order to explain, the two-good situation from the article of Salinger (1995) is used.

Let $f(v_i, v_j)$ be the joint probability density function of the valuations $PR(v_i > p_i)$. If the two goods are not bundled, demand for good i is given by;

$$y_i(p_i) = \int_0^{U_j} \int_{p_i}^{U_i} f(v_i, v_j) dv_i dv_j = \int_{p_i}^{U_i} g(v_i) dv_i$$

Where $g(v_i)$ is the density of reservation prices for good i, U_i and U_j are the upper bounds of the ranges of valuations of the goods.

Now suppose the good is bundled and let $V_B = v_1 + v_2$. The demand for the bundle is then given by;

$$y_B(p_B) = \int_{p_B}^{U_i+U_j} g(V_B) dV_B$$

With the uniformly distributed probability density function used before, demand for the bundle is given by;

$$y_B = 1 - \tfrac{1}{2} p_b^2, \qquad 0 \leq p_b \leq 1$$
$$y_B = \frac{1}{2}(2 - p_b)^2, \qquad 1 \leq p_b \leq 2$$

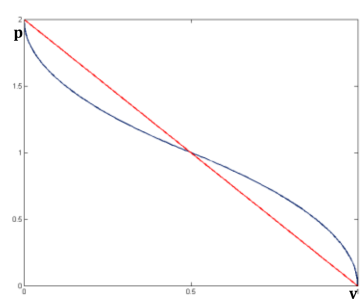


FIGURE 16, 2 GOODS BUNDLE DEMAND CURVE

In Figure 16 the straight line (red) still represents the aggregated demand curve of the sole goods, while the blue line represents the demand curve of the bundle. As can be seen from the graph the demand curve of the bundle differs from the a'-la-carte offering. The middle part of the blue line is more flattened than the red one; this implies less heterogeneity in valuation, while in the tails the heterogeneity is higher. Because price times demand is revenue, the bundle is favorable over a'-la-carte when the price is below 1 while a'-la-carte is favorable when the price is higher than 1. As the optimal price is at the mean in a'-la-carte situation and there are only two goods bundled, it is likely the optimal situation for bundling is around the mean as well. Because the demand curve is more flat around the mean a slightly lower price will gain relatively more demand compared to a'-la-carte pricing, hence higher revenue. This can be proved mathematically as well.

By calculating the first derivative of $\frac{\partial R(p_b)}{\partial p_b} = y_B * p_b$, R^* can be determined.

$$p_b^* = \begin{cases} 0 \le p_b \le 1, & 1 - \frac{3}{2}p_b^2 = 0 \\ 1 \le p_b \le 2, & \frac{3}{2}p_b^2 - 2p_b = 0 \end{cases} \qquad p_b^* = \begin{cases} \sqrt{\frac{2}{3}} \\ \frac{4}{3} \end{cases}$$

Given the two optimal values of p_b^* the optimal revenue R^* is;

$$R^* = \begin{cases} \sqrt{\frac{2}{3}} * 1 - \frac{1}{2}\left(\sqrt{\frac{2}{3}}\right)^2 & = 0.5443^* \\ \frac{4}{3} * \frac{1}{2}(2 - \frac{4}{3})^2 & = 0.2963 \end{cases}$$

So despite the slightly lower price the overall revenue of the bundle is higher, $(0.5443 > \frac{2}{4})$.

In a multiple (> 2) goods scenario, let $f(v_1, \dots, v_k)$ be the joint probability density function of the valuations $PR\left(\sum_1^k v_i > \sum_1^k p_i\right)$. Now suppose the good is bundled and let $V_B = v_1 + \cdots + v_k$. The demand for the bundle is then given by;

$$y_B(p_B) = \int_{p_B}^{U_1 + \cdots + U_k} g(V_B) dV_B$$

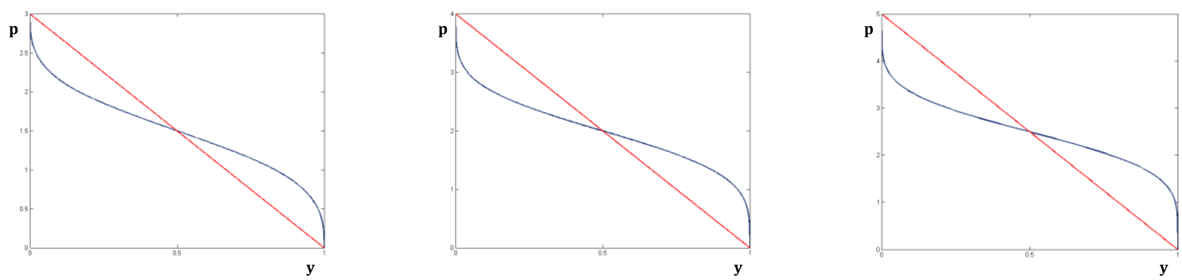
This problem can be solved using convolution theory, based on Fourier transformations. However in general (Uspensky 1937), the distribution of the sum of independent variables with uniform distribution $\in [0,1]$ $(U_1 + \cdots + U_n)$ has a density function of;

$$y_B^n(p_B) = \int_{p_B}^{U_1 + \cdots + U_k} \frac{1}{(n-1)!} \sum_{k=0}^{n} -1^k \binom{n}{k} (p_B - k)^{n-1} \, dp_B \,, \qquad n - 1 \le p_B \le n$$

So in the five-good case the demand function is;

$$y_b(p_B) = \begin{cases} 1 - \dfrac{{p_B}^5}{120}, & 0 \le p_B \le 1 \\ .775 - \dfrac{((p_B - 2) * (-4{p_B}^4 + 17{p_B}^3 - 16{p_B}^2 + 18p_B - 11)}{120}, & 1 \le p_B \le 2 \\ .225 - \dfrac{((p_B - 3) * (-6{p_B}^4 + 57{p_B}^3 - 179{p_B}^2 + 213p_B - 136)}{120}, & 2 \le p_B \le 3 \\ \dfrac{1 + ((p_B - 4) * (-4{p_B}^4 + 59{p_B}^3 - 314{p_B}^2 + 694p_B - 499)}{120}, & 3 \le p_B \le 4 \\ \dfrac{-(p_B - 5)^5}{120}, & 4 \le p_B \le 5 \end{cases}$$

In Figure 17 the cases for $n = 3, 4 \,\&\, 5$ are displayed and there is a clear trend towards a more flattened middle part of the curve, which makes it easier to determine the optimal price and increase the optimal revenue. A more detailed outline of the steps taken to find these graphs can be found in Appendix D.



n=3 **n=4** **n=5**

FIGURE 17, BUNDLED DEMAND GRAPHS (N=3, 4, 5)

4.3.4 CORRELATED VIRTUAL GOODS

In the previous subsections the assumption of i.i.d. were applicable, but as discussed in subsection 3.5 the aim is to include correlated goods in the model. In order to test whether bundling is also favorable when the goods are (partly) substitutes, the relation between two goods is expressed in α_{ij} where α can be in the interval [0,1]. When $\alpha_{ij} = 0$ there is no relation between good i and good j, while when $\alpha_{ij} = 1$ projects i and j can be regarded as full substitutes i.e., when one of the two goods is purchased there is no need for the other anymore. Another way of thinking about substitutes is in terms of changing demand of one good when the price of the other changes.

This results in a $n \times n$ correlation matrix whose i, j entry is the correlation between good i and j and $\alpha_{ii} = 1$. Consequently, it is a positive-semidefinite matrix because all eigenvalues are positive. The correlation matrix is symmetric because of the reciprocal character of correlation, described in subsection 3.5. The correlation between good i and j equals the correlation between j and i.

In the uncorrelated case the demand for each good is $1 - p_i$, but in this case there is a relationship between the goods of α_{ij}. Imaging $\alpha_{ij} = 0.5$, then of the consumers of good j, the average valuation of good i declines to 50% of the original value. This equals a decline of 50% in demand, so 50% of the consumers who bought good j do not need good i anymore.

So the demand of good 1 (y_1) depends on the demand of good 2 (y_2) and 3 (y_3), which depends on the price of the goods. But now a problem arises; it is possible to calculate y_1 when knowing y_2 and y_3, but both y_2 and y_3 depend on y_1 as well. Because y_2 and y_3 are unknown y_1 is also unknown.

The α_{ij} relationship is equal to the relationship defined in a market interaction model with substitutes and complements. After all, good 2 is a competitor of good 1 since good 2 sales harm good 1 sales and vice versa. In Varian (1992) a model is given to describe the effects of substitutes in Cournot and Bertrand competition models. The models' initial situation is perfect substitutes, i.e. two competitors sell the exact same good, while in this study the initial situation is the precise opposite i.e., the goods are completely uncorrelated. However this does not harm the usability of the consumers' inverse demand function of the competition models.

$$p_1 = \alpha - \beta y_1 - \gamma y_2$$

$$p_2 = \alpha - \gamma y_1 - \beta y_2$$

Where $\alpha = 1, \beta = 1$ and $\gamma = \alpha_{ij}$. Given that $\alpha_{ii} = 1$, rewriting these equations gives:

$$1 - p_1 = \alpha_{11} y_1 + \alpha_{12} y_2$$

$$1 - p_2 = \alpha_{21} y_1 + \alpha_{22} y_2$$

Generalizing this to the three-good case discussed earlier, the problem becomes a multivariate optimization problem which can be solved by using the linear system $A\boldsymbol{y} = \boldsymbol{b}$.

$$\alpha_{11} y_1 + \alpha_{21} y_2 + \alpha_{31} y_3 = (1 - p_1)$$

$$\alpha_{12} y_1 + \alpha_{22} y_2 + \alpha_{32} y_3 = (1 - p_2)$$

$$\alpha_{13} y_1 + \alpha_{23} y_2 + \alpha_{33} y_3 = (1 - p_3)$$

Solving such linear system problems in more theoretical situations can be done using Cramer's rule (Varian 1992). Cramer's rule enables to find the component y_i of the solutions vector by replacing the i^{th} column of the matrix A with the column vector $\boldsymbol{b}$ to form a matrix A_i. y_i is the determinant of A_i divided by the determinant of A;

$$y_i = \frac{|\boldsymbol{A}_i(\boldsymbol{p})|}{|\boldsymbol{A}|}$$

The company's revenue in each period is $R(\boldsymbol{p}) = \boldsymbol{p} * \boldsymbol{y} = \boldsymbol{p} * \frac{|\boldsymbol{A}_i(\boldsymbol{p})|}{|\boldsymbol{A}|}$.

In order to obtain $\boldsymbol{p}^*$ and R^* the first and second order conditions have to be calculated as showed in the previous subsection. In this case calculating the first and second order condition is more complex because of the correlation between different goods.

$$1^{st} \ order \ condition \qquad \boldsymbol{D}R(\boldsymbol{p}^*) = \left(\frac{\partial R(\boldsymbol{p})}{\partial p_i}, \dots, \frac{\partial R(\boldsymbol{p})}{\partial p_k}\right) = \boldsymbol{0}$$

To determine the second order condition, the Hessian matrix is used again, like in subsection 4.3.2.

$$2^{nd}\ order\ condition \qquad \boldsymbol{h}^T H \boldsymbol{h} \leq 0$$

The optimal value of p can be derived from these formula's ($\boldsymbol{p}^* = \boldsymbol{0.5}$), while R^* depends on the correlation matrix.

4.3.5 PURE BUNDLING WITH CORRELATED VIRTUAL GOODS

1. Only one good is offered as virtual good, so all (k) virtual goods are offered in one bundle.
2. A consumer will always buy the bundle if the price is lower or equal to the valuation of all bundled goods altogether ($p_b \leq \sum_{i=1}^{k} v_i$).

In subsection 4.3.3, bundling uncorrelated goods was discussed, while subsection 4.3.4 describes correlated goods. The aim of this subsection is to combine both subsections in order to model a bundle with correlated goods.

Although copulas could be useful to find the correlated joint probability density function, simulation is chosen over copulas. First of all copulas are difficult to obtain and need to preselect a probability distribution (Nelsen 1998), which is unknown to the researchers. Secondly, in nearly all cases, analytical analysis of the copulas is not possible, making it necessary to perform numerical analysis, which is based on simulation as well.

Simulation results are in subsection 4.4.2. An outline of the simulation code is given in Appendix E. Below the used formulas, for the 3 goods example, is given.

$$V_b = \max(0, v_1) + \max(0, v_2 - \alpha_{12} * v_1) + \max\ (0, v_3 - \alpha_{23} * v_2 - \alpha_{12} * v_1)$$

The valuation of a good within a bundle can never be below zero i.e., a free good within the bundle does not influence the bundle negatively. Therefore the *max* statement is included in the formula.

The simulation simulates n independent customers with a $U \in [0,1]$ valuation for each good i, each entering the system. If the population size is sufficient an accurate distribution of bundles' demand can be obtained. As mentioned before, results are in subsection 4.4.2.

4.3.6 WRAP UP

In this subsection a model given consumers' uniform valuation is discussed in various settings. In every subsection one property changed, while the last subsection combined the results of two subsections in order to describe a bundling model with correlated goods. Yet, the results of this subsection do not give any insight into the aim of this section; find when bundling is favorable. In the next subsection the mathematical results from this subsection are used to determine when what solution is the best one.

4.4 Theoretical results

4.4.1 SIMULATION

Simulation is the imitation of a process, by representing certain key characteristics of the system, with the goal to gain insight into the functioning of the system. In order to get reliable data 100,000 customers are simulated, such that the theoretical and empirical distributions are assumed to be indistinguishable.

In the simulation 100,000 customers enter the system with a $U \in [0,1]$ valuation of all k goods. For every customer the bundle valuation given the individual valuation and the correlation between different goods is calculated as described in the previous section. The Matlab code of the simulation can be found in Appendix E.

From this simulation there are two important properties to assess, average correlation and the variance of the correlation. Both properties are explained in more detail below.

Average correlation

As of every good only one item is in the bundle, an aggregated value for α can be found. The correlation matrix has to be multiplied by the demand column vector $\boldsymbol{b}$. Because the diagonal values are not relevant and always 1, k should be extracted from the sum. The remainder has to be divided by 2 times the number of goods, since all α's are double counted in the matrix.

$$\begin{bmatrix} \alpha_{11} & \cdots & \alpha_{k1} \\ \vdots & \ddots & \vdots \\ \alpha_{1k} & \cdots & \alpha_{kk} \end{bmatrix} * \begin{bmatrix} y_1 \\ \vdots \\ y_k \end{bmatrix} = \frac{A_{1\cdot} * \boldsymbol{b} + \cdots + A_{k\cdot} * \boldsymbol{b} - k}{2 * k}$$

But since all values in column vector $\boldsymbol{b}$ are 1, the value of $\hat{\alpha}$ is simply the sum of elements of the matrix divided by the number of goods.

$$\hat{\alpha} = \left(\sum_{i,j=0}^{k} \alpha_{ij} - k \right) / 2k$$

Variance of the correlation

Variance describes how far values lie from the mean because although the average can be equal the variance can differ greatly. To test the effect of variance a couple of schemes are used. While $\hat{\alpha} = 0.5$ in all cases, α_{ij} are different. The schemes tested are in Table 7.

	n=3	n=5
1	$\alpha_{12} = \alpha_{13} = \alpha_{23} = 0.5$	$\alpha_{12} = \alpha_{13} = \alpha_{14} = \alpha_{15} = \alpha_{23} = \alpha_{24} = \alpha_{25} = \alpha_{34} = \alpha_{35} = \alpha_{45} = 0.5$
2	$\alpha_{12} = 0.4,\ \alpha_{13} = 0.3,\ \alpha_{23} = 0.8$	$\alpha_{12} = 0.45, \alpha_{13} = 0.4, \alpha_{14} = 0.35, \alpha_{15} = 0.3, \alpha_{23} = 0.55, \alpha_{24} = 0.6, \alpha_{25} = 0.65, \alpha_{34} = 0.7, \alpha_{35} = 0.5, \alpha_{45} = 0.5$
3	$\alpha_{12} = 0.2,\ \alpha_{13} = 0.6,\ \alpha_{23} = 0.7$	$\alpha_{12} = 0.4, \alpha_{13} = 0.3, \alpha_{14} = 0.2, \alpha_{15} = 0.1, \alpha_{23} = 0.6, \alpha_{24} = 0.7, \alpha_{25} = 0.8, \alpha_{34} = 0.9, \alpha_{35} = 0.01, \alpha_{45} = .99$
4	$\alpha_{12} = 0.01,\ \alpha_{13} = 0.99,\ \alpha_{23} = 0.5$	$\alpha_{12} = 0.01, \alpha_{13} = 0.01, \alpha_{14} = 0.01, \alpha_{15} = 0.01, \alpha_{23} = 0.01, \alpha_{24} = 0.99, \alpha_{25} = 0.99, \alpha_{34} = 0.99, \alpha_{35} = 0.99, \alpha_{45} = 0.99$

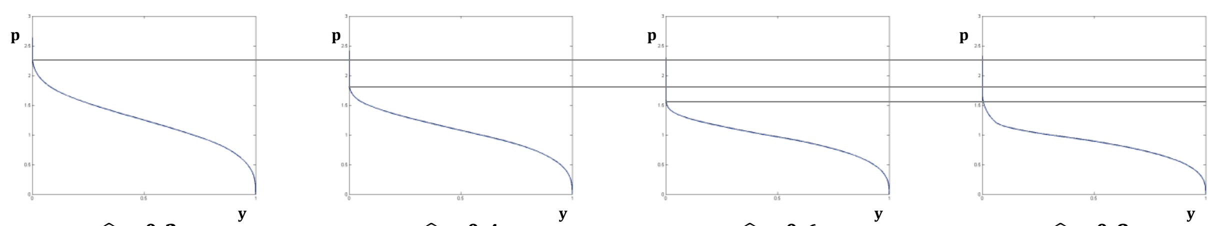
TABLE 7, VARIANCE TEST SCHEME

4.4.2 RESULTS

The results of the simulation are given below. All calculations are performed using Matlab, which uses a lot of matrices to save results and prepare the graphs. Only the graphs are provided in this study, but the matrices can be constructed using the Matlab code from Appendix E. First the three-good case is shortly discussed, but only in the five-good case the findings are described extensively, followed by observations from the model.

