A Study on Consumer Spending Behaviours to Improve Business Modelling Strategy in the Australian App Market

by

Maen Zubaydi

Thesis

Submitted in fulfillment of the requirements for the degree of

Doctor of Philosophy

Central Queensland University

School of Engineering and Technology
Associate Professor Ergun Gide
Professor William Guo

Original Thesis Submission date: November 2019

Revised Thesis Submission date: September 2020

Abstract

The mobile app market is one of the fastest growing markets in the modern technological age. This market started with the introduction of the iPhone to the mobile device market; the iPhone revolutionised smartphones in terms of technology and ease of use, and therefore became an instant hit that dominated the market for many years.

Based on popular demand from the software developer community, Apple allowed third party developers to build native applications on iPhone, by creating a software development kit (SDK) and a distribution market for developers to create and sell apps directly to customers. Through these actions, Apple democratised the sale of software by allowing independent developers to sell their own software, and this move attracted hundreds of thousands of developers to the mobile app industry. Today, Apple, and also Android, platforms boast large developer communities and supply over three billion smartphone users worldwide.

The mobile app markets have enabled developers to become direct app sellers to customers. However, this has created new challenges for the app sellers. Besides building quality apps, developers now need to determine the right business model for their products or services, determine price, conduct market research, and handle all app promotion. App sellers that have evolved into developer studios with specialised staff have coped better with app market challenges. However, small and independent developers still struggle with the business end of their operation, and as a result suffer low earnings in a highly competitive market.

In the mobile app marketplace, business modelling strategy depends, in part, on understanding consumer spending behaviour. Developers need to distinguish and monitor consumers' spending behaviour patterns that are associated with their products and continuously adapt their business models. Therefore, consumer spending behaviour studies are necessary to inform the market of what consumers like in mobile apps and how they spend money on apps.

This study aims to address one of the most important business challenges that developers face, by producing business modelling guidelines based on app product characteristics, which help developers select business models that are more suited for consumer spending behaviour associated with their products, and as a result better monetise their products in the mobile app marketplace.

The study paradigm of this research is rooted in positivism, in which quantitative research is conducted to obtain objective truth. Hypotheses regarding associations between pleasure, utility, peer interaction, currency models, and the perception of price and willingness to spend money on the app product are tested using statistical techniques, such as regression analysis, paired t-test, and one-way ANOVA. The tests will address research gaps on what drives users to purchase apps by measuring consumer spending (defined in Section 1.3 and explained in Section 3.3) when buying mobile apps.

Study findings showed that mobile app users prefer spending on functional apps rather than entertainment apps; however, they become more willing to spend on entertainment apps the longer they use them. Findings also showed that the use of native currency in apps is associated with more willingness by users to spend money. Results indicated no association between social status or social competition and willingness to spend money, which means that peer influence in mobile game networks does not influence consumers' willingness to spend money.

Further analysis showed that female mobile app gamers are more conservative towards app spending than male mobile app gamers despite reporting their economic means to be statistically equal. Network game players and high-income professionals spend the most time playing mobile app games and are also the most excessive spenders among all sociodemographic groups.