Three-good case

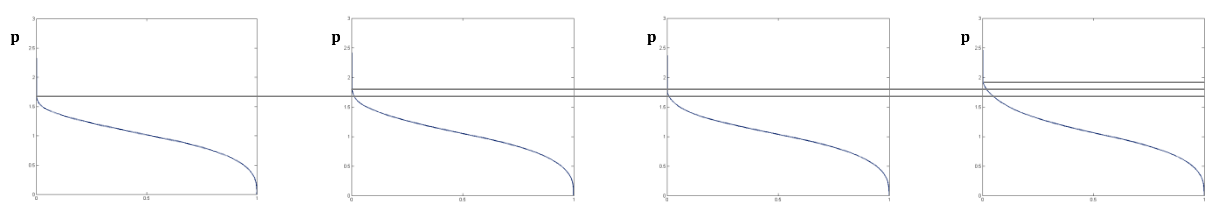
First the simulation was performed with a fixed variance (0) and varying average. As can be seen from the graphs below, when the $\hat{\alpha}$ increases the whole bundling demand curve moves down. To make this effect more clear the grey horizontal line was added. This implies bundling uncorrelated goods is favorable over bundling more correlated goods as was expected from the previous subsections. This however does not say anything about whether or not bundling is favorable over a'-la-carte pricing. This will be discussed in more detail in the five-good case. Note that the decline of the demand line is stronger when $\hat{\alpha}$ moves from 0.2 to 0.4 than from 0.6 to 0.8 where almost no effect can be observed.



$\hat{\alpha} = 0.2$ $\hat{\alpha} = 0.4$ $\hat{\alpha} = 0.6$ $\hat{\alpha} = 0.8$

FIGURE 18, THREE GOODS VARYING $\hat{\alpha}$

Below are the graphs of the simulation where the $\hat{\alpha}$ was fixed at 0.5 while the variance changed as described in Table 7. Again the grey line was added to show the effect. Although the effect is not as significant as when shifting the $\hat{\alpha}$, the demand curve slightly shifts upwards when the variance increases. Again this says nothing about bundling versus a'-la-carte pricing, it just shows that bundling a set of goods with high variance in the correlation between the goods is favorable over a set of goods with low variance i.e., bundling goods with completely different correlations is favorable over bundling goods that are more or less equal in their correlation.



1 2 3 4

FIGURE 19, THREE GOODS VARYING VARIANCE

Five-good case

In the three-good case only the bundle was considered, but to compare whether or not bundling is favorable over a'-la-carte pricing, combined sole good demand and prices need to be taken into account as well. Therefore the simulation from the three-good case is done again, but extended to five goods and compared to the aggregated demand of the individual goods. In Appendix E the used Matlab code can be found.

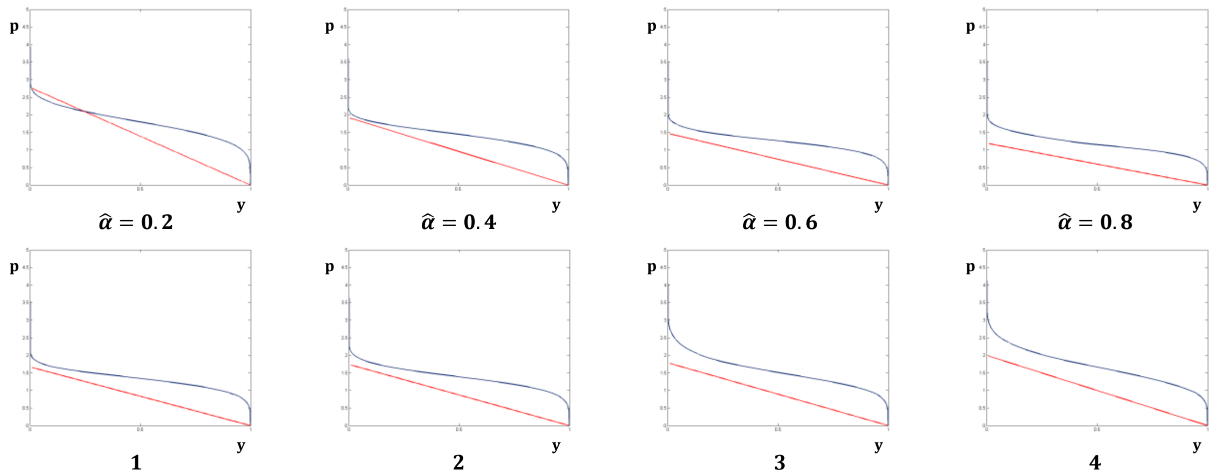


FIGURE 20, FIVE-GOOD CASE

The effects observed in the three-goods case are, as expected, observed again in the five-good case. The demand curve shifts downwards when $\hat{\alpha}$ increases, while the demand curve shifts upwards when the variance of correlation increase. The absolute effects are obviously stronger in the five-good case. Note that exactly the same effects occur in the a'-la-carte situation.

Given that price is on the vertical axis and revenue equals price times demand, the revenue and hence the profits are, in seven of the eight graphs above, by definition higher while bundling. As can be seen in all graphs but the first, the blue curve (bundling) is on every single price point on top of the red line (a'-la-carte). Therefore the price with a given demand is always higher and therefore profits are always higher. But as the first graph shows, intersection can occur as well. Known is, from the previous subsections, that the optimal price point for a'-la-carte pricing is half way. Because the bundling demand curve is in that point ($y = 0.5$) on top of the aggregated demand curve, the profit is by definition higher. The minimum additional profit bundling elicit is $\left(p_b(0.5) - p_i(0.5)\right) * 0.5$.

The degree to which bundling is favorable differs depending on variation in correlation and variance of correlation. This suggests that when bundling does have a negative impact on the total revenue, as several motives showed in subsection 4.2 with some correlation configuration, a'-la-carte pricing could become favorable over bundling. In subsection 4.4.4 this will be discussed in more detail.

These findings lead to the following four observations.

OBSERVATION 1 More correlation has a negative impact on the inverse demand functions of both bundling and a'-la-carte pricing, with uniform $\epsilon[0,1]$ valuations, although the degree to which both are sensitive to correlation differs.

OBSERVATION 2 A higher variance within the correlation between the goods has a positive impact on the inverse demand functions of both bundling and a'-la-carte pricing, with uniform $\epsilon[0,1]$ valuations, although the degree to which both are sensitive to this variance differs.

OBSERVATION 3 Adding more goods with uniform $\epsilon[0,1]$ valuations to the bundle increase the maximum of the average profit per good, while the maximum of the average profit per good given a'-la-carte pricing remains equal.

OBSERVATION 4 Bundling, with more than three goods, is always favorable over a'-la-carte pricing, with uniform $\epsilon[0,1]$ valuations, although the degree to which bundling is favorable differ.

4.4.3 OTHER DISTRIBUTIONS

The simulations in the previous subsection showed that it is always favorable to bundle even if the correlation between goods and variance between correlations is high. However, multiple aspects are left out of the study, that are important to consider, especially given the demographics of eBuddy.

One aspect is expense restrictions (Bakos and Brynjolfsson 2000). If a company decides to sell a bundle exclusively, customers with a limited amount of money will not buy the bundle although the individual valuations and hence the valuation of the bundle is higher than the price. This effect is particularly important when bundling large amounts of goods (Bakos and Brynjolfsson 2000), but relevant to eBuddy as well since the largest part of eBuddy's users are teenagers i.e., low income customers.

Another related aspect is that competitors, who offer a chat client and virtual goods a'-la-carte, might be preferred by potential users. This will lead to lower sales and hence lower revenue for the company. This will be discussed in more detail in the next subsection.

One simulation is done with an $\exp(\lambda)$ valuation, which describes an exponential distribution with mean $\lambda = 1$. The probability density function is $f(x) = \lambda e^{-\lambda x}$ and others already studied this distribution for bundling with uncorrelated goods (Wu, Hitt et al. 2008). In Figure 21 the five-good demand curve for both the bundled situation and the a'-la-carte situation is showed. Note that, the average valuation of the $\exp(1)$ distribution is higher, but the density at lower prices (< 1) is also higher and hence the customer with a limited amount of money compared to other is imitated. Consequently it is impossible to directly compare the results from the previous simulations with these and other distribution results.

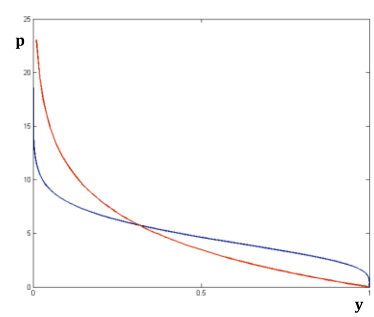


FIGURE 21, DEMAND CURVE EXP(1) DISTRIBUTION

As was shortly discussed in subsection 2.3.3 sales in the Apple App Store follow a power law. A classic example of this behavior, first observed by Zipf (Naumis and Cocho 2008), is the size of cities. The distribution the data follows is highly skewed to the right i.e., many fairly small towns and a few big cities. What Zipf discovered, and is known as Zipfs' law, is that when the cities are ranked from the biggest to the smallest city and the rank and city size are plotted on double logarithmic axis, a straight line appears, which implies a power law. In many real-world phenomenon's, like word frequencies, web hits and wealth distribution the power law, in a discrete form, can be observed (Newman 2005).

The probability density function of the power law applicable to the Apple App Store is $f(x) = Cx^{-\beta}$, where C is the cutoff point (1) and β differs per country and category in the Apple App Store but is most found around 1.25 (Spriensma 2010). This distribution has an even higher density at low prices than the exponential distribution, as can be seen for the five-good case in Figure 22.

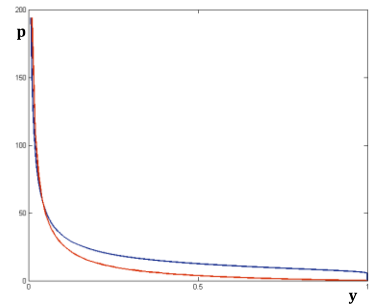


FIGURE 22, DEMAND CURVE PL(1.25) DISTRIBUTION

An advantage of the numerical approach in the last subsection is that it is easier to examine the performance with other valuation distribution. The first aspect discussed, stated there are customers with a limited amount of money i.e., the valuation distribution deviates to more weight at the lower tail. In the previous subsection both the price and demand could move between [0,1] as result of the uniform distribution. Due to the nature of the used distributions this restriction could not hold in this simulation. Because of one of the properties of virtual goods from subsection 2.4.2, the assets property, the demand is limited to 1. Hence the price of each good can differ over a larger range.

Derived from the market interaction model the use of α was justified while simulating with the uniform distribution in subsection 4.4.2. As the simulation is extended to other distributions the use of α is open to discussion. Because the simulation remains essentially the same, except from the valuation distributions the α can be used as a measure of correlation. Note that this says nothing about the way the α can be incorporate in a non-numerical situation.

The same settings as in the previous subsection are used while simulating for the exponential and power law distribution, however only the five-good case is evaluated (See Appendix E).

Exponential distribution

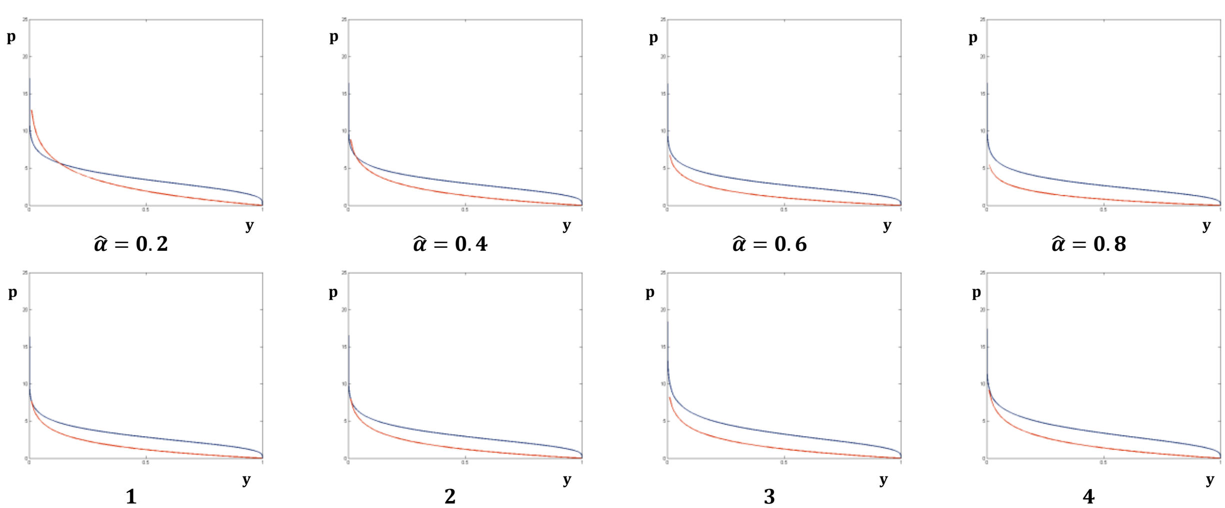


FIGURE 23, EXPONENTIAL DISTRIBUTION CASE

The same pattern as in the uniform case can be observed with the exponential distribution. First, the bundling' demand curve is in almost all cases (except $\hat{\alpha} = 0.2$ and $\hat{\alpha} = 0.4$) on top of the a'-la-carte demand curve and as will be quantified in the next subsection bundling yields always higher revenue. When increasing the $\hat{\alpha}$, the a'-la-carte demand curve clearly move downwards while the bundles' demand curve remains fairly stable, it slightly moves downwards as well. The tuning of the variance within the correlation carries a positive effect, especially to the bundles' demand curve while a'-la-carte offering is fairly stable. As mentioned, both effects were observed with the uniform distribution as well, but are much stronger as will be proven in the next subsection.

Power law distribution

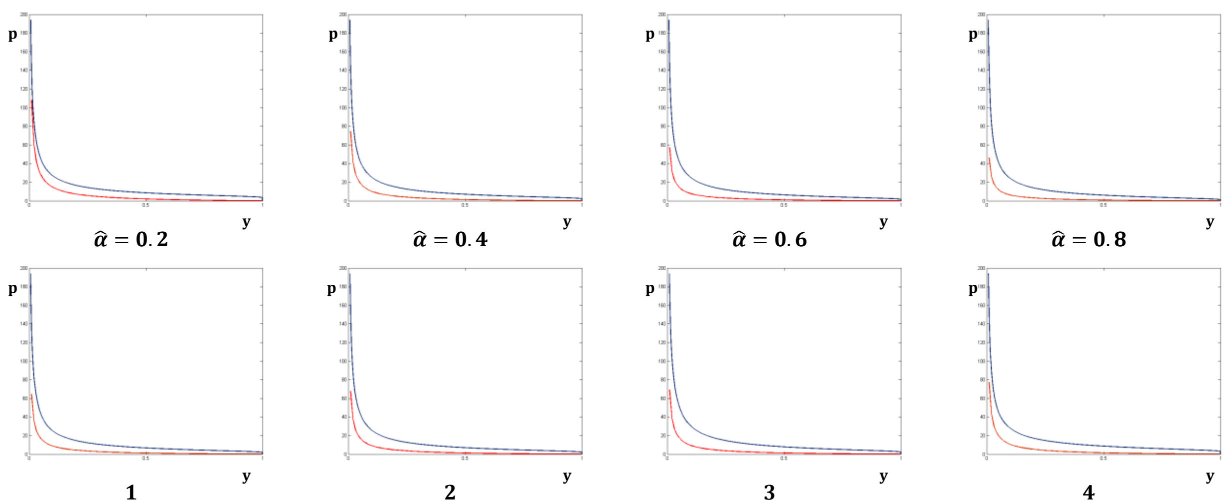


FIGURE 24, POWER LAW DISTRIBUTION CASE

What was observed in the exponential case can be observed (Figure 24) with the power law distribution too. The effects are stronger than in the exponential case and consequently stronger than in the uniform case. This presumes that, the more skewed the distribution, the stronger the observed effects, which will be numerically proven in the next subsection. It is clear from Figure 24, that given the power law distribution, the demand curve is on top of the a'-la-carte offering. The joint distribution is fairly stable while the sole good demand curve is still vulnerable to differences in the correlations between goods. This effect can also be observed while changing the variance within the correlation but then carry a positive effect in a'-la-carte demand as the demand curve moves to the stable bundle demand curve in Figure 24.

These findings lead to the following two observations.

OBSERVATION 5 Observations 1 & 2 applicable to the uniform distribution $\epsilon[0,1]$ are applicable to the exponential distributions as well.

OBSERVATION 6 Observations 1 & 2 applicable to the uniform distribution $\epsilon[0,1]$ are applicable to the power law distribution as well.

4.4.4 THE DEGREE TO WHICH BUNDLING IS FAVORABLE

As could be noticed from the last two subsections, the degree to which bundling is favorable over a'-la-carte pricing depends primarily on the value of $\hat{\alpha}$ and the chosen distribution.

Moreover, although there are no direct costs involved, there are some issues that need attention. First of all, although bundling might be efficient, it restricts the choice of consumers. It might provoke frustration and unhappiness, hence in customer relationship bundling might not be the right thing to do (Liebowitz and Margolis 2009). Another related aspect is that competitors, who offer a chat client and virtual goods a'-la-carte, might be preferred by potential users. This will lead to lower usage and hence lower revenue for the company.

It is difficult to get an idea to what extent this will influence the joint distribution of the bundle. Nevertheless, it is possible to determine for each distribution and $\hat{\alpha}$ combination, the tipping point i.e., the point when a'-la-carte pricing becomes more profitable than bundling. This tipping point is represented by a new variable β. $\beta \epsilon [0,1]$ represents the degree to which bundling is favorable over a'-la-carte pricing.

$$\sum p_i * y_i = \beta * (p_B * y_B)$$

$$\beta = \frac{\sum p_i * y_i}{(p_B * y_B)}$$

In Table 8 the results of the simulation in the three- and five-good case (See Appendix E) are provided, which are intuitive given the graphs from the previous subsection. If for example a negative demand of 40% is expected from only offering a bundle of 5 goods, the $\hat{\alpha}$ must, in case of an uniform distribution, be larger than 0.2 to gain higher profits.

$\hat{\alpha}$	β_{Uniform} N=3 – N=5	$\beta_{\text{Exponential}}$ N=3 – N=5	$\beta_{\text{Power law}}$ N=3 – N=5
0.1	0.79 - 0.68	0.69 - 0.57	0.27 - 0.22
0.2	0.74 - 0.61	0.64 - 0.50	0.26 - 0.21
0.3	0.69 - 0.55	0.59 - 0.45	0.25 - 0.20
0.4	0.65 - 0.51	0.55 - 0.40	0.25- 0.19
0.5	0.62 - 0.47	0.52 - 0.37	0.24 - 0.17
0.6	0.59 - 0.44	0.49 - 0.34	0.23 - 0.16
0.7	0.56 - 0.41	0.47 - 0.31	0.22 - 0.15
0.8	0.53 - 0.39	0.44 - 0.28	0.21 - 0.14
0.9	0.51 - 0.36	0.42 - 0.26	0.20 - 0.12
1	0.49 - 0.35	0.40 - 0.24	0.19 - 0.11

TABLE 8, SIMULATION β RESULTS

What can be concluded from Table 8 is that in general the five-goods case shows significant decrease in the value of β compared to the three-good case i.e., significant increase in the degree to which bundling is favorable over a'-la-carte pricing when the number of goods increase. This finding is in line with bundling uncorrelated goods (Bakos and Brynjolfsson 1999). Moreover the gap between both the three- and five-good case becomes wider when the $\hat{\alpha}$ increases i.e., the five-good bundle is less reluctant to more correlated goods than the three-good bundle. Finally bundling in a more left skewed distribution is more favorable over a'-la-carte pricing than in a more uniform distribution as can be seen from the lower value of β when simulating the exponential and power law distribution (with three and five goods).

These findings lead to the following four observations.

OBSERVATION 7 Bundling with more than three goods is always favorable over a'-la-carte pricing, although the degree to which bundling is favorable differ.

OBSERVATION 8 The more goods are added to the bundle the more favorable it becomes to bundle over a'-la-carte pricing.

OBSERVATION 9 The more skewed the valuation distribution is to the left, the more favorable bundling becomes over a'-la-carte pricing.

OBSERVATION 10 When more goods are added to the bundle the bundle becomes less vulnerable to increasing correlation.

4.4.5 WRAP UP

By simulation some rather unexpected results are found. Although it was not explicitly stated in any paper the notion existed that bundling uncorrelated goods was favorable over bundling correlated good. Simulation showed the exact opposite. This preconceived opinion existed because many contributors wrote that the results were only valid to uncorrelated goods (Salinger 1995; Bakos and Brynjolfsson 1999; 2000).

While bundling is always favorable over a'-la-carte pricing in the simulation, in subsection 4.4.4 the degree to which bundling is favorable are given. If considering several problems in customer satisfaction and behavior of competitors, it might be, in certain cases, better to drop the bundle and sell single features.

4.5 Conclusions

Although in this section a highly stylized model is used which is also based on a number of premises, it is in line with the models of several influential contributors (Salinger 1995; Bakos and Brynjolfsson 1999; 2000). The uniform distribution $\in [0,1]$ is almost never observed in the real world and based on earlier research at eBuddy not applicable to their situation. However as others proved before (Wu, Hitt et al. 2008) the results can even be better with other distributions, like broader width uniform- and exponential distributions. In this section is proved that not only in uncorrelated cases this is valid but is applicable to correlated goods as well.

This section started to study effects when bundling virtual goods but the findings are more general. The findings can be applied to basically all goods with zero marginal costs and as was discussed in section 2, all information goods share this property and thus these results are applicable to all information goods. Note that because distribution of the software will not be as easy as with in-app virtual goods, the value of β should be estimated higher.

In this section the valuations of the goods were assumed to be mutually independent in all simulations. Although, theoretical convenient, one can ask questions about the tenability of this. Partial substitutes are not only substitutes in demand i.e., why will a customer have a higher valuation for a substitute good? Although counterintuitive it is frequent, imaging a gaming console like the Playstation which is twice the price of the Xbox, when a consumer bought one of the two the need to buy the other will disappear for almost all consumers. Besides, this effect is likely to be only applicable when goods are full substitutes and those edge cases should be approach with more caution anyway.

To use this model two unknowns have to be estimated, 1) the valuation distribution of the consumers and 2) the value of α_{ij} for every combination of goods. For the first it is, although unknown, relative easy to get an idea of. The latter however is more difficult to assess, therefore in the next section an attempt to perform an educated estimation of α_{ij} is made.

5 CORRELATION

Key in the last subsection is the correlation between virtual goods. Proven in the model is, that if correlation between the available goods is high it is more profitable to bundle, while a higher variation in correlations is favorable as well. Therefore in this section a framework is provided to assess the correlation between virtual goods.

5.1 Definitions

In this section various new terms will be introduced. To increase readers' convenience in this subsection, all definitions of new terms used in this section are given in alphabetical order.

CONSTRUCTS	*An explanatory variable which is not directly observable.*
CONSTRUCT OPERATIONALIZATION	*The process making the concept measurable and to understand it in terms of empirical observations.*
CROSS-SECTIONAL DESIGNS	*A class of research methods that involve observation of all of a population, or a representative subset, at a defined time.*
CRONBACH'S ALPHA	*Measure of reliability for a set of two or more constructs indicators. Values range between 0 and 1, with higher values indicating higher reliability among the indicators.*
ERROR VARIANCE	*Unreliable and inexplicable variation in a variable.*
FACTOR LOADING	*Weighting which reflect the correlation between the original variables and derived factors.*
HYPOTHESIS	*A proposed explanation for an observable phenomenon.*
INSTRUMENT VALIDITY	*The extent to which an instrument measures what it is supposed to.*
INTERNAL VALIDITY	*The validity of (causal) inferences in scientific studies, based on experiments*
STATISTICAL VALIDITY	*The degree to which an observed result, can be relied upon and not attributed to random error in sampling and measurement.*

5.2 Dimensions

As described multiple times before, a virtual good can, according to Lehdonvirta (2009), be described on three dimensions, the utilitarian-, the hedonic- and the social-dimension. By thinking in dimension as a XYZ plane as in Figure 25, where utilitarian dimension is represented by x, the hedonic by y, and finally the social dimension by z, the distance between the different goods can be quantified.

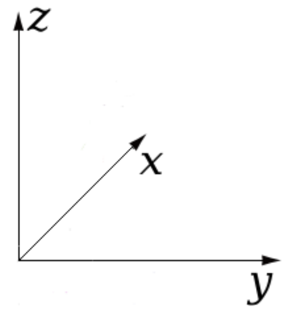


FIGURE 25, XYZ PLANE

If $0 \leq x, y, z \leq 1$ the maximum distance between two goods is $(1 + 1 + 1)^{1/2} = 1.73$, so in order to normalize to 1, which is necessary given the properties of α in the previous section, the results have to be divided by 1.73.

Since it is impossible to measure the dimension directly, attributes that reflect the dimensions are needed. These attributes are described in the next subsection. However since exact measurement of α is only possible by using the interval scale to measure the attributes, exact measurement is impossible. Usage of the interval scale is only possible when there is a precise indication of the value of each category and the differences among them (Rea and Parker 1992) like income, height and age. As the attributes in the next subsection do not consent to those criteria one might argue measuring is a waste of time. But as the ordinal scale still measures the extent to which an item possess the characteristics of the attribute, at least an educated guess of the distance can be made, which is better than no information at all. Logically this limits the decision power of the tests.

Measurement of correlation by these three dimensions is only valid in the narrow case of virtual goods at eBuddy and is as result a measure, but certainly not the only one. Other states beyond virtual goods require more research. Given this is omitted in the previous sections other measures are left out of this section as well.

5.2.1 ATTRIBUTES

In Table 9 the attributes corresponding to the dimensions are listed. Lehdonvirta (2009) describes attributes of the goods itself, where other authors tried to describe motivations to purchase virtual goods. The results are quite similar, but are not directly comparable.

Dimension	Attribute
Functional	Performance
	Functionality
Hedonic	Visual Appearance and sounds
	Background fiction
	Provenance
	Customizability
	Cultural references
	Branding
Social	Rarity

TABLE 9, ATTRIBUTES OF VIRTUAL GOODS (LEHDONVIRTA 2009)

Lehdonvirta (2009) performed an exploratory case study based on:

- First-hand use experience
- Interviews with developers (EVE Online, Habbo Hotel, IRC-Galleria and Jippii.com)
- Interviews with professional virtual goods traders (N = 2)
- Previous literature
- Numerous informal discussions with users and players, both computer-mediated and face-to-face

While the study of Lehdonvirta (2009) certainly does not follow any structured method to determine the dimension like in this study, the results are still useful. According to de Vaus (2001) the main issue related to this type of research (explanatory) is mixing correlation and causation i.e., are the attributes really affecting the dimension. Lehdonvirta (2009) starts with an extensive overview of literature and based on this literature performed theory building, which was consistent with earlier literature in both virtual goods and more tangible commodities. Some researchers believe the case study should only be used to generate hypotheses for future, more rigorous, testing (Vaus 2001), which is agreed by Lehdonvirta (2009) in the limitations and further research section.

So, more rigorous testing is necessary, before this study can obtain the attributes and dimensions as the basis of the correlation coefficient. Besides it is important to note that several of the attributes represent a positional characteristic instead of an absolute one i.e., their value stems from how they compare to other goods and the surrounding environment (Lehdonvirta 2009). This property fits within the goal of this study as several virtual goods should be positioned in order to determine the best selling bundles.

5.2.2 CONSTRUCTS

In Table 10 the constructs and the corresponding definition are given (retrieved from the dictionary (most appealing definition), and slightly adjusted).

Abbr:	Construct:	Definition:
PERF	Performance	The degree to which an item improves the way the app functions.
FUNC	Functionality	The degree to which an item increases the abilities and options of the app.
VAAS	Visual Appearance and Sounds	The degree to which an item improves the look of the app and enables the configuration of sounds.
BAFI	Background fiction	The degree to which an item provides underlying background information.
PROV	Provenance	The degree to which an item has historical value.
CUST	Customizability	The degree to which an item enables the user to change according to the individual requirements.
CURE	Cultural references	The degree to which an item enables the user to express their real-life national identity.
BRAN	Branding	The degree to which an item identifies and differentiates the user from the other users.
RARI	Rarity	The degree to which an item is scarce.

TABLE 10, DEFINITIONS OF THE CONSTRUCTS

But in order to test whether the dimensions move along with the expected corresponding constructs, the dimensions have to be tested as well. Therefore in Table 11 the dimensions and the corresponding definitions are given.

Abbr:	Dimension:	Definition:
DFUN	Functional	The degree to which an item is capable of functioning and is practical rather than decorative.
DHED	Hedonic	The degree to which an item pursuits of or devotion to pleasure of the senses.
DSOC	Social	The degree to which an item is relating to or considered appropriate to one thought superior.

TABLE 11, DEFINITIONS OF THE DIMENSIONS

When looking at the definitions of all constructs and dimensions the provenance constructs does not fit within the eBuddy environment. Historical value might be applicable to the focus of Lehdonvirta (2009) study, games, but cannot be included into the virtual goods eBuddy will offer. Therefore provenance is excluded from the research. This is also the case with the background fiction construct, virtual goods sold by eBuddy will not have an underlying story as games characters might have. Although rarity is an outsider as well, this construct can occur, in for example very expensive or limited-sale goods. Finally, the visual appearance and sounds construct actually measures two different properties and as the guidelines (Rea and Parker 1992) used in this research said this should be avoided. Therefore in this study only the visual appearance will be measured.

5.2.3 HYPOTHESES

Expected is a positive relation for all of the constructs towards the connected dimensions in Figure 26. When following the line of use in other papers, each connection in Figure 26 would be accompanied by a hypothesis i.e., this leads to 12 hypotheses. As all hypotheses are equal in nature only the three types are discussed.

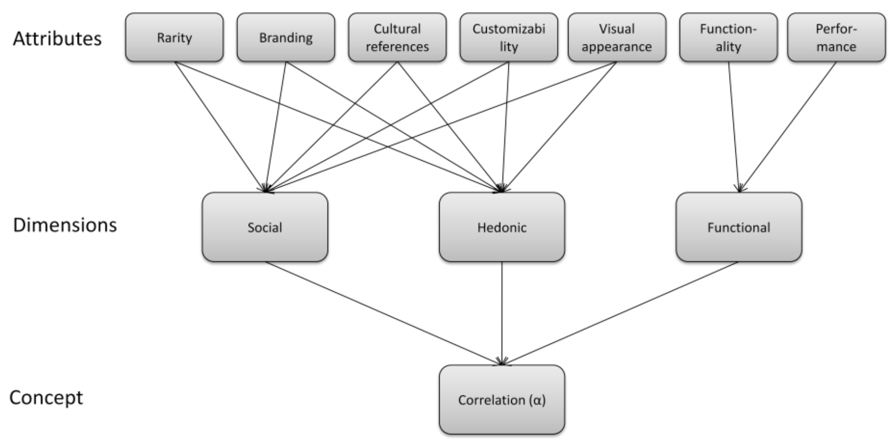


FIGURE 26, CONSTRUCTS NETWORK

HYPOTHESIS TYPE 1 The functional dimension (*DFUN*) is positively influenced by performance (*PERF*) and functionality (*FUNC*)

HYPOTHESIS TYPE 2 The hedonic dimension (*DHEF*) is positively influenced by visual appearance (*VAAS*), background fiction (*BAFI*), customizability (*CUST*), cultural reference (*CURE*), branding (*BRAN*) and rarity (*RARI*).

HYPOTHESIS TYPE 3 The social dimension (*DSOC*) is positively influenced by visual appearance (*VAAS*), background fiction (*BAFI*), customizability (*CUST*), cultural reference (*CURE*), branding (*BRAN*) and rarity (*RARI*).

5.2.4 WRAP UP

In this subsection the outline of what this study wants to test is given. In order to make an educated guess about the α introduced in section 4 the dimensions introduced in subsection 2.4.2 are used. With the attributes defined in this subsection, constructs are defined and causal relations are proposed. To validate this subsections' propositions, in the next subsections the set-up and implementation of the survey is discussed to check whether the relations really exist.

5.3 Survey design

5.3.1 Method of testing

There is nothing about the logic of cross-sectional designs that requires a particular method of data collection. It is essential to obtain a structured set of data that enables systematic comparison between cases or groups of cases. The most used, and preferred method in this study, is the structured questionnaire. Given the population to perform the test on, the best way is a self-administered survey by the respondent via an online survey system. There are several weaknesses of this method. When assuming mail is equal to online surveys, there is 1) no control over who completes the questionnaire, 2) avoidance of refusal bias, 3) not suited to handle more complex and time consuming questions (Vaus 2001).

In general, the larger the sample the better, but beyond a certain point increases have more marginal benefits (Vaus 2001). In the population used in this study (eBuddy) to find sufficient participants should not be a problem given surveys executed before. However there are some issues that can become a problem like response rate and demographics. These issues are discussed in more detail in the next subsections.

5.3.2 Design

In order to perform this explanatory research with quantitative data this study will use a cross sectional design, 1) because the observations relies on existing variations, 2) the data are collected at one point of time and 3) there is no random allocation to 'groups' (Vaus 2001).

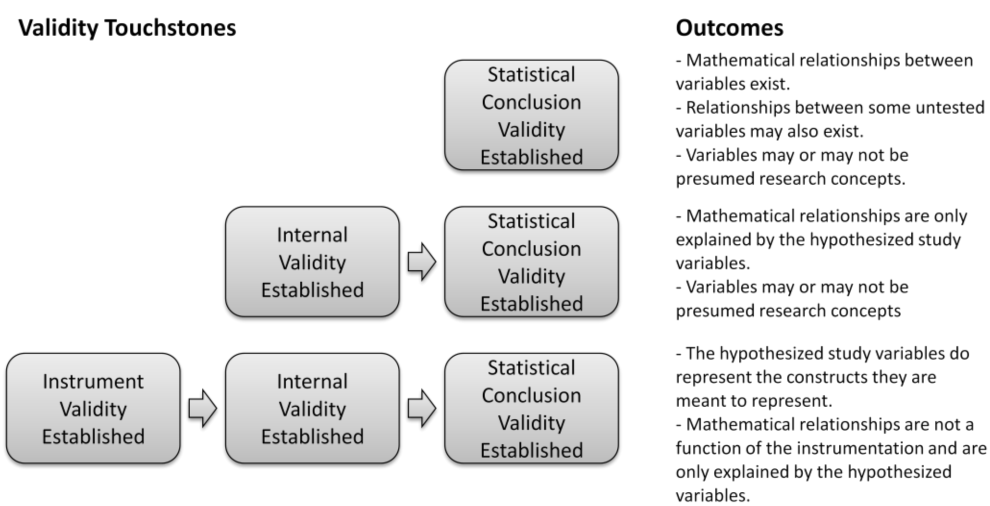


FIGURE 27, VALIDITY TOUCHSTONES (STRAUB, 1989)

The problem of rigor in research has always persisted, especially in dynamic and ever changing fields like Information System research. Therefore Straub (1989) proposed a method to validate of the instruments in order to find reliable i.e., the same results on repeated occasions (Vaus 2001), findings and interpretations.

Straub assessed three top journals for three years and found that only 17% of the articles reported reliability, 13% validated their constructs and 19% either did a pretest or a pilot test. 11 years later an equal research was conducted and found that significant progress was made (Boudreau, Gefen et al. 2001), proving that among researchers the issues brought up by Straub were relevant.

The proposed method of Straub exists of three phases to strengthen the empirical findings by instrument validation, internal validity and statistical conclusion validity. The findings are summarized in Figure 27. This is more or less in line with the book of de Vaus (2001).

5.3.3 STATISTICAL VALIDITY

The problem of confounding variable is in a cross sectional design tackled at the data analysis stage rather than at the data collection stage. Differences between groups are removed after the data have been collected. In order to do so matching information is needed e.g., when we want to distinguish groups based on age, the age of the participants is needed. In the subsection 5.4.1 more information about the matching information is provided.

5.3.4 INTERNAL VALIDITY

In cross sectional design threats for internal validity stems from 2 sources; problems in establishing cause and problems at the level of meaning (Vaus 2001). To address the first problem a preliminary literature review was performed to get rid of alternative explanations. Albeit it is impossible to completely eliminate alternative explanations, it supports a priori for arguing a case. The latter, to provide meaningful explanations, is harsh in cross sectional design but less relevant as well. This questionnaire does not aim to explain why for example rarity provoke the social dimension; this is done by others before (Lehdonvirta 2009). The focus is on proving the relationships.

Another known threat is the non-responders bias, which is especially applicable in this situation as eBuddy's users are numerous, but do not have a strong bonding with the company and most likely do not have interest in the survey. Unfortunately this problem cannot be solved; however some effort can be made by making the objectives and time consumption clear beforehand.

Common method variance refers to the amount of spurious covariance shared among variables because of the common method used in collecting data i.e., variance that is attributable to the measurement method rather than to the constructs the measures represent (Podsakoff, MacKenzie et al. 2003). This is a severe threat in general and especially to surveys that collect the responses at one point in time. Given the difficulties with linking the data and expected unwillingness to participate in the second round of questionnaires, the study is caught in the single setting. In order to reduce the common method variance, in this study the guidelines of item and questionnaire design of Rea and Parker (1992) are applied. There are procedures available to test for Common method variance after data collection as will be discussed in subsection 5.5.4.