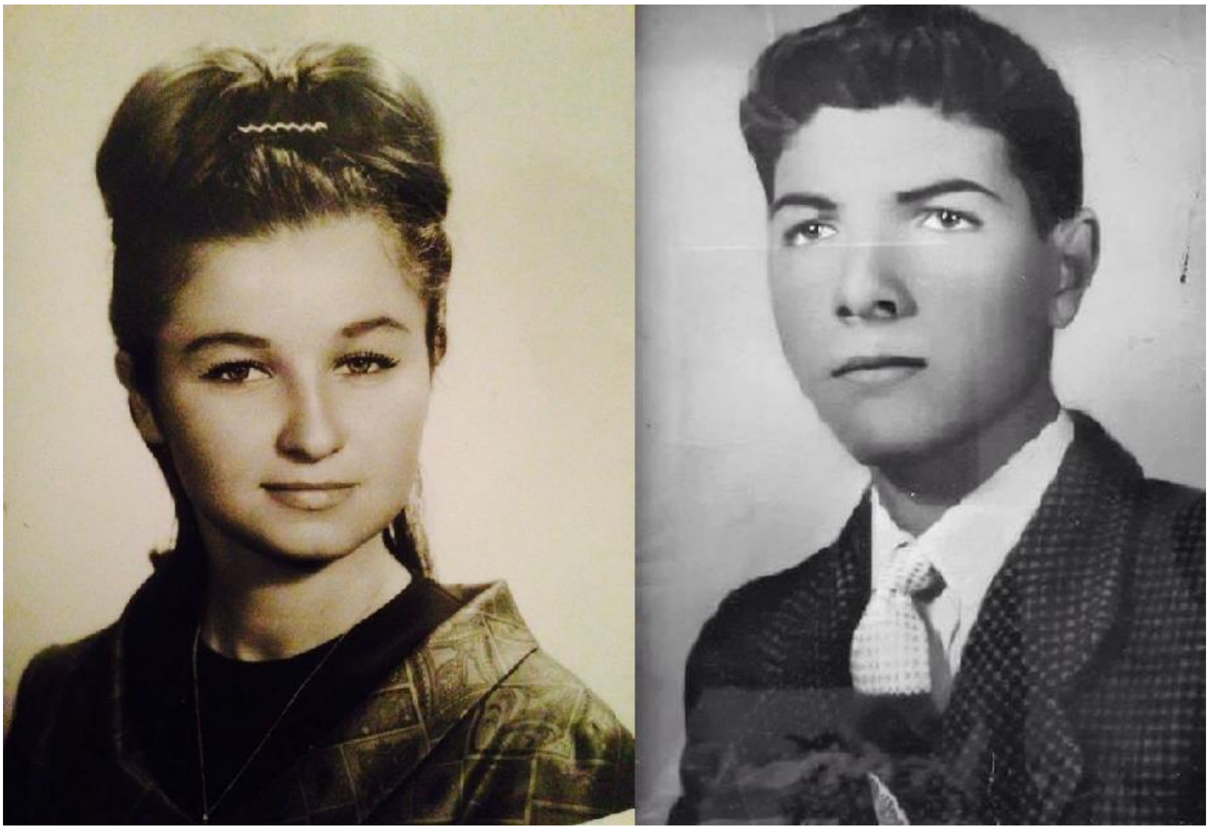
Finally, this study's main contribution is the proposed business model, which is based on factors which influence consumers' spending behaviours. The study's practical contribution consists of a set of guidelines and a decision flowchart that classifies Google Play platforms' monetisation models by earning potential and guides developers into selecting the most appropriate model based on the expected user behaviour of their products.

Keywords: apps, games, applications, mobile app sellers, pain of paying, freemium, mobile app distribution platforms, mobile app users, native currency

Dedication

I dedicate this thesis to my late parents who loved me unconditionally and supported me growing up. I could not have asked for better parents.

It pains me that they are no longer in this world as they departed before I completed my studies. They both encouraged me to pursue this degree and wanted to be present at my graduation ceremony. I wish I could have spent the last 5 years back home with them. However, I am grateful that I embarked on this research journey to honour them in their final years.



Acknowledgements

First, I would like to express my thanks and appreciation to my supervisor, Associate Professor Ergun Gide of the School of Engineering and Technology at Central Queensland University, for his unrelenting support and guidance that helped me complete my research. Despite his busy schedule, he always found time for me whenever I needed help with my thesis and was there for me when I suffered family loss. His work ethic and professionalism were a great source of inspiration for me during this journey and will continue to be so for the remainder of my career.

I would also like to thank Professor William Guo for being the associate supervisor for this research. Special thanks go to Professor Susan Kinnear for her support and kind words during the difficult times I had after losing my parents.

I would also like to extend my thanks to the Graduate Research Office for supporting and funding this research. I am very glad that I chose this university to do my research study and I feel proud to be a CQUniversity student.

Professional editor, John McAndrew, provided copyediting and proofreading services, according to the guidelines laid out in the university-endorsed national “Guidelines for Editing Research Theses”.

Finally, I would like to thank my family and friends overseas for their continuous support and encouragement during my studies over the past 5 years.

Candidate's Statement

By submitting this thesis for formal examination at CQUniversity Australia, I declare that it meets all requirements as outlined in the Research Higher Degree Theses Policy and Procedure.

Acknowledgement of Professional Services

Professional editor, John McAndrew, provided copyediting and proof-reading services, according to the guidelines laid out in the University-endorsed national guidelines, ‘The editing of research theses by professional editors.

Declaration of Authorship and Originality

By submitting this thesis for formal examination at CQUniversity Australia, I declare that all the research and discussion presented in this thesis is original work performed by the author. No content of this thesis has been submitted or considered either in whole or in part, at any tertiary institute or university for a degree or any other category of award. I also declare that any material presented in this thesis performed by another person or institute has been referenced and listed in the reference section.