5.3.5 INSTRUMENT VALIDITY

Instrument validity is based on three criteria: content validity, construct validity and reliability (Straub 1989). The instrument is content valid when the measures tap the different aspects of the concepts as defined. Construct validity measures of a construct actually measure what the construct is supposed to measure. Construct validity can be accepted when both convergent i.e., degree to which a measure is correlated with other measures that it should correlate with, and divergent validity i.e., degree to which the measure does not correlate with other measures that it theoretically should not be correlated with, is showed. Reliability measures the extent to which the measure gives the same reading when used on repeated occasions. Reliability is commonly assessed by using Cronbach alphas.

Invalidated instruments are a waste given it unnecessarily lowers the quality of the research. So given the restrictions of the research it is key to obtain the highest instrument validity as possible. In order to do so the sorting procedure of Moore and Benbasat (1991) is used. After the sorting procedure, a pre-test is used to assess the reliability and other procedures of the survey. After this pre-test a larger pilot-test is used to technically asses construct validity and reliability.

Phase		Methods	Content validity	Construct validity	Reliability
1	Conceptual validation	Qualitative	x	x	x
2	Pretest	Qualitative	x	x	x
3	Pilot test	Composite Reliability Factor analysis		x	x
4	Survey	Composite Reliability Factor analysis		x	x

TABLE 12, ASSESSSMENT OF VALIDITY

5.3.6 WRAP UP

In this subsection the instruments to make this study robust are explained. Before the implementation can be done, a few issues have to be discussed.

First the way the questionnaire is presented will be discussed. eBuddy is a web based service and through the advertisement platform, empty inventory can be used to mention the survey to users. Participants that are already logged in to eBuddy can click on the banner and can in that way voluntary participate in the survey.

The questionnaire will be in English to avoid cross-language issues in the validity of the research. Therefore only users that have a certain level of the English language should be allowed to participate. The only way to guarantee a proper knowledge of the language is to include only native speakers. Therefore only users that are from the United States, United Kingdom, Australia, Canada and Ireland will be invited to participate in the survey. This country selection also minimizes cross-cultural factors and economical differences since all five are wealthy countries and according to Hofstede[28] the countries are culturally more or less equal (see Table 13).

Country	Power distance	Individualism	Masculinity	Uncertainty avoidance	Long-term orientation
U.S.	40	91	62	46	29
U.K.	35	89	66	35	25
Australia	36	90	61	51	31
Canada	39	80	52	48	23
Ireland	28	70	68	35	-

TABLE 13, CULTURAL DIMENSION, HOFSTEDE[29]

5.4 Survey implementation

5.4.1 CONSTRUCT OPERATIONALIZATION

As Lehdonvirta (2009) mentioned the nine attributes should be broken down into more detailed features aimed at specific types of goods. In this study the seven remaining attributes (see Figure 26) are used as constructs and operationalized by questions aimed at the virtual goods eBuddy offers.

Survey questions

Most studies use validated constructs, definition and questionnaires to set up a survey, but in this new area of research no pre-validated surveys are available. Therefore all questions have to be invented from scratch. In order to secure reliability the guidelines of Rea and Parker (1992) are taken into account as are the steps of the previous subsection to validate the instruments.

The guidelines are divided into two categories, 1) phrasing and 2) formatting. Where phrasing refers to how to construct a sequence of words with the right meaning, while formatting refers to the arrangement of the questions and scaling issues (Rea and Parker 1992).

By focusing on good phrasing, the survey should be comprehensive to all participants and all questions produce unbiased answers. First of all the wording in the survey should be simple, straight forward and to the point without loss of substance. Besides, efforts must be devoted to avoid ambiguity within the questions, multipurpose questions and manipulative information. Finally it is really important to construct questions with unbiased words or phrases.

Construct & Questions	
Functional	
DFUN1	I think [..] is a functional feature to eBuddy.
DFUN2	The [..] is a practical good.
DFUN3	I will use [..] because it supports eBuddy functioning.
Hedonic	
DHED1	I think [..] will make eBuddy more attractive.
DHED2	The [..] is a decorative good.

[28] http://www.geert-hofstede.com/

[29] http://www.geert-hofstede.com/hofstede_dimensions.php

DHED3	I will use [..] because it excites me.
Social	
DSOC1	I think [..] has no use except increasing my status.
DSOC2	The [..] is a status good.
DSOC3	I will use [..] because it's exclusive.
Performance	
PERF1	I think [..] will improve eBuddy performance.
PERF2	The [..] is a quality good.
PERF3	I will use [..] because it makes something functioning better.
Functionality	
FUNC1	I think [..] extends the capabilities of eBuddy.
FUNC2	The [..] is a capacity increasing good.
FUNC3	I will use [..] because it enables more options in eBuddy.
Visual Appearance	
VAAS1	I think [..] will extend the visual appearance of eBuddy.
VAAS2	The [..] is a manifestation good.
VAAS3	I will use [..] because it makes eBuddy look nicer.
Customizability	
CUST1	I think [..] enables me to change eBuddy's look and feel.
CUST2	The [..] is a personalization good.
CUST3	I will use [..] because it enables customization.
Cultural references	
CURE1	I think [..] allows me to express where I come from.
CURE2	The [..] is an ethnic tied good.
CURE3	I will use [..] because it reflects my background and values.
Branding	
BRAN1	I think [..] will identify who I am.
BRAN2	The [..] is a personal branding good.
BRAN3	I will use [..] because it differentiates me from other users.
Rarity	
RARI1	I think [..] is exclusive.
RARI2	The [..] is a show off good.
RARI3	I will use [..] because it is scarce.

TABLE 14, SURVEY QUESTIONS

Formatting

Closed questions entail compared to open questions more considerations (Rea and Parker 1992). As discussed in subsection 5.2 the interval scale is preferable but impossible to use. Therefore the ordinal scale will be used. Although findings suggest the number of response categories beyond five to seven does not yield substantial gains in reliability, construct validity may (Sosik, Kahai et al. 2009). And therefore the responses are divided in a seven point likert scale; on a continuum from totally disagree to totally agree.

The scales will be presented horizontally, while the questions are vertically located. The questions are within each category randomly presented to participants.

Some survey questions are needed to collect matching information as discussed in subsection 5.3.3. In this survey the following characteristics are collected;

- Country
- Age
- Gender
- Date of start using eBuddy
- Login behavior of eBuddy
- Messages send via eBuddy per session
- Willingness to pay

The first three questions (closed) are asked at the beginning of the survey, while the latter four (three open / one closed) are asked at the end, as proposed by Rea and Parker (1992). This information can be matched against information retrieved from the database of eBuddy, in order to determine whether or not the survey sample is representative.

Archetypes
In order to secure construct validity, for all seven constructs an archetype has been constructed measuring if the construct actually reflects what it should measuring (convergent) and not should measure (divergent) as discussed in subsection 5.3.5. An archetype is an ideal (exemplified) example. In the pre-, pilot test and actual survey the archetypes of Table 15 will be used.

Archetypes	
APERF	**iPad version** This package changes the eBuddy iPhone app to work properly on the iPad
AFUNC	**Skype chat** This package enables you to start chatting with your friends on Skype.
AVAAS	**New backgrounds** This package includes 10 new funny backgrounds.
ACUST	**Colorize your eBuddy** This package enables you to colorize the eBuddy app and add multiple new fonts to chat.
ACURE	**National flag** When installed your screen picture will be a moving picture of your country.
ABRAN	**Smiley package of your favorite brand** This smiley package of your favorite brand (like coca cola or apple) can be used in every chat you make to all people.
ARARI	**Shining diamond** Only available for a limited time!! A beautiful screen picture of a shining diamond.

TABLE 15, ARCHETYPES

5.4.2 CONCEPTUAL VALIDATION

As mentioned already in subsection 5.3.2 a structured validation procedure (Moore and Benbasat 1991) is used to confirm if the concepts validated in other studies are applicable. The study of Moore et al. (1991) focuses on developing instruments to measure perceptions, as in this study is done as well, measuring the perception of virtual goods. And although the study is done in a different setting, this framework is, to some extent adjusted, used. The procedure exist of two stages, a blind sorting round without prior knowledge and a sorting round with knowledge about the definitions to determine the right category for every item.

First round

In the first round unskilled people were used to match the questions to the constructs and dimensions. First the goal and the exercise were explained comprehensively with an example. When the participant said he or she fully understood the process, all seven constructs and three dimensions, printed on a paper, were laid down on a table. The shuffled deck of questions (30) and archetypes (7) was given to the participant to sort the questions to the right construct. This exercise was done with four participants, so each construct can have a maximum score of 16 in Table 16, while each dimension can have a maximum score of 12.

		1	2	3	4	5	6	7	8	9	10
1	Functional	**6**	0	0	4	1	0	1	0	0	0
2	Hedonic	0	**6**	0	0	0	3	1	0	2	0
3	Social	0	1	**7**	0	0	0	0	0	3	1
4	Performance	2	0	0	**10**	4	0	0	0	0	0
5	Functionality	3	0	0	3	**10**	0	0	0	0	0
6	Visual appearance	0	4	0	0	0	**11**	1	0	0	0
7	Customizability	1	1	0	0	0	1	**13**	0	0	0
8	Cultural reference	0	0	0	0	0	0	0	**16**	0	0
9	Branding	0	1	3	0	0	1	0	0	**11**	0
10	Rarity	0	0	1	0	0	0	0	0	0	**15**

TABLE 16, SORTING ROUND 1 RESULT

In this sorting round, some errors in the survey were clearly visible. All three dimensions were only sort well in half of the cases, which is not a good score. On the other hand most errors in the other constructs were at least contributed to the right dimension i.e., according to the classification of Table 9. Given the low error rate of 7, 8, 9 and 10 these are left intact, but all other need some (slight) adjustments. Although branding did not score well, this error was attributable to only one person, who, most likely, did not understand the concept; therefore the branding questions are not adjusted. All of the archetypes were sorted perfectly correct. The problematic questions are discussed below, while the adjusted questions are in Table 17.

- ***DFUN3***: This question looked at lot like question *PERF3*, and is therefore replaced.
- ***DHED2***: This question was answered wrong 4 times and placed each time at *VAAS*.
- ***DSOC3***: This question was used twice (*RARI1*).
- ***PERF2***: The definition of quality good was not clear to the participants.
- ***FUNC1***: Was not clear, but according to the researchers this question measures exactly what it should, so was not adjusted.
- ***VAAS2***: See *DHED2*.

Adjusted questions	
DFUN3	I will use [..] because it supports eBuddy's utility.
DHED2	The [..] is a pleasure of the senses good.
DSOC3	I will use [..] because it facilitate my social rank.
PERF1	I think [..] will increase the quality of working with eBuddy.
PERF2	The [..] is a performance good.
VAAS2	The [..] is a decorative good.

TABLE 17, ADJUSTED QUESTIONS AFTER SORTING ROUND 1

Second round

In the second round another approach was taken. This time people with knowledge i.e., eBuddy employees, were used to perform the sorting round. The procedure was a little bit different because now no information about the construct was given. So after the deck with questions was given to the participant, they were asked to sort the deck into 10 categories. In this round three employees of eBuddy participated and hence the maximum score in Table 18 is nine for both the constructs and the dimensions.

		1	2	3	4	5	6	7	8	9	10
1	Functional	**9**	0	0	0	0	0	0	0	0	0
2	Hedonic	0	**9**	0	0	0	0	0	0	0	0
3	Social	0	0	**8**	0	0	0	0	0	0	1
4	Performance	0	0	0	**9**	0	0	0	0	0	0
5	Functionality	0	0	0	0	**9**	0	0	0	0	0
6	Visual appearance	0	0	0	0	0	**9**	0	0	0	0
7	Customizability	0	0	0	0	0	0	**9**	0	0	0
8	Cultural reference	0	0	0	0	0	0	0	**9**	0	0
9	Branding	0	0	0	0	0	0	0	0	**9**	0
10	Rarity	0	0	1	0	0	0	0	0	0	**8**

TABLE 18, SORTING ROUND 2 RESULTS

In this round almost no errors were made, except from one switch between *RARI* and *DSOC*. However some changes are made based on feedback the researchers received about wording and vague meaning, see Table 19. Next to the changes the following considerations were given:

- Does everyone know what a good is?
- Personal, showoff and status good are very closely related.

Adjusted questions	
BRAN1	I think [..] will identifies what I'm like.
BRAN3	I will use [..] because it distinguish me from other users.
DHED2	The [..] is a pleasure good.

TABLE 19, ADJUSTED QUESTIONS AFTER SORTING ROUND 2

5.4.3 PRE-TEST

In the pretest the online survey tool surveymonkey[30] was used. This tool is used in the final survey as well. In this pre-test friends were used to assess the survey. 10 participants were asked to complete the survey, and were afterwards asked to evaluate the questionnaire. Misinterpretation of questions result in measurement errors and therefore variations in the results were examined in detail. For this pretest the archetype *ACUST* is used.

The feedback included notes about the colors and font, grammar and some small textual adjustments. These notes were processed immediately. More serious remarks on the survey were:

- Introduction text was not sufficient
- Too many choices (seven point likert scale)

[30] http://nl.surveymonkey.com/

The introduction text was slightly adjusted both formatting wise and textual to make more clear what was tested. The likert scale was reconsidered but kept based on seven points; however the pilot test has to prove that seven points is not too many.

Some considerations brought up in the second round were not confirmed in this test. Since the participants were unfamiliar with the subject and did not have issues understanding the items, these are left unaffected.

5.4.4 PILOT STUDY

In the pilot study a trail of the final survey is conducted. On the eBuddy website the advertisement to direct eBuddy users to the survey is showed, but only for a limited time (24 hours). In that way attracted 620 people to start the survey i.e., complete the first page of the survey. Based on these results some preliminary statistics were drawn; the Cronbach alphas (α) and composite reliability (ρ_c). These statistics are explained in more detail in subsection 5.5.3 but a rule of the thumb to show good internal consistency, indicates that both coefficients should be above .7 (Podsakoff, MacKenzie et al. 2003). For the pilot test the archetype *ACUST* is used again. The results of the pilot study are in Table 20 and are reviewed using the procedures proposed in subsections 5.5.2 and 5.5.3. Of the 205 completed the survey only 102 are used in the analysis.

Construct	α	ρ_c	To be adjusted
Functional	0.7192	0.8416	
Hedonic	0.7227	0.8443	
Social	0.5296	0.7588	*DSOC1, DSOC3*
Performance	0.7919	0.8782	
Functionality	0.7225	0.8435	
Visual appearance	0.7256	0.8454	
Customizability	0.6341	0.8021	
Cultural reference	0.7111	0.8384	
Branding	0.5553	0.7693	*BRAN1, BRAN3*
Rarity	0.4543	0.7340	*RARI1, RARI2, RARI3*

TABLE 20, RESULTS OF THE PILOT STUDY

As can be seen from Table 20 the questions addressed in second round of the conceptual validation (subsection 5.4.2), were relevant since the social, branding and rarity construct show low reliability (low Cronbach alpha). Although the composite reliability of all constructs is sufficient (> 0.7) to accept the results and composite reliability is more accurate than Cronbach alphas, some questions are rephrased.

Adjusted questions	
DSOC1	I think [..] will confirm my status.
DSOC2	The [..] is a prestige good.
BRAN1	I think [..] will allow to represent my preferences.
BRAN3	I will use [..] because it differentiate me from other users.
RARI1	I think [..] is only limited available.
RARI2	The [..] is a scarce good.
RARI3	I will use [..] because it is rare.

TABLE 21, ADJUSTED QUESTIONS

5.4.5 WRAP UP

In this subsection several steps are taken to make sure the questionnaire is content valid, construct valid and reliable. However due to limited access to validate with the populations in the first three validation steps it remain difficult to state if the survey is valid. To clarify a small example is given, the instruments that are a valid measure of third grader's math skills probably are not a valid measure of high school calculus student's math skills. But given the results of the pilot test there is strong evidence that this survey is valid for this specific purpose and this specific group of people. The final survey can be found in Appendix F, while the results are in the next subsection.

5.5 Correlation survey results

5.5.1 STATISTICAL TECHNIQUE

As this study is more focused towards theory building than testing existing hypothesis other statistical techniques are applicable than proposed in the theory de Vaus (2001) used before in this study. Soft modeling seems to be more suitable in this situation. Soft modeling is a mathematically rigorous procedure that leads to efficient predictions and is well suited for research constrained by conditions of low information, nascent or emerging theory, and subjective observations of phenomena (Sosik, Kahai et al. 2009). A common method of soft modeling is the partial least squares (PLS) algorithm. PLS is a data reduction technique first introduced around 1975 by Herman Wold for use in the econometrics field and is a generalization of multiple linear regressions. Another technique is LISREL which is used quite frequent as well but is more suited for confirmatory testing (Sosik, Kahai et al. 2009) and therefore omitted in this study.

Usage of PLS is increasingly popular in a wide variety of academic and practitioner domains, like in the fields of education, engineering, chemistry, bioinformatics, and project management (Sosik, Kahai et al. 2009). Despite popular, many studies in MIS research performed erroneous PLS analysis (Carte and Russell 2003). That does not say PLS analysis is inappropriate, it just proves researchers have to be careful using these kinds of statistics. In order to prevent this study from errors made in other studies, the guidelines of many cited article of Gefen et al. (2000) are used.

Because PLS is better suited for more exploratory research and additionally does not require normality of data distributions, observation independence, or variable metric uniformity (Sosik, Kahai et al. 2009), PLS analysis will be used to confirm statistical validity. A regular used software package to perform the PLS analysis is SmartPLS (Ringle, Marc/Wende et al. 2005), which is used in this study as well.

5.5.2 SAMPLE SELECTION & DESCRIPTION

The survey was advertised for in the same manner as in subsection 5.4.4 and therefore needed advertisement inventory in a few of the highest income countries, which was limited. Therefore the researchers decided to only test for one archetype *AFUNC*, since after all, the only purpose is to validate the attributes. The survey was advertized for 6 days.

The advertising redirecting users to the survey resulted in 1462 of users starting the survey i.e., completing at least the first page. Of these 1070 did not complete the survey and were therefore excluded from the research. Of the remaining 392, 273 responses had to be deleted. Although respondent self-select to participate in the survey many do not answer serious e.g., answer all questions with totally agree, or answer category in the same manner. This consistent answering might result in unreliable cases and even overall skewed output and limited divergent validity.

In order to deal with this problem the variance within a case is considered. For each matrix of questions (1, 2, 3) the variance is calculated, when the variance of a case is zero, it's considered a false entry and omitted from the research. For extremely high values, the cases were reviewed per case and omitted when the researchers suspect not serious behavior.

With the 119 responses left, the sample characteristics are in Table 22, where the population characteristics are retrieved from eBuddy's database.

		Population characteristics	**Sample characteristics**
Gender	Male	48%	32%
	Female	52%	68%
Age	0-12	4%	16%
	13-24	73%	72%
	25-35	14%	8%
	35+	9%	4%
Country	Australia	17%	22%
	Canada	28%	22%
	Ireland	1%	2%
	United Kingdom	30%	33%
	United States	22%	21%
Messages		310 p/m	884 p/m
Login		7 p/m	17 p/m

TABLE 22, SAMPLE CHARACTERISTICS

5.5.3 MEASUREMENT MODEL

The first step in PLS is to test for reliability and validity of the model. Both Cronbach alphas (α), which is commonly applied and the composite reliability (ρ_c), a typical test for PLS, can be used. Because Cronbach alphas assume equal weighting of items and therefore are less useful since weighting is unknown, only composite reliability will be used to evaluate reliability.

$$\rho_c = \frac{(\sum \lambda_i)^2 \sigma_i}{(\sum \lambda_i)^2 \sigma_i + \sum \Theta_{\mathrm{ii}}}$$

Where λ_i, σ_i, and Θ_{ii}, are the factor loading (see Appendix G), factor variance, and unique/error variance respectively.

According to the guidelines followed in this study the composite reliability should be above 0.7 (Gefen, Straub et al. 2000). As can be seen in Table 23 the value of composite reliability is higher than 0.7 for all constructs hence the reliability of the survey is sufficient.

Construct	Mean	Std. dev	Range	CR
Functional	4.69	1.30	1-7	0.7849
Hedonic	4.71	1.28	1-7	0.7843
Social	4.20	1.33	1-7	0.8131
Performance	4.71	1.20	1-7	0.7768
Functionality	4.82	1.38	1-7	0.8424
Visual appearance	4.43	1.34	1-7	0.8311
Customizability	4.58	1.23	1-7	0.7989
Cultural reference	3.98	1.34	1-7	0.8093
Branding	4.32	1.27	1-7	0.7932
Rarity	3.79	1.20	1-7	0.7679

TABLE 23, DESCRIPTIVE STATISTICS

In order to secure construct validity, both convergent and divergent validity, as discussed in subsection 5.3.5 must be observed. Convergent validity can be examined by Average Variance Extracted (AVE) and should be higher than 0.5 according to the guidelines followed in the study of Gefen et al. (2000). AVE measures the amount of variance captured by a construct in relation to the variance due to random measurement error.

$$AVE = \frac{\sum(\lambda_i)^2\,\sigma_i}{\sum(\lambda_i)^2\,\sigma_i + \sum \Theta_{\mathrm{ii}}}$$

	AVE	DFUN	DHED	DSOC	PERF	FUNC	VAAS	CUST	CURE	BRAN	RARI
DFUN	**0.55**	**1**									
DHED	**0.55**	0.70	**1**								
DSOC	**0.59**	0.61	0.67	**1**							
PERF	**0.54**	0.81	0.72	0.51	**1**						
FUNC	**0.64**	0.76	0.69	0.63	0.72	**1**					
VAAS	**0.62**	0.64	0.71	0.69	0.54	0.66	**1**				
CUST	**0.57**	0.65	0.72	0.65	0.62	0.67	0.75	**1**			
CURE	**0.59**	0.52	0.57	0.69	0.44	0.55	0.62	0.57	**1**		
BRAN	**0.56**	0.66	0.76	0.75	0.62	0.66	0.74	0.69	0.67	**1**	
RARI	**0.53**	0.47	0.52	0.61	0.46	0.53	0.52	0.49	0.64	0.58	**1**

TABLE 24, CONSTRUCTS CORRELATIONS

The values of the AVE in Table 24 (bold values on the second column) are higher than 0.5 in all cases and hence the convergent validity is sufficient within the survey. Divergent validity is observed when a construct shares more variance with its items than with all other constructs. This can be assessed by comparing the correlation for a particular construct with and the correlations with the other constructs (Gefen, Straub et al. 2000). On the diagonal is the normalized value of the construct correlation, which is higher than the correlation with all other constructs, proving divergent validity.

5.5.4 COMMON METHOD VARIANCE

Common method variance is problematic because the actual phenomenon under investigation becomes hard to differentiate from measurement artifacts. Podsakoff et al. (2003) systematically classified such causes of common method variance into the following four categories: common rater effects, item characteristic effects, item context effects, and measurement context effects. Generally speaking, there are two primary ways to control for method biases, through the design of the study's procedures and statistical controls. The first is already considered in subsection 5.3.4 by following survey guidelines (Rea and Parker 1992). There are several statistical remedies available, but single-method-factor approaches is the only one applicable to this study's situation. Advantages of this method are estimating method biases at the measurement level and controlling measurement error, while disadvantages are that they only control for a single source of method bias at a time and assume that Method × Trait interactions are not present. On the latter issue, the empirical evidence suggests that, although theoretically possible, Method × Trait interactions is unlikely to be very strong (Podsakoff, MacKenzie et al. 2003).

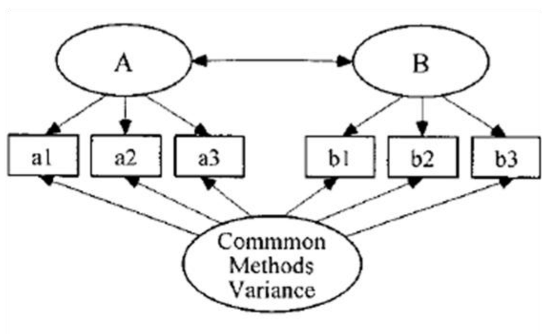


FIGURE 28, SINGLE-METHOD-FACTOR APPROACHES (Podsakoff, MacKenzie et al. 2003)

Using this approach, as can be seen in Figure 28, indicators (a1, …., b3) are allowed to manipulate the theoretical constructs (A,B), as well as the common method variable. So each indicator is determined by its construct and the method factor. However, PLS does not allow an indicator to be defined by two variables. Therefore, the conversion strategy as described in Liang et al. (2007) is used to test this model using PLS (see Appendix I). By converting each indicator into a single-indicator construct the PLS software can perform the method of Podsakoff et al. (2003).

As in this study bootstrapping with 1000 runs is used the t-distribution threshold of ∞ is used to determine the significance level (p). In pursued of many papers, the following notation and thresholds are used:

T $p = 0.1$
* $p = 0.05$
** $p = 0.01$
*** $p = 0.001$

As can be seen from Appendix H the common method variance is rather low, as only one factor loading of the method factor was significant. The explained variance of indicators is only 58%, but on the other hand only 1% is explained by the method factor. Hence in this study, the method variance is unlikely to be a major concern. To test for significance the two-sided t-distribution is used to assess the t-statistic i.e., the null hypothesis states there is no common method variance, and the alternative hypothesis is that it exists in either direction.

5.5.5 FINDINGS

Chin et al. (2003) suggested that PLS procedures can be descriptive accurately by using 1000 iterations of bootstrap resample procedure and a path weighted scheme for the PLS algorithm (see Appendix I). The bootstrapping procedure provides significance levels for all the tested paths by means of the T-statistic. These T-statistics were evaluated by a one-sided t-distribution test as the direction in which the constructs affect each other was known, see subsection 5.2.3. The same notation as in the previous subsection to show significance level is used. And as can be seen from Table 25 eight out of the 12 relations are regarded as significant.

	Hypothesis	β	T-statistic
H1	Branding -> Hedonic	0.39	2.8125**
H2	Branding -> Social	0.31	2.6251**
H3	Cultural references -> Hedonic	0.00	0.0298
H4	Cultural references -> Social	0.22	1.8433*
H5	Customizability -> Hedonic	0.28	2.0876*
H6	Customizability -> Social	0.11	1.0396
H7	Functionality -> Functional	0.50	6.9906***
H8	Performance -> Functional	0.32	3.3173***
H9	Rarity -> Hedonic	0.08	0.9306
H10	Rarity -> Social	0.14	1.4116^T
H11	Visual Appearance -> Hedonic	0.17	1.5954^T
H12	Visual Appearance -> Social	0.17	1.2414

TABLE 25, RESULTS OF BT ALGORITHM

So, as expected because Lehdonvirta (2009) proposed a gradational influence in the hedonic and social dimension (Table 9), not all relationships were significant. Since *CUST* and *VAAS* were on the top of Table 9 a significant relation between those constructs and *DHED* was expected. Weak significant support ($p > 0.1$) was found for H11 (Visual Appearance -> Hedonic), while significant support ($p > 0.05$) was found for H5 (Customizability -> Hedonic). H6 (Customizability -> Social) and H12 (Visual Appearance -> Social) were not significant.

Because *CURE* was exactly in the middle of Table 9, no assumption about this construct could be made. In this survey significant ($p > 0.05$) support was found for H4 (Cultural references -> Social) while no significance at all was found for H3 (Cultural references -> Hedonic).

BRAN and *RARI* were expected to be related to *DSOC*. For H10 (Rarity -> Social) weak significance ($p > 0.1$) could be found while for H9 (Rarity -> Hedonic) no significant support was found. However both H1 (Branding -> Hedonic) and H2 (Branding -> Social) showed significance ($p > 0.01$) and therefore the relation between *BRAN* and two dimensions was found.

For both *PERF* and *FUNC* only one relation was tested as indicated by Lehdonvirta (2009). Both H7 (Functionality -> Functional) and H8 (Performance -> Functional) showed strong significant support ($p > 0.001$).

5.5.6 WRAP UP

In this subsection, both the results as the reliability of the data are discussed. To start with the latter, for three characteristics is tested. The common method variance subsection showed that it is unlikely that the cross-sectional nature i.e., measurement at one point in time, affects the results. The measurement model subsection showed that all indicators to assume internal validity were positive. The extracted values of composite reliability, convergent- and divergent validity were above the proposed thresholds used in other studies. The sample characteristics indicated that, although the country- and age distribution was more or less according to the distribution derived from the database, the usage statistics strongly deviated. These statistics indicate that participants are generally speaking more frequent users than the average user, which is reasonably to assume, given in subsection 5.3.4 the bonding with the brand eBuddy already was discussed. This problem is impossible solve when users can self-select whether or not to participate in the survey. On the other hand frequent users of eBuddy will be more likely to buy virtual goods and hence can be a representative sample of the potential virtual good clients.

The results confirm most of the expectations of the researchers, although some strange values can be observed. The functional dimension is indeed strong significantly influenced by performance and functionality. The hedonic dimension is influenced by customizability and visual appearance while also the unexpected branding significant influences the hedonic dimension. The social dimension is influenced by rarity, cultural reference and also by branding.

Thus all constructs significantly influence only one dimension except for the branding construct, see Figure 29. This is a convenient result, when looking to the purpose of this section as will be discussed in the next subsection.

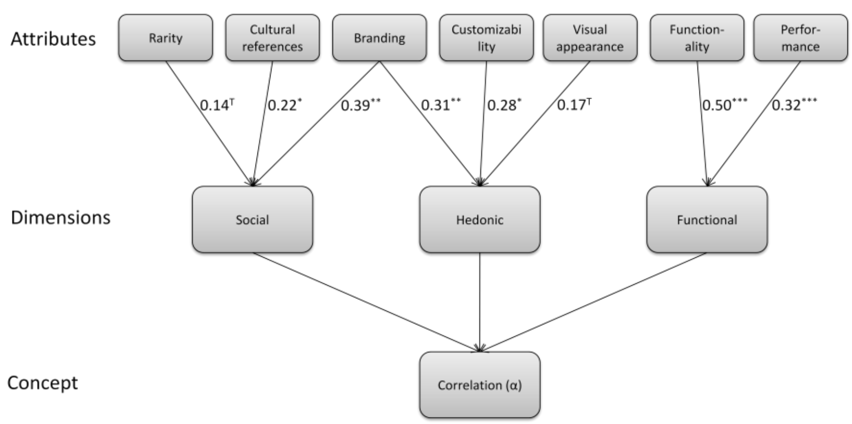


FIGURE 29, SIGNIFICANT RELATIONS (PLS RESULTS)

5.6 Conclusions

From the previous section one important property, the α, only had theoretical use i.e., there was no exact way to determine the α values of different goods. In this section the aim was to find at least an educated estimation for α. Lehdonvirta (2009) studied explorative the dimensions and attributes of virtual goods that alter the purchase motivations of consumer. The dimensions (significantly influenced by) were functional (performance, functionality), hedonic (customizability, visual appearance, branding), social (rarity, cultural reference, branding).

The significant attributes can be used to determine relative distance between goods, thus reflecting a measurement of the α. As the attributes (except branding) only significantly influence one dimension, the dimensions seem rather distinct and hence strengthen the idea of the dimensions and subsequently the idea of measurement of α.

Given the structured and rigid method of validating the survey, reliable results were expected and although all indicators of reliability were sufficient there is one major drawback in the research. Apparently the user base of eBuddy is not keen on answering the surveys seriously (only 119 (8%) out of 1462). Besides the way the survey was presented to the users might have inclined this problem as well. Therefore more testing should be done among users with more bonding to the good and in more strict settings. This might ignore many users and therefore the sample would be smaller, but will most likely improve the results and therefore the predicting value of the survey.

Because the archetype connected to functionality was tested, high mean values were expected on that particular construct. As can be seen in Table 23, the value of functionality was higher than all other values as were the values of the related constructs performance and functional. However all constructs scored between 3.5 and 5, which is a small bandwidth above the average of the seven point likert scale. As participant tend to answer around the middle (Rea and Parker 1992) the power to determine a real world reflecting value for α as proposed in subsection 5.2.1 is not valid. Therefore the second level (Figure 29) between dimensions and the concept should be studied. Unfortunately due to managerial decisions at eBuddy, the in-app store planned to go live early October 2010 was delayed, prohibiting the researchers to test the predicting value of the survey.

As was mentioned before, the results found in this section are only valid for a very small subset of virtual goods. The results cannot be generalized to other kinds of virtual goods as described in subsection 2.4.2 because other attributes could be applicable. Besides, eBuddy's population is not representative to the population of other apps and hence the results are limited in that sense as well.

6 DISCUSSION

In this chapter, conclusions about the research problem will be formulated. Then, implications for theory and management will be given, to conclude with the limitations of this study and recommendations for further research.

6.1 Conclusions

A conclusion is a proposition that is reached after considering the evidence, arguments or premises. Conclusions are a fundamental feature in academic or research work.

Every section already ended with a short conclusion that answered a part of the research questions. In this section the answer to the overall research goal is discussed. The research goal, as defined in subsection 1.2, was "*What configuration of product characteristics and pricing will increase profitability of mobile App developers?*".

In the first two sections a mostly qualitative analysis was done by discussing product characteristics and pricing methods. To start with the product characteristics, based on developments in the most mature store, the Apple App Store, the most promising method to monetize an app is selling virtual goods in the app itself. In the third section all applicable price discrimination methods were discussed and while many seemed feasible to implement in the mobile ecosystem, only one was selected as the most viable method i.e., yields the highest expected returns.

So from these two sections a premise for the proceeding of the study was taken, the best pricing method based on both price discrimination theory and mobile app store characteristics is virtual goods. A part of the research problem was answered by these questions as well since virtual goods define already product characteristics and pricing.

However the first two sections do not answer the configuration part of the research problem, so the proposition that should derive from these premises is how to configure virtual goods. Bundling of strictly unrelated goods was proven to be highly profitable (Salinger 1995; Bakos and Brynjolfsson 1999). So, under circumstances applicable to this study's situation, combining multiple goods in one package was chosen to investigate in more detail. However, as versioning, bundling and virtual goods are conceptually equal, where correlation is the differentiator between these three, existing bundling' theory had to be adjusted. From section 4 can be concluded that bundling goods with zero costs is favorable for all goods; completely uncorrelated to perfect substitutes. In addition it is shown that bundles are less sensitive to correlation effects and remain relatively more profitable with skewed income distributions. For all effects described, the following rule holds; the more goods are bundled the stronger the effects in favor of the bundle.

Although, as was showed by the literature, there are no direct costs involved in producing, distributing and selling virtual goods there are sufficient reasons to suppose that bundling negatively influences demand. Therefore in Table 8 measures to adjust for those effects are given.

Because correlation of goods was only a theoretical idea without any real world propositions, a first attempt to find a measurement of this correlation is made. From preliminary literature it can be concluded that there are three dimensions influencing motivations to purchase virtual goods. That these three dimensions could be used to measure the correlation is used as a premise. The findings of section 5 suggest that the seven attributes tested in this study significantly influence one or two dimensions and therefore, given the premises, could be used as a measurement of correlation. As this study was rather explorative of nature, the results are only valid within eBuddy and even there should be validated by further research.

It is clear from the results described above; the research problem could not directly be answered. The problem was *"What configuration of product characteristics and pricing will increase profitability of mobile App developers?"*.

So given an existing situation with an app with several product features first the correlation between the goods should be tested with the survey provided in Appendix F, then the most applicable distribution should be chosen and finally an estimation of the loss of demand due to bundling has to be selected. With this set of estimations an indication of the best configuration can be derived from this study. As bundling is strongly favorable over a'-la-carte pricing when correlation is high, bundling in the high correlated case is more likely to occur than in uncorrelated cases.

If the initial situation is a clean sheet where new virtual goods can be introduced, the best configuration of virtual good characteristics is to find goods that are the least correlated and bundle the most variance causing virtual goods regardless of the applicable distribution.

6.2 Theoretical Implications

As mentioned in subsection 1.4 this study focused on the theoretical perspective rather than eBuddy's situation because the goals of the graduation report are mostly academic of nature. As the study was mainly explorative some theoretical implications can be derived, which are discussed per section below.

The first two sections were not written with the purpose of theory building, the goal was rather to build a good understanding of the environment. Since almost no research was done on mobile App Stores, the results of section 2 could still be seen as a contribution to the academic world. Especially the description of the six most important App Stores with the critical success factors of Chen et al. (2004) is relevant. One of the going properties of virtual goods, the interconnected property i.e., virtual goods must not exist in isolation (Lehdonvirta 2009; Shang, Chen et al. 2010) was challenged by the researchers as not necessarily applicable to virtual goods.

Albeit the results of section 3 were even more descriptive than in section 2, the addition of virtual goods to existing field of price discrimination methods was not widely available in academic literature. As this study showed virtual goods are in essence equal to versioning because it is based on self-selection of the desired quality (in a broad way) by customers. But it is also much more flexible than versioning and believed by the researchers to replace versioning on the web in the near future where in-app payments will become the leading way of paying for additional features.

More interesting from a theoretical perspective is section 4. While bundling in a strictly uncorrelated case has been studied by many authors (Bakos and Brynjolfsson 1999; 2000; Wu, Hitt et al. 2008), no relevant papers about the correlated case were available to the researchers. By generalizing the economic models describing how companies compete (Varian 1992) a model describing how products cannibalize each other sales could be derived. This resulted in an economic model to show bundling is also favorable when goods are correlated when the uniform distribution $\in [0,1]$ is applicable. Since the uniform distribution is almost never observed in the real world, several other distributions more applicable to mobile ecosystems were tested. In line with other distributions tested on uncorrelated goods (Wu, Hitt et al. 2008), the exponential distribution was tested and in line with earlier research on distributions applicable to App Stores (Spriensma 2010), the power law distribution was tested. Both distributions yielded even better results, showing that bundling becomes even more favorable over a'-la-carte pricing when the distribution is more skewed to the left i.e., a higher percentage of low income consumers but also a small percentage of very high income consumers.

Finally in section 5, the attributes from the study of Lehdonvirta (2009) were tested. As his study was explorative of nature, the attributes were untested. By surveying the population of eBuddy in this study the relation between the dimensions and the attribute could be proven for almost all attributes. However, as the demographics of eBuddy do not represent the real world demographics it is impossible to generalize the results. But this study's results could be used as a starting point for further research as will be discussed in subsection 6.4.

6.3 Managerial Implications

The findings of this study can be used by the principal eBuddy in multiple ways, which will be discussed in this subsection.

Although this study does not prove virtual goods are the best monetization strategy to implement, sufficient empirical evidence is available. Several research firms launched reports to describe the growth in virtual goods and the profitability of that industry. The lasting question was whether the eBuddy client is well positioned to offer virtual goods. As eBuddy already decided (and postponed) to build an in-app store to sell virtual goods further research on that topic was omitted from this study.

While eBuddy postponed the in-app store to temporarily focus on more important business cases, the store will eventually become an important part of the monetization strategy of eBuddy. Lehdonvirta (2009) studied attributes of virtual goods that increase purchase motivations and while this study did not test whether these goods really increased the motivations the attributes should certainly be taken into account when execute the virtual good strategy.

What this study did test for was if the attributes by Lehdonvirta (2009) did invoke to the proposed dimension, to determine whether a set of virtual goods should be bundled. For several attributes (performance, functionality, visual appearance, customizability, branding, cultural reference and rarity) this relationship was proven and with the survey of Appendix E eBuddy will be able to preliminary test their virtual goods and decide which goods to bundle together. As the in-app store was not available by the time this study was performed the results could not be tested and thus back testing is necessary.

In the model constructed in this study are two unknown variables. The first, the α value could be determined by the attributes described above. The second unknown variable is the distribution of eBuddy's users. This distribution should reflect the aggregated willingness to pay of eBuddy's users. This distribution is difficult to determine precisely, but given the demographics of eBuddy's current user base a bias towards low income users is expected. Therefore the exponential and power law distributions were tested to show results in those distributions. Accordingly to the simulations bundling is even more favorable with more skewed distributions and hence bundling is even more favorable to eBuddy.

Finally while virtual goods have many advantages there are several disadvantages, like cannibalization when switching from the current monetization model, freemium, to virtual goods especially when bundling many goods together, implying high bundle prices. Although no exact measure can be given, managers in charge can have an intuitive feeling of the effects. This effect can be compared to Table 8, to determine whether or not the chosen virtual good bundling strategy should be executed.

Several potent price discrimination strategies are omitted in the research, like customized bundling (Viswanathan and Anandalingam 2005) and price skimming. Especially price skimming has proven to be a viable strategy, and should be used by eBuddy to address low income consumers. The best way is probably with once in a while special price promotions like eBuddy already does. Customized bundling is more complex and not studied in a correlated good case, so it is difficult to give reliable recommendations.

6.4 Limitations and further research

Several concerns were already considered in the previous sections of this study, however other matters were found over the course of this study as well. In this section these subjects are discussed.

To start with the limitations, first of all the results from this study have a purely theoretical nature. Although practically relevant, implementation of the results needs careful attention. Especially since no behavior of competitors is included into the model and only producers' surplus is considered. β was introduced to adjust for these effects, but does not provide a measurement of these effects. Therefore careful research has to be done about how consumers' surplus would increase retention and the effect of competitors on the model performance.

There are two concepts important when developing research; internal- and external validity (Vaus 2001) and hence need to be considered while discussing the limitations of this study. In this study close attention has been paid to both concepts especially in conducting the survey. Below both concepts are discussed for the whole study.

To start with the internal validity i.e., the extent to which the structure of the research design enables drawing unambiguous conclusions. In this study a lot of attention is paid to methodological issues. This study started with a structured literature search to not miss an important paper, which can literally sink the research project. As in this study the relative new topic of virtual goods is covered and a lot of literature was only written in the last few years, a small additional literature review was conducted at the end of the process. The only relevant paper found was the paper of Shang et al. (2010), which is used in this study. Since section 2, 3 and 4 are based on this literature review the internal validity of these sections is considered sufficient. In section 5 survey research is conducted and a lot of attention is paid to guarantee internal validity, however due to problems in the eBuddy user base internal validity was harmed. When surveying more reliable groups with the same questionnaire the results should be more reliable.

The second concept is external validity; which refers to the extent to which results from this study can be generalized beyond this particular study. As in the whole study the general perspective is used, the conclusions of this study are not solely suited to eBuddy and hence can be generalized beyond this study. The exception, as discussed before, is section 5, which need more rigor research on the attributes to guarantee external validity i.e., an unrepresentative sample survey, hence attributes are only valid to eBuddy user base. This study is about virtual goods but the economic model of section 4 can be generalized beyond virtual goods. The limitation applicable is that it can only be generalized to goods with zero costs. No research is done to multiple bundles within one firm, hence the results cannot be generalized to multiple bundles as was studied in the uncorrelated case already (Wu, Hitt et al. 2008).

As in this study several new fields in literature are explored a broad range of research opportunities was available. Hence the researchers had to narrow down the opportunities to keep focused. Therefore many interesting further research opportunities are available in this field.

To start with the limitation of this research, the attributes of Lehdonvirta (2009) in section 5, are discussed. As both internal- and external validity is not as desired, more research has to be done to check if the dimensions and attributes are correlated. As the research of Lehdonvirta (2009) only considered social games and in this study virtual goods were considered in a more general perspective broader theory building should be done as well, to find possible additional attributes.

Because the economic model is in many ways similar to the work of Bakos et al. (1999), which is a many cited work about bundling, the papers which cited their paper offer a broad range of further research opportunities. As was discussed in section 3, customized bundling is a viable price discrimination method and only studied in the uncorrelated case, hence customized bundling i.e., allowing customers to choose to bundle up to N goods out of a larger pool of J goods (Wu, Hitt et al. 2008), is a interesting topic for further research. In the same study the issue of multiple bundles was studied, which is one of the limitations of this study. By adjusting the simulations from this study multiple bundles can be imitated. This is especially important when applying the study's findings to versioning. Because the idea of versioning is to get customers to segment themselves according to their willingness to pay, multiple bundles with partly equal functionalities (see Figure 13) are important to consider.

In practice, goods will have different means or variances. Even the same good may have different valuations at different times (Wu, Hitt et al. 2008). It is also possible that there is not one consumer group, but multiple consumers groups can be defined (Venkatesh and Chatterjee 2006). Therefore more variable testing should be done, where the valuation of goods and consumers types are not fixed. One restriction in this model is, because of the nature of virtual good, that demand is limited to 1 for each consumer. In many other examples this is not the case and hence a nice suggestion for further research is to extend the model to multiple purchases per customer.

While in this study piracy was excluded since it was not relevant in the closed ecosystem of Apple it starts to become a problem. Download figures of the eBuddy Pro app provided by Apple deviate by 20% of the number of activated apps on devices reported by Flurry. The only explanation is that 20% of the apps are not downloaded from the Appstore but from third party App Stores (piracy). As this behavior is likely to be more applicable to more open platforms like Java and Android, the topic is starting to be of interest for further research. On the other hand virtual goods provide better ways to prevent for piracy and the effects hereof are not studied, hence this is a viable research opportunity.

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Appendix A: Company profile eBuddy

eBuddy was founded in 2004 by the current owners Jan-Joost Rueb, Onno Bakker and Paulo Taylor and received investments from several venture capital parties like Lowlands Capital and Prime Technology Ventures. The project originated from a bet Taylor had with some friend, where he claimed to make Instant Messaging (IM) possible on mobile telephones. Phones by that time were not that sophisticated and therefore the messenger was available via Internet without any software download requirements. Bakker and Rueb saw business potential and jumped in the IM market.

After years of tremendous growth in both users and employees, eBuddy now serves over 30 million users on a monthly basis and employs more than 60 people in an office at the Keizersgracht in Amsterdam. Naturally, with the success, competitors jumped on the bandwagon as well, offering similar products as eBuddy does.

Currently there are two main markets eBuddy focuses on:

- Web messaging; offers instant messaging through all major instant messaging networks on any computer connected to the Internet, without the need for software installation;
- Mobile messaging; offers instant messaging through all major instant messaging networks on any mobile phone or mobile gaming device connected to the Internet.

A person who wishes to use instant messaging chooses one or more of the worldwide instant messaging networks; MSN (Microsoft), AIM (America Online), Yahoo, Facebook, Hyves, Google Talk or the Chinese QQ. These networks all provide software, called a chat application that needs to be installed on a computer. With this application, a person can chat with his contacts. The networks are not integrated, so a person who for example uses Microsoft's MSN is not able to chat with his contacts that use America Online's AIM.

Web messaging replaces the need for the installation of a chat application on a computer and is accessible through a web browser on any computer connected to the Internet. Mobile messaging gives users the ability to use instant messaging on the road, using their regular mobile phone. Both products are also capable of collecting all contacts from different instant messaging networks together, replacing the need for multiple chat applications if a person uses more than one instant messaging networks to chat with his contacts.

While web messaging is continuously developed and improved, the product is essentially the same as it was in 2004. In mobile the developments obliged eBuddy to change the strategy. Nowadays eBuddy develops apps for several platforms like iOS, Android and Java. Although most people still use IM via the computer, mobile devices are catching up. In Augustus 2010, 40% of the traffic on the eBuddy network origin from mobile device.

APPENDIX B: LITERATURE REVIEW PROCESS

This literature search is conducted to provide a stable basis for the research eBuddy, Twente University and the researchers agreed on. The overall objective of the study is to find the perfect strategy for eBuddy to price their products in mobile Appstores.

This document follows a structured way to find relevant articles in order to make sure the research will, in the end, not miss an important paper, which can literally sink the research project.

USED DATABASE FOR SEARCH

To find the most relevant articles different databases are available, however the coverage of important journals is not guaranteed in every database. Unfortunately no topic related database is a known, like Ingenta (http://www.ingentaconnect.com) covers the IS related top journals the best, by indexing 24 of the top 25 journals (Schwartz and Russo 2004).

However as an article in the MIS Quarterly complains about submitted new articles to the journal "focus solely on North American or a small set of top publications" and "that does not excuse an author from investigating all published articles in a field"(Webster and Watson 2002), therefore the more general databases of Scopus (http://www.scopus.com), Web of Science (http://www.isiwebofknowledge.com/) and early distribution database SSRN (http://www.ssrn.com) are used.

KEYWORDS & CRITERIA

Given the proposal the following keywords are identified to retrieve literature about the following topics:

- Competitive environment

"Competitive environment" + e-business, "Competitive environment" + digital good*, model + "competitive environment" + internet, online customer behavior

- Freemium

Freemium, two-sided digital market*, two-sided market* + online, two-sided market* + internet

- Pricing models

Pricing model* digital good*, pricing model* internet software, price elasticit* + internet, versioning digital good*

- Testing models

Testing pricing model*

To identify relevant articles and guarantee more or less that the information is not outdated the following criteria are used to assess each retrieved article at the very beginning of the research.

- The article is written in the last 10 years

- The article is written in Dutch or English
- Research field of the article is; behavior science, business & economics, computer science or mathematics
- The article is unbiased / neutral
- Content of the article is relevant
- The article is available to the researchers

The two first criteria were easy to apply given databases' additional information. The last criterion happened only few times because articles or books were not accessible, however no really essential papers have been missed. The fourth objective was met by checking whether an article was not written by a biased organization e.g., apple writes a report about Appstores. Finally the fifth criterion was assessed by whether or not the article fitted within the scope of the study e.g., no articles about broadband Internet connections when searched for digital goods.

METHOD

To score the articles on their scientific relevance a checklist was established, where the researchers could assess the articles on the awarding criteria which are defined below (van der Linde 2004). There were 3 classifications of awarding criteria identified; selection, review and general. These classification were the basis of the underlying criteria, the score of each criteria can either be 0 or 1 and has a weight, so at the end each article got a rating. By using swing weights the relative importance of the different criteria was assessed.

Since there are 7 criteria and the sum of the weights equals 1, the maximum score is 10. Therefore an article receives an A when the score is equal to or above 8 (≥8), a B when the score is between 6 and 8 and a C when below 6 (<6).

Articles in category C were discarded. Articles rank A or B were used in the research. Table A. 1 shows the criteria and the corresponding weights; while in Table A. 2 the corresponding threshold are stated.

Classification	Abbr.	Criteria	weight
Design of the research	S1	Number of references	0.05
	S2	Approximation to the subject of this research	0.30
	S3	Explanation about how the research is done	0.15
Review	R1	Number of citations	0.20
	R2	Availability of a critical discussion on the result(s)	0.15
General	G1	Publication date	0.10
	G2	Type of university degree of the author	0.05

TABLE A. 1, CLASSIFICATIONS, CRITERIA AND WEIGHTS

Criteria	Minimum: 0 points	Maximum:1 point
Number of references	Less than 20	More than 20
Approximation to the subject of this research	Does not answer (a part of) the research questions	Answers (a part of) the research question
Explanation about how the research is done	Explanation not included	Explanation included
Above the average of	< 5 citations	≥ 5 citations

citations		
Availability of a critical discussion of the result(s)	Discussion not included	Discussion included
Publication date	Before 2005	After 2005
Type of university degree of the author	Less qualified than PhD	PhD degree or higher

TABLE A. 2, CRITERIA AND SCORING REQUIREMENTS

RESULTS & SCORING

Figure A. 1 shows the discarded articles in every step of the process. The first block contains all the articles found in the searching engines given the keywords mentioned before. The next step was eliminating all the articles which were not available and are irrelevant based on the abstract.

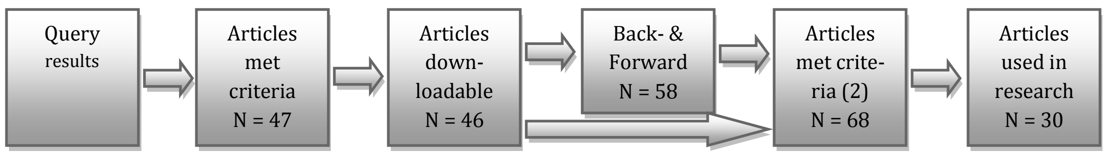

FIGURE A. 1, DISCARDED ARTICLES FLOWCHART

The references of the remaining articles were used to conduct a forward- and backward search; in this extended research the relevant articles (based on availability and abstract) are included.

At this stage all articles needed to be assessed based on the awarding criteria defined in Table A. 1 and the scoring method in Table A. 2. As explained before only the articles with the classification A or B in Table A. 3 – Table A. 6 are included in the final literature research.

Competitive environment	**Design of the research**			**Review**		**General**			
	S1	S2	S3	R1	R2	G1	G2	Total score	Rank
(Slater and Olson 2002)	0	1	1	1	0	0	1	7	**B**
(Loebbecke and Powell 2002)	1	1	1	1	1	0	1	9	**A**
(Krueger, Swatman et al. 2004)	1	0	1	0	1	0	1	6	**B**
(Chandrashekaran, Grewal et al. 2010)	1	1	1	0	1	1	1	8	**A**
(Krieger and Müller 2003)	1	1	0	0	0	0	1	4	**C**
(Ulieru and Verdon 2009)	1	1	0	0	0	1	1	5	**C**

TABLE A.3, LITERATURE FOUND KEYWORD 'COMPETIVE ENVIRONMENT'

Freemium	Design of the research			Review		General			
	S1	S2	S3	R1	R2	G1	G2	Total score	Rank
(Sidak 2006)	1	1	0	1	0	1	1	7	**B**
(Cadre, Bouhtou et al. 2009)	0	0	1	0	0	1	1	3	**C**
(Wang and Lu 2008)	0	1	1	0	0	1	1	6	**B**
(Anderson and Gabszewicz 2006)	1	1	1	1	0	1	1	8	**A**
(Bakos and Katsamakas 2008)	1	1	1	0	1	1	1	8	**A**
(Vogelsang 2010)	1	1	1	0	0	1	1	6.5	**B**
(Li, Liu et al. 2010)	0	0	1	0	0	1	1	3	**C**
(Varian 2007)	0	1	1	1	0	1	1	8	**A**
(Parker and Van Alstyne 2005)	1	1	1	1	0	1	1	8	**A**

TABLE A.4, LITERATURE FOUND KEYWORD 'FREEMIUM'

Pricing	Design of the research			Review		General			
	S1	S2	S3	R1	R2	G1	G2	Total score	Rank
(Jagannathan and Almeroth 2004)	0	0	1	0	0	0	1	2	**C**
(Johnson 2007)	0	0	1	0	0	1	1	3	**C**
(Brynjolfsson, Dick et al. 2010)	1	1	1	0	1	1	1	8	**A**
(Lang and Vragov 2005)	1	0	1	1	0	1	1	5	**C**
(Li, Chang et al. 2009)	0	0	0	0	0	1	1	1.5	**C**
(Stevans and Sessions 2005)	0	0	1	1	0	1	1	5	**C**
(Khouja, Hadzikadic et al. 2008)	1	1	1	0	1	1	1	8	**A**
(Bakos and Brynjolfsson 2000)	1	1	1	1	0	0	1	7.5	**B**
(Altinkemer and Bandyopadhyay 2000)	0	1	1	1	1	0	1	8	**A**
(Bhattacharjee, Gopal et al. 2006)	1	1	1	0	1	1	1	8	**A**
(Goel, Hsieh et al. 2006)	0	0	1	0	0	1	1	3	**C**
(Bansal, Chen et al. 2010)	0	1	1	0	0	1	1	6	**B**
(Kannan and Kopalle 2001)	1	1	1	1	0	0	1	7.5	**B**
(Bhattacharjee, Gopal et al. 2003)	1	1	1	1	0	0	1	7.5	**B**
(Ghose and Sundararajan 2006)	0	1	1	0	0	1	1	6	**B**
(Aron, Sundararajan et al. 2006)	1	1	0	1	1	1	1	8.5	**A**
(Chellappa and Shivendu 2005)	1	1	1	1	1	1	1	10	**A**
(Sundararajan 2004)	1	1	1	1	1	0	1	9	**A**
(Jagannathan, Nayak et al. 2002)	1	1	1	0	1	0	1	7	**B**
(Goldengorin, Keane et al. 2007)	0	0	1	0	0	1	1	3	**C**
(Liang and He 2005)	0	0	1	0	0	1	1	3	**C**
(Fathian, Sadjadi et al. 2009)	1	0	1	0	1	1	1	5	**C**
(Gurnani and Karlapalem 2001)	0	1	1	1	0	0	1	7	**B**
(Bhargava, Choudhary et al. 2001)	0	1	1	1	0	1	1	7	**B**
(Yamori, Bessho et al. 2008)	0	1	1	0	0	1	1	6	**B**
(Jain and Kannan 2002)	1	1	1	1	1	0	1	9	**A**
(Li and Lin 2009)	1	1	1	0	0	1	1	6.5	**B**

(Viswanathan and Anandalingam 2005)	**1**	**1**	**1**	**0**	**0**	**1**	**1**	**6.5**	**B**
(Fan, Kumar et al. 2007)	1	1	1	0	1	1	1	8	**A**
(Archak, Ghose et al. 2007)	1	1	1	0	1	1	1	8	**A**
(Wu and Chen 2008)	1	1	1	0	1	1	1	8	**A**

TABLE A.5, LITERATURE FOUND KEYWORD 'PRICING'

Forward & backward search	**Design of the research**			**Review**		**General**			
	S1	S2	S3	R1	R2	G1	G2	Total score	Rank
(Lassila and Brancheau 1999)	1	0	1	1	0	0	1	4.5	**C**
(Bakos and Brynjolfsson 1999)	1	1	1	1	1	0	1	9	**A**
(Venkatesh and Chatterjee 2006)	1	1	1	1	1	1	1	10	**A**
(Benkler 2002)	1	0	0	1	0	0	1	3	**C**
(Kaplan and Duchon 1988)	1	1	0	1	1	0	1	7.5	**B**
(Shankar, Carpenter et al. 1998)	1	0	1	1	0	0	1	4.5	**C**
(Balasubramanian and Mahajan 2001)	1	1	1	1	1	0	1	9	**A**
(Bernstein and Federgruen 2004)	1	0	1	1	0	0	1	4.5	**C**
(Chen and Xie 2007)	1	1	1	1	1	1	1	10	**A**
(Lee and Mendelson 2008)	1	0	1	1	1	1	1	7	**B**
(Tomak and Keskin 2008)	1	1	1	0	0	1	1	6.5	**B**
(Economides 1996)	1	1	1	1	0	0	1	6.5	**B**
(Rysman 2009)	1	1	1	0	0	1	1	6.5	**B**
(Barnes 2002)	1	0	0	1	0	0	1	3	**C**
(Rennhoff and Serfes 2009)	1	1	1	0	1	1	1	8	**A**
(Gallaugher and Wang 2002)	1	1	1	1	0	0	1	7.5	**B**
(Iyengar, Jedidi et al. 2008)	1	1	1	0	1	1	1	8	**A**
(Xu and Hu 2007)	1	1	0	0	0	1	1	5	**C**
(Post 2009)	0	1	1	0	1	1	1	7.5	**B!**
(Lee, Yu et al. 2006)	0	1	1	0	0	1	1	6	**B**
(Liebowitz and Margolis 2009)	1	1	1	0	1	1	1	8	**A!**
(Krämer 2009)	1	0	1	1	1	1	1	7	**B**
(Png and Wang 2010)	1	0	1	0	1	1	1	5	**B**
(Varian 2000)	0	1	0	1	1	0	1	7	**B**
(Chang and Yuan 2008)	1	1	1	0	0	1	1	6.5	**B!**
(Dhar and Wertenbroch 2000)	1	1	1	1	1	0	1	9	**A**
(Wu, Hitt et al. 2008)	1	1	1	0	1	1	1	8	**B**
(Weber 2008)	1	1	0	0	1	1	1	6.5	**B**
(Kumar and Sethi 2009)	1	0	0	0	1	1	1	4.5	**C**
(Kauffman and Walden 2001)	1	0	0	1	1	0	1	4.5	**C**
(Biswas 2004)	1	0	0	1	1	0	1	4.5	**C**
(Chellappa and Kumar 2005)	1	1	1	1	1	1	1	10	**A**
(Fishburn, Odlysko et al. 1997)	0	1	1	1	0	0	1	7	**B**
(Coiera 2000)	0	1	1	1	0	0	1	7	**B**
(Bhargava and Choudhary 2001)	0	1	0	1	0	0	1	5.5	**C**
(Chen and Png 2003)	1	0	1	1	0	0	1	4.5	**C**

(Bhaskar and To 2004)	**1**	**1**	**1**	**1**	**0**	**0**	**1**	**6.5**	**B**
(Okada 2005)	1	1	1	1	1	1	1	10	**A**
(Hann and Terwiesch 2003)	0	0	1	1	0	0	1	4	**C**
(Voss, Spangenberg et al. 2003)	1	0	0	1	1	0	1	4.5	**C**
(Pauwels and Weiss 2008)	1	0	1	0	1	1	1	5	**C**
(Rochet and Stole 2002)	1	0	1	1	0	0	1	4.5	**C**
(Yang and Ye 2008)	1	0	0	1	1	1	1	6.5	**B**
(Zhou, Miao et al. 2009)	0	1	0	0	0	1	1	4.5	**C**
(Funk 2009)	0	0	1	0	0	1	1	3	**C**
(Choudhary, Ghose et al. 2005)	1	1	1	1	0	1	1	8	**B**
(Tesauro and Kephart 2002)	0	1	1	1	0	0	1	7	**B**
(Choudhary, Tomak et al. 1998)	1	1	1	0	1	0	1	7	**B**
(Dewan, Jing et al. 2003)	1	0	0	1	1	0	1	4.5	**C**
(Dubé, Sudhir et al. 2005)	1	0	1	1	0	1	1	5.5	**C**
(Bakos 1997)	1	0	1	1	0	0	1	5.5	**C**
(Bakos, Brynjolfsson et al. 1999)	1	0	1	1	1	0	1	6	**B**
(Hagel 3rd and Rayport 1997)	0	1	0	1	1	0	1	7	**B**
(Chuan-Chuan Lin and Lu 2000)	1	0	1	1	0	0	1	4.5	**C**
(Han and Shum 2006)	1	0	1	1	0	1	1	5.5	**C**
(Zinkhan, Kwak et al. 2003)	1	1	1	1	1	0	1	9	**A!**
(Bhargava and Choudhary 2008)	1	1	1	1	0	1	1	8	**A**

TABLE A.6, LITERATURE FOUND, BACK- & FORWARDSEARCH

LINKING CONCEPTS

By reading each individual article more thoroughly a helpful tool to structure the information (overload) is to identify a couple concepts and categorize each article into these concepts(Webster and Watson 2002). These concepts are at the same time the basis of the literature part of the thesis. A concept is a cognitive unit of meaning—an abstract idea or a mental symbol sometimes defined as a "unit of knowledge," built from other units which act as a concept's characteristics. The concepts used in this study are;

- **Business model -** business model describes the rationale of how an organization creates, delivers, and captures value - economic, social, or other forms of value.

- **Economic model -** a theoretical construct that represents economic processes by a set of variables and a set of logical and/or quantitative relationships between them.

- **Price elasticity -** price elasticity is a measure used in economics to show the responsiveness, or elasticity, of the quantity demanded of a good or service to a change in its price.

- **Price discrimination -** price discrimination, or price differentiation, exists when sales of identical goods or services are transacted at different prices from the same provider

- **Bundling -** product bundling is a marketing strategy that involves offering several products for sale as one combined product.

- **Versioning -** versioning refers to creating vertically differentiated variants of a product and allowing consumers to self-select their preferred product type.

- **Network effects -** In economics and business, a network effect (also called network externality) is the effect that one user of a good or service has on the value of that product to other people.

- **Information goods -** in economics and law is a type commodity whose main market value is derived from the information it contains. It may also include services (information services).

- **Customer behavior -** is the study of when, why, how, and where people do or do not buy product.

This concept matrix will be the starting point for the literature part of the thesis. After reading all the articles rated A and B, the literature will be synthesized by discussing each identified concept producing a framework for the thesis.

	Business model	Economic model	Price elasticity	Price discrimination	Bundling	Versioning	Network effects	Information goods	Customer behavior
Business model	*8*	-	-	-	-	-	-	-	-
Economic model	1	*18*	-	-	-	-	-	-	-
Price elasticity	1	5	*21*	-	-	-	-	-	-
Price discrimination	1	6	**2**	*23*	-	-	-	-	-
Bundling	0	3	**4**	9	*15*	-	-	-	-
Versioning	0	2	**0**	4	3	*7*	-	-	-
Network effects	1	7	6	4	**1**	**0**	*16*	-	-
Information goods	6	14	15	17	13	6	9	*49*	-
Customer behavior	0	2	3	7	**2**	**0**	3	8	*16*

APPENDIX C: ALGORITHMS TO EXTRACT INFORMATION FROM DATABASE

Versioning algorithm

```
FOREACH app in the subset (top 100 Free Overall U.S. 1 October 2010)

      IF inapp.parentid = app.id AND inapp.publisher = app.publisher
      AND inapp.type = 'inapp'

            RETURN app.in_app_purchases = 1

      IF paidapp.name LIKE %app.name% AND paidapp.publisher = app.publisher
      AND paidapp.type = 'paid'

            RETURN app.paidversion = 1
```

Results

Price skimming algorithm

```
FOREACH app in the subset (top 100 Paid Overall U.S. 1 January 2010)

      FOREACH day between 20100201 and 20100931

            IF app.price(201001) > app.price

                  RETURN app.priceloweroverthe yeat = 1

      IF app.price(201001) > app.price(20101001)

            RETURN app.pricelowerfirstoctober = 1

      ELSEIF app.price(201001) < app.price(20101001)

            RETURN app.pricehigherfirstoctober = 1
```

Results

```
SELECT r.rank, a.name, r.price, r2.price FROM rankings r

  JOIN appstore_instances ai ON (r.appstore_instance_id = ai.id)

  JOIN countries cn ON (cn.id = ai.country_id)

  JOIN applications a ON (r.application_id = a.id)

  JOIN rankings r2 ON (r.application_id = r2.application_id AND r2.date = 20101001 AND
r2.rankcategory_id = 1)

  JOIN appstore_instances ai2 ON (r2.appstore_instance_id = ai2.id)

  JOIN countries cn2 ON (cn2.id = ai2.country_id)

WHERE r.date = 20100101

  AND cn.name = "United States"
```

```
  AND r.rankcategory_id = 1

  AND ai.device_id = 1

  AND ai2.device_id = 1

  AND cn2.name = "United States"

ORDER BY r.rank;
```

Tie-in algorithm

```
FOREACH app in the subset (top 100 Paid && Free Overall U.S. 1 October 2010)

      IF inapp.parentid = app.id AND inapp.publisher = app.publisher
      AND inapp.type = 'inapp'

            RETURN app.in_app_purchases = 1
```

The results are qualitatively assessed based on the description of the in app purchase.

Results

```
SELECT r.rank, a.name, r.price, inapp.in_app_purchases FROM rankings r

  JOIN appstore_instances ai ON (r.appstore_instance_id = ai.id)

  JOIN countries cn ON (cn.id = ai.country_id)

  JOIN applications a ON (r.application_id = a.id)

  LEFT JOIN application_details inapp ON (inapp.application_id = r.application_id AND
inapp.date > 20100901)

WHERE r.date = 20101001

  AND cn.name = "United States"

  AND r.rankcategory_id = 82

  AND ai.device_id = 1

ORDER BY r.rank;
```

APPENDIX D: JOINT UNIFORM DISTRIBUTION

This problem can be solved using convolution theory, based on Fourier transformations, but in general (Uspensky 1937), the distribution of the sum $U_1 + \cdots + U_n$ of independent variables with uniform distribution on [0,1] has a density function of:

$$y_B^n(p_B) = \int_{p_B}^{U_1+\cdots+U_k} \frac{1}{(n-1)!} \sum_{k=0}^{n} -1^k \binom{n}{k} (p_B - k)^{n-1}\, dp_B\,, \qquad n-1 \leq p_B \leq n$$

In the two good case

$$y_B(p_B) = \int_{p_B}^{U_i+U_j} g(V_B) dV_B$$

Where,

$$g(p_B) = \begin{cases} p_B, & 0 \leq p_B \leq 1 \\ 2 - p_B. & 1 \leq p_B \leq 2 \end{cases}$$

So by integrating over p_B,

$$y_B = \int_{p_B}^{1} p_B dp_B = 1 - \frac{1}{2} p_b^2, \qquad 0 \leq p_b \leq 1$$

$$y_B = \int_{p_B}^{2} 2 - p_B dp_B = \frac{1}{2}(2 - p_b)^2, \quad 1 \leq p_b \leq 2$$

Below the $g(p_B)$ for the three-, four- and five-good case is given, but only the five-good case is elaborated into a demand function.

For $n = 3$,

$$g(p_B) = \begin{cases} \frac{1}{2} {p_B}^2, & 0 \leq p_B \leq 1 \\ \frac{1}{2}(-2{p_B}^2 + 6p_B - 3), & 1 \leq p_B \leq 2 \\ \frac{1}{2}({p_B}^2 + 6p_B + 9), & 2 \leq p_B \leq 3 \end{cases}$$

For $n = 4$,

$$g(p_B) = \begin{cases} \frac{1}{6}{p_B}^3, & 0 \le p_B \le 1 \\ \frac{1}{6}(-3{p_B}^3 + 12{p_B}^2 - 12p_B + 4), & 1 \le p_B \le 2 \\ \frac{1}{6}(3{p_B}^3 - 24{p_B}^2 + 60p_B - 44), & 2 \le p_B \le 3 \\ \frac{1}{6}(-{p_B}^3 + 12{p_B}^2 - 48p_B + 64), & 3 \le p_B \le 4 \end{cases}$$

For $n = 5$,

$$g(p_B) = \begin{cases} \frac{1}{24}{p_B}^4, & 0 \le p_B \le 1 \\ \frac{1}{24}(-4{p_B}^4 + 20{p_B}^3 - 30{p_B}^2 + 20p_B - 5), & 1 \le p_B \le 2 \\ \frac{1}{24}(6{p_B}^4 - 60{p_B}^3 + 210{p_B}^2 - 300p_B + 155), & 2 \le p_B \le 3 \\ \frac{1}{24}(-4{p_B}^4 + 60{p_B}^3 - 330{p_B}^2 + 780p_B - 655), & 3 \le p_B \le 4 \\ \frac{1}{24}({p_B}^4 - 20{p_B}^3 + 150{p_B}^2 - 500p_B + 625), & 4 \le p_B \le 5 \end{cases}$$

$$y_b(p_B) = \begin{cases} 1 - \frac{{p_B}^5}{120}, & 0 \le p_B \le 1 \\ .775 - \frac{((p_B - 2) * (-4{p_B}^4 + 17{p_B}^3 - 16{p_B}^2 + 18p_B - 11)}{120}, & 1 \le p_B \le 2 \\ .225 - \frac{((p_B - 3) * (-6{p_B}^4 + 57{p_B}^3 - 179{p_B}^2 + 213p_B - 136)}{120}, & 2 \le p_B \le 3 \\ \frac{1 + ((p_B - 4) * (-4{p_B}^4 + 59{p_B}^3 - 314{p_B}^2 + 694p_B - 499)}{120}, & 3 \le p_B \le 4 \\ \frac{-(p_B - 5)^5}{120}, & 4 \le p_B \le 5 \end{cases}$$

Appendix E: Simulation Matlab code

3 *goods uniform*

```
%Number of products
k = 3;
%number of customers
n = 100000;
%bundle value vector
bv=zeros(n,2);

%Simulate n customers
for j=1:n
    %valuationvector
    v=zeros(k,1);
    for i=1:k
        v(i) = rand(1);
    end
    bv(j,1)  =  max(0,v(1))  +  max(0,(v(2)-A(1,2)*v(1)))  +  max(0,(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-
A(1,2)*v(1))));

end

R=zeros(k/0.01,3);

for i=1:100*k
    p = i/100;
    R(i,1) = p;
    for j=1:n
        if bv(j,1) >= p
            R(i,2) = R(i,2) + p;
        end
    end
    R(i,3) = R(i,2) / p;
end

detA = det(A);
Result=zeros(100,12);
t = 1;

for t=1:100
    i=t/100;
    j=t/100;
    k=t/100;
                    for l=1:3
                        PA = A;
                        PA(1,l) = (1-i);
                        PA(2,l) = (1-j);
                        PA(3,l) = (1-k);
                        if l == 1
                            Result(t,1) = i;
                            Result(t,6) = (det(PA)/detA);
                        elseif l == 2
                            Result(t,2) = j;
                            Result(t,7) = (det(PA)/detA);
                        elseif l == 3
                            Result(t,3) = k;
                            Result(t,8) = (det(PA)/detA);
                        end
                    end
                    Result(t,11)     =     max(0,Result(t,6)*i)     +     max(0,Result(t,7)*j)     +
max(0,Result(t,8)*k);
                      Result(t,12) = Result(t,11)/(t/100);
End
```

5 goods uniform

```
%Number of products
k = 5;
%number of customers
```

```
n = 100000;
%bundle value vector
bv=zeros(n,2);

%Simulate n customers
for j=1:n
    %valuationvector
    v=zeros(k,1);
    for i=1:k
        v(i) = rand(1);
    end
    bv(j,1)  =  max(0,v(1))  +  max(0,(v(2)-A(1,2)*v(1)))  +  max(0,(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-
A(1,2)*v(1))))    +    max(0,(v(4)-A(1,4)*v(1)-A(2,4)*(v(2)-A(1,2)*v(1))-A(3,4)*(v(3)-A(1,3)*v(1)-
A(2,3)*(v(2)-A(1,2)*v(1)))))   +   max(0,(v(5)-A(1,5)*v(1)-A(2,5)*(v(2)-A(1,2)*v(1))-A(3,5)*(v(3)-
A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1)))-A(4,5)*(v(4)-A(1,4)*v(1)-A(2,4)*(v(2)-A(1,2)*v(1))-
A(3,4)*(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1))))));
end

R=zeros(k/0.01,3);

for i=1:100*k
    p = i/100;
    R(i,1) = p;
    for j=1:n
        if bv(j,1) >= p
            R(i,2) = R(i,2) + p;
        end
    end
    R(i,3) = R(i,2) / p;
end

detA = det(A);
Result=zeros(100,12);
t = 1;

for t=1:100
    i=t/100;
    j=t/100;
    k=t/100;
    m=t/100;
    n=t/100;
                    for l=1:5
                        PA = A;
                        PA(1,l) = (1-i);
                        PA(2,l) = (1-j);
                        PA(3,l) = (1-k);
                        PA(4,l) = (1-m);
                        PA(5,l) = (1-n);
                        if l == 1
                            Result(t,1) = i;
                            Result(t,6) = (det(PA)/detA);
                        elseif l == 2
                            Result(t,2) = j;
                            Result(t,7) = (det(PA)/detA);
                        elseif l == 3
                            Result(t,3) = k;
                            Result(t,8) = (det(PA)/detA);
                        elseif l == 4
                            Result(t,4) = m;
                            Result(t,9) = (det(PA)/detA);
                         elseif l == 5
                            Result(t,5) = n;
                            Result(t,10) = (det(PA)/detA);
                        end
                    end
                    Result(t,11)    =    max(0,Result(t,6)*i)    +    max(0,Result(t,7)*j)    +
max(0,Result(t,8)*k) + max(0,Result(t,9)*k) + max(0,Result(t,10)*k);
                    Result(t,12) = Result(t,11)/(t/100);
End
```

5 goods exponential

```
%Number of products
k = 5;
%number of customers
n = 100000;
%bundle value vector
bv=zeros(n,2);

%Simulate n customers
for j=1:n
    %valuationvector
    v=zeros(k,1);
    for i=1:k
        v(i) = exprnd(1);
    end
    bv(j,1) = max(0,v(1)) + max(0,(v(2)-A(1,2)*v(1))) + max(0,(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1)))) + max(0,(v(4)-A(1,4)*v(1)-A(2,4)*(v(2)-A(1,2)*v(1))-A(3,4)*(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1))))) + max(0,(v(5)-A(1,5)*v(1)-A(2,5)*(v(2)-A(1,2)*v(1))-A(3,5)*(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1)))-A(4,5)*(v(4)-A(1,4)*v(1)-A(2,4)*(v(2)-A(1,2)*v(1))-A(3,4)*(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1))))));

end
R=zeros(k/0.01,3);

for i=1:461*k
    p = i/100;
    R(i,1) = p;
    for j=1:n
        if bv(j,1) >= p
            R(i,2) = R(i,2) + p;
        end
    end
    R(i,3) = R(i,2) / p;
end

detA = det(A);
Result=zeros(100,12);
t = 1;

for t=1:100
    i=t/100;
    j=t/100;
    k=t/100;
    m=t/100;
    n=t/100;
                    for l=1:5
                        PA = A;
                        PA(1,l) = -log(i);
                        PA(2,l) = -log(j);
                        PA(3,l) = -log(k);
                        PA(4,l) = -log(m);
                        PA(5,l) = -log(n);
                        if l == 1
                            Result(t,1) = i;
                            Result(t,6) = (det(PA)/detA);
                        elseif l == 2
                            Result(t,2) = j;
                            Result(t,7) = (det(PA)/detA);
                        elseif l == 3
                            Result(t,3) = k;
                            Result(t,8) = (det(PA)/detA);
                        elseif l == 4
                            Result(t,4) = m;
                            Result(t,9) = (det(PA)/detA);
                         elseif l == 5
                            Result(t,5) = n;
                            Result(t,10) = (det(PA)/detA);
                        end
                    end
```

```
                    Result(t,11)    =    max(0,Result(t,6)*i)    +    max(0,Result(t,7)*j)    +
max(0,Result(t,8)*k) + max(0,Result(t,9)*k) + max(0,Result(t,10)*k);
                    Result(t,12) = Result(t,11)/(t/100);
End
```

5 goods power law

```
%Number of products
k = 5;
%number of customers
n = 100000;
%bundle value vector
bv=zeros(n,2);

%Simulate n customers
for j=1:n
    %valuationvector
    v=zeros(k,1);
    for i=1:k
        %price between 0,1 with a exp. distribution.
        v(i) = 1*(1-rand(1)).^(-1/1.25);
    end
    bv(j,1)  =  max(0,v(1))  +  max(0,(v(2)-A(1,2)*v(1)))  +  max(0,(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-
A(1,2)*v(1))))    +    max(0,(v(4)-A(1,4)*v(1)-A(2,4)*(v(2)-A(1,2)*v(1))-A(3,4)*(v(3)-A(1,3)*v(1)-
A(2,3)*(v(2)-A(1,2)*v(1)))))   +   max(0,(v(5)-A(1,5)*v(1)-A(2,5)*(v(2)-A(1,2)*v(1))-A(3,5)*(v(3)-
A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1)))-A(4,5)*(v(4)-A(1,4)*v(1)-A(2,4)*(v(2)-A(1,2)*v(1))-
A(3,4)*(v(3)-A(1,3)*v(1)-A(2,3)*(v(2)-A(1,2)*v(1))))));
end

R=zeros(k/0.01,3);

for i=1:3881*k
    p = i/100;
    R(i,1) = p;
    for j=1:n
        if bv(j,1) >= p
            R(i,2) = R(i,2) + p;
        end
    end
    R(i,3) = R(i,2) / p;
end

detA = det(A);
Result=zeros(100,12);
t = 1;
for t=1:100
    i=t/100;
    j=t/100;
    k=t/100;
    m=t/100;
    n=t/100;
                    for l=1:5
                        PA = A;
                        PA(1,l) = (i^(1/-1.25))-1;
                        PA(2,l) = (j^(1/-1.25))-1;
                        PA(3,l) = (k^(1/-1.25))-1;
                        PA(4,l) = (m^(1/-1.25))-1;
                        PA(5,l) = (n^(1/-1.25))-1;
                        if l == 1
                            Result(t,1) = i;
                            Result(t,6) = (det(PA)/detA);
                        elseif l == 2
                            Result(t,2) = j;
                            Result(t,7) = (det(PA)/detA);
                        elseif l == 3
                            Result(t,3) = k;
                            Result(t,8) = (det(PA)/detA);
                        elseif l == 4
                            Result(t,4) = m;
                            Result(t,9) = (det(PA)/detA);
                         elseif l == 5
```

```
                            Result(t,5) = n;
                            Result(t,10) = (det(PA)/detA);
                        end
                    end
                    Result(t,11)     =     max(0,Result(t,6)*i)     +     max(0,Result(t,7)*j)     +
max(0,Result(t,8)*k) + max(0,Result(t,9)*k) + max(0,Result(t,10)*k);
                    Result(t,12) = Result(t,11)/(t/100);
End
```

To determine β

```
restriction=zeros(10,2);
for looper=1:10
A = looper/10;
```

➔ Code of case tested

```
for beta=1:100
    beta2 = 100-beta;
    C = max(R);
    if (Result(50,11) > (beta2/100) * C(1,2) / 100000) && ind == 0
        restriction(looper,1) = A;
        restriction(looper,2) = beta2 / 100;
        ind = 1;
    end
end
ind = 0;
end
```

APPENDIX F: QUESTIONNAIRE

New product features

1. Introduction

The eBuddy Team is always trying to improve our Instant Messaging services. In order to improve our services, we are curious about your perceptions of new features. Therefore we started this research.

We would like to ask you to fill in this survey with care, in order to maintain the reliability of this research. Filling in the questionnaire will take approximately 5 minutes of your time. The questions are presented on 3 pages.

Most questions are using statements to create insights in your attitude and beliefs. Please determine to what extent you agree or not with each statement based upon your own experiences. There are no wrong answers!

Your answers will be treated confidentially.

Thanks in advance!

The eBuddy Team

Next

New product features

2. General information

*1. What is your gender?

Male   Female

*2. What is your age?

*3. Which country are you from?

Prev   Next

New product features

3. Product features 1

We are testing the feature: *Skype chat*

With this package you can start chatting via Ebuddy with your friends on **Skype**.

Please keep this description in mind answering this survey.

***1. I think "Skype chat"**

	Totally disagree	.	..	...	....	.....	Totally agree
is only limited available							
enables me to change eBuddy's look and feel							
allows me to express where I come from							
is a functional feature to eBuddy							
will make eBuddy more attractive							
will confirm my status							
will increase the quality of working with eBuddy							
will extend the visual appearance of eBuddy							
extends the capabilities of eBuddy							
will allow me to represent my preferences							

***2. The "Skype chat"**

	Totally disagree	.	..	...	....	.....	Totally agree
is a personal branding good							
is a personalization good							
is a practical good							
is a capacity increasing good							
is a decorative good							
is an ethnic tied good							
is a prestige good							
is a scarce good							
is a pleasure good							
is a performance good							

Prev Next

New product features

4. Product features 2

We are testing the feature: *Skype chat*

With this package you can start chatting via Ebuddy with your friends on **Skype**.

Imaging you like "Skype chat", and you really want to use it.

***1. I will use "Skype chat" because it**

	Totally disagree	.	..	...	....	.....	Totally agree
facilitates my social rank							
makes something functioning better							
reflects my background and values							
makes eBuddy look nicer							
enables me to customize eBuddy							
differentiate me from other users							
supports eBuddy's utility							
excites me							
is rare							
enables more options in eBuddy							

***2. Since when are you using eBuddy?**

	MM	DD	YYYY
Date?	/	/	

***3. eBuddy usage**

How many times a month on average did you login on eBuddy over the last three months?

How many messages do you approximately send per login on eBuddy?

***4. How much USD are you willing to pay for "Customize your eBuddy"?**

- 0
- 0.99
- 1.99
- 2.99
- 3.99
- 4.99+

Prev Next

New product features

5. Thank you!

Thank You!

Thanks for participating in this eBuddy survey!

The eBuddy team

Prev Done

Appendix G: Factor analysis

	DFUN	DHED	DSOC	FUNC	PERF	VAAS	CUST	CURE	BRAN	RARI
DFUN1	**0,67**	0,48	0,34	0,60	0,47	0,31	0,34	0,28	0,38	0,19
DFUN2	**0,79**	0,55	0,49	0,63	0,63	0,45	0,49	0,41	0,54	0,42
DFUN3	**0,75**	0,51	0,52	0,57	0,58	0,62	0,61	0,46	0,54	0,42
DHED1	0,57	**0,62**	0,40	0,60	0,56	0,49	0,48	0,28	0,41	0,21
DHED2	0,49	**0,79**	0,55	0,53	0,51	0,52	0,58	0,42	0,60	0,41
DHED3	0,51	**0,79**	0,55	0,47	0,47	0,57	0,54	0,56	0,65	0,51
DSOC1	0,45	0,52	**0,71**	0,39	0,46	0,45	0,54	0,53	0,60	0,35
DSOC2	0,53	0,58	**0,81**	0,46	0,52	0,54	0,48	0,52	0,60	0,60
DSOC3	0,43	0,46	**0,78**	0,31	0,47	0,61	0,49	0,55	0,52	0,45
FUNC1	0,55	0,44	0,31	**0,78**	0,47	0,36	0,48	0,27	0,44	0,26
FUNC2	0,70	0,64	0,52	**0,80**	0,61	0,45	0,50	0,41	0,55	0,45
FUNC3	0,67	0,59	0,37	**0,82**	0,60	0,46	0,52	0,36	0,49	0,38
PERF1	0,55	0,45	0,36	0,56	**0,72**	0,36	0,46	0,33	0,40	0,35
PERF2	0,62	0,57	0,56	0,56	**0,79**	0,55	0,50	0,42	0,58	0,42
PERF3	0,48	0,46	0,46	0,41	**0,69**	0,51	0,51	0,46	0,45	0,40
VAAS1	0,62	0,58	0,49	0,52	0,62	**0,78**	0,64	0,45	0,62	0,41
VAAS2	0,37	0,56	0,61	0,28	0,38	**0,74**	0,48	0,51	0,56	0,41
VAAS3	0,49	0,53	0,53	0,47	0,53	**0,84**	0,65	0,52	0,58	0,41
CUST1	0,30	0,41	0,42	0,25	0,42	0,39	**0,62**	0,43	0,48	0,29
CUST2	0,58	0,65	0,55	0,62	0,56	0,61	**0,83**	0,43	0,57	0,44
CUST3	0,55	0,54	0,50	0,48	0,53	0,66	**0,81**	0,46	0,53	0,36
CURE1	0,47	0,48	0,56	0,45	0,42	0,47	0,44	**0,78**	0,58	0,44
CURE2	0,33	0,43	0,44	0,31	0,39	0,41	0,38	**0,70**	0,40	0,54
CURE3	0,39	0,42	0,58	0,24	0,45	0,56	0,49	**0,81**	0,56	0,50
BRAN1	0,46	0,48	0,46	0,46	0,51	0,38	0,40	0,47	**0,67**	0,32
BRAN2	0,57	0,59	0,60	0,48	0,53	0,60	0,55	0,46	**0,76**	0,45
BRAN3	0,47	0,62	0,61	0,46	0,45	0,65	0,59	0,58	**0,81**	0,52
RARI1	0,28	0,38	0,32	0,31	0,28	0,14	0,23	0,28	0,29	**0,60**
RARI2	0,41	0,39	0,50	0,36	0,47	0,43	0,34	0,56	0,50	**0,79**
RARI3	0,33	0,39	0,49	0,34	0,38	0,52	0,46	0,53	0,46	**0,77**

APPENDIX H: COMMON METHOD BIAS ANALYSIS

	Substantive loading (R_1)	${R_1}^2$	Method Loading (R_2)	${R_2}^2$
DFUN1	0.86***	0.74	-0.22	0.05
DFUN2	0.79***	0.62	-0.01	0.00
DFUN3	0.58**	0.34	0.20	0.04
DHED1	0.57*	0.32	0.08	0.01
DHED2	0.89***	0.79	-0.11	0.01
DHED3	0.74***	0.55	0.04	0.00
DSOC2	0.80***	0.64	0.02	0.00
DSOC3	0.88***	0.77	-0.11	0.01
DSOC1	0.63***	0.40	0.09	0.01
FUNC1	0.99***	0.98	-0.23 T	0.05
FUNC2	0.63***	0.40	0.20	0.04
FUNC3	0.79***	0.62	0.03	0.00
PERF1	0.82***	0.67	-0.13	0.02
PERF2	0.66***	0.44	0.13	0.02
PERF3	0.73***	0.53	-0.01	0.00
VAAS1	0.69***	0.48	0.13	0.02
VAAS2	0.70***	0.49	0.00	0.00
VAAS3	0.96***	0.92	-0.12	0.02
CUST1	0.76***	0.58	-0.15	0.02
CUST2	0.71***	0.50	0.12	0.02
CUST3	0.82***	0.67	-0.02	0.00
CURE1	0.72***	0.52	0.07	0.01
CURE2	0.73***	0.53	-0.04	0.00
CURE3	0.84***	0.71	-0.03	0.00
BRAN1	0.84***	0.71	-0.17	0.03
BRAN2	0.64**	0.41	0.12	0.02
BRAN3	0.78***	0.61	0.02	0.00
RARI1	0.65***	0.42	-0.09	0.01
RARI2	0.78***	0.61	0.02	0.00
RARI3	0.74***	0.55	0.05	0.00
Average		0.58		0.01

Appendix I: SmartPLS Models

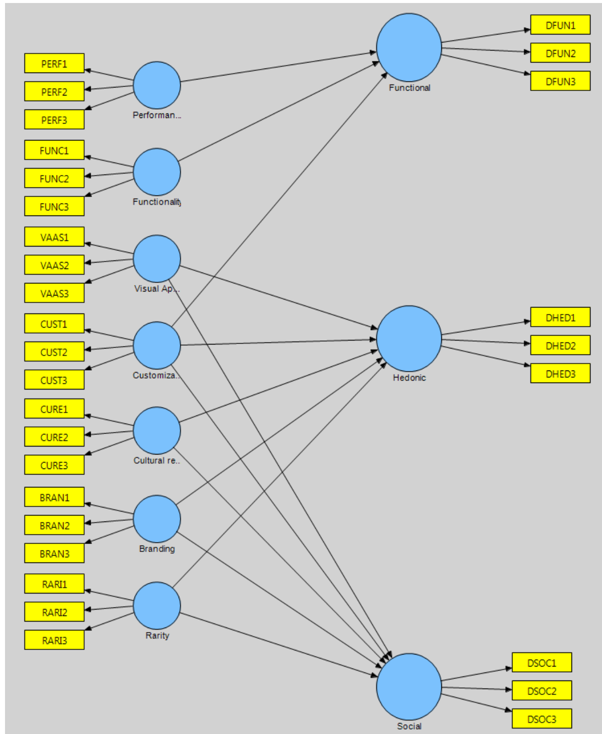

FIGURE A. 2, PLS STANDARD MODEL

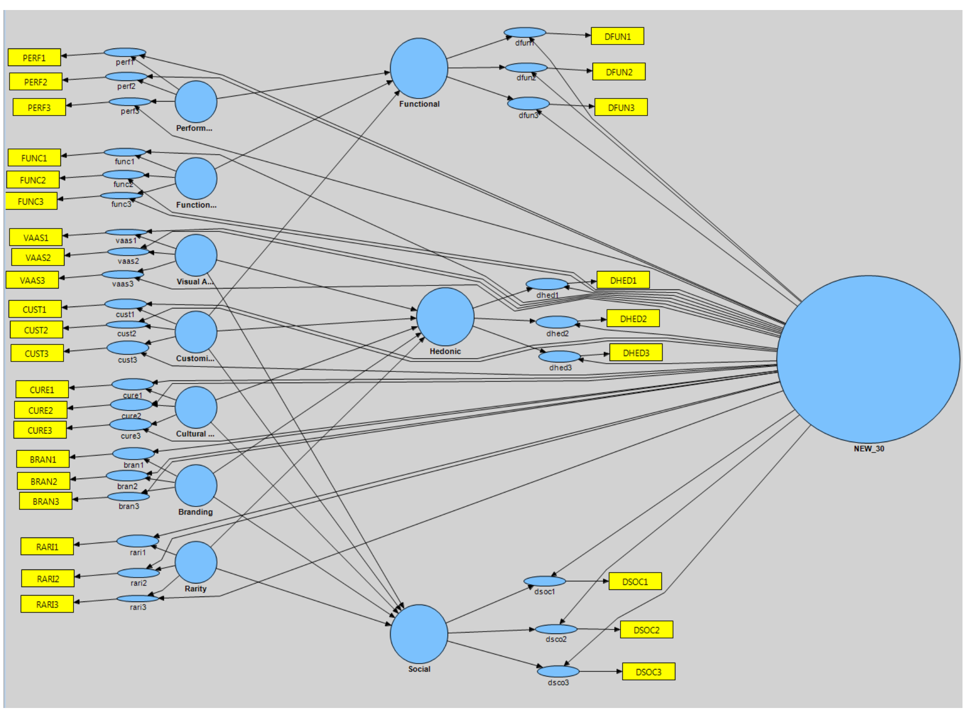

FIGURE A. 3, PLS COMMON METHOD VARIANCE MODEL