Copyright Statement

Declaration of Co-authorship

Title of Paper	Status / Bibliographic Reference	Nature of Candidate's Contribution	Nature of Co-Authors' Contributions
A study of Consumer Spending Behaviour in the Australian Mobile Application Market	Published / Zubaydi, M, Gide, E & Guo, W (2018), 'A study of consumer spending behaviour in the Australian mobile application market', *2018 5th Asia-Pacific world congress on computer science and engineering (APWC on CSE)*, pp. 259-264, Nadi, Fiji. DOI: 10.1109/APWConCSE.2018.00049	Candidate's contributions include literature review, data collection, data analysis, discussion of results and recommendations (75%)	Co-authors' Contributions include edits and revisions to manuscript drafting (25%)
Australian mobile user segmentation based on usage and purchasing measurements	Conference paper accepted for publication/ Zubaydi, M & Gide, E (2019), 'Australian mobile user segmentation based on usage and purchasing measurements', *6th IEEE CSDE 2019, the Asia-Pacific conference on computer science and data engineering*, CQUniversity, Melbourne, Australia.	Candidate's contributions include literature review, data collection, data analysis, discussion of results and recommendations (75%)	Co-author's Contributions include edits and revisions to manuscript drafting (25%)
Usage and spending on mobile games: A comparison between Australian single-player gamers and	Conference paper accepted for publication / Zubaydi, M & Gide, E (2019). 'Usage and spending on mobile games: A comparison between Australian single-player gamers and multi-player gamers', *6th IEEE CSDE 2019, the Asia-Pacific conference on computer*	Candidate's contributions include literature review, data collection, data analysis, discussion of results and	Co-author's Contributions include edits and revisions to manuscript drafting (25%)

multi-player gamers	*science and data engineering 2019*, CQUniversity, Melbourne, Australia.	recommendations (75%)	

Table of Contents

Contents

List of Tables

List of Figures

List of Equations

CHAPTER 1 - INTRODUCTION

Mobile apps are software programs that run on a range of mobile devices such as smartphones and tablets. The most distinguishing characteristic of mobile apps, when compared to desktop applications, are the touchscreen interface-oriented design, low pricing, and centralised distribution environment, like App Store and Google Play (Liu, Au & Choi 2014).

Apple was the first to capitalise on the mobile app revolution triggered by the success of its iPhone. They launched the first mobile app distribution platform that offered apps created by third-party developers for iPhone users worldwide. Google joined the market by acquiring the Android operating system that runs smartphones created by Apple's competitors, such as Samsung and HTC. They then went on to launch the Android Market (now part of Google Play) app distribution platform. As of today, Google Play is currently the second largest platform after Apple in terms of profitability (Bloomberg 2005; Business Insider 2015).

One of the revolutionary aspects of this industry is that it created an opportunity for software developers to create and sell mobile apps for smartphone users. Thanks to app stores, app products can be distributed to millions of users at only a small cost to developers. This opportunity has attracted thousands of developers to develop and sell apps, reaching a community of hundreds of thousands on both Google Play and App Store.

One of the major challenges of selling mobile applications is consumer perception regarding the monetary worth of these applications. In contrast with buying physical merchandise or desktop software, consumers perceive that apps should be offered free of charge. Despite the market's stellar success, this perception persists among most smartphone users, who resist buying apps even though app prices average around US$ 4.5 apiece (Ariely 2013; Statista, 2018).

This study has surveyed Australian mobile app users regarding their app preferences, and shopping behaviour, to determine how certain app experiences or expectations correlate with their willingness to pay for using mobile apps. The research findings of this study contribute to and expand upon the body of knowledge built by previous research on consumer behaviour in the mobile app market.

1.1 Overview

This chapter discusses the thesis background, scope and limitations, research problems and significance, states research objectives and questions, and, finally, briefly outlines the research methodology adopted for this study.

1.2 Chapter Objectives

This chapter's objectives are as follows:

- Introduce thesis topic and discuss the challenges app sellers face in the mobile app market.
- Highlight the significance of conducting research on consumer behaviour of mobile apps, and how this thesis contributes to the current body of knowledge.
- Briefly discuss the survey target sample, variables tested, and analyses conducted to test the thesis hypotheses.

1.3 Research Significance

The mobile app industry has grown exponentially over the last decade, with new markets reaching maturity every year (Arora, Ter Hofstede & Mahajan 2017; Digi Capital 2014; Kang 2014; Kim, Lee & Son 2011; Liu, Au & Choi 2014; Miller 2018; Zubaydi, Gide & Guo 2018). By the end of 2014, the two biggest app distribution platforms in the industry, Google Play and Apple's App Store, had reached over a million app offerings on their stores, along with over a quarter of a million app developers building mobile apps on their systems (refer to Figure 1.1 and Figure 1.2).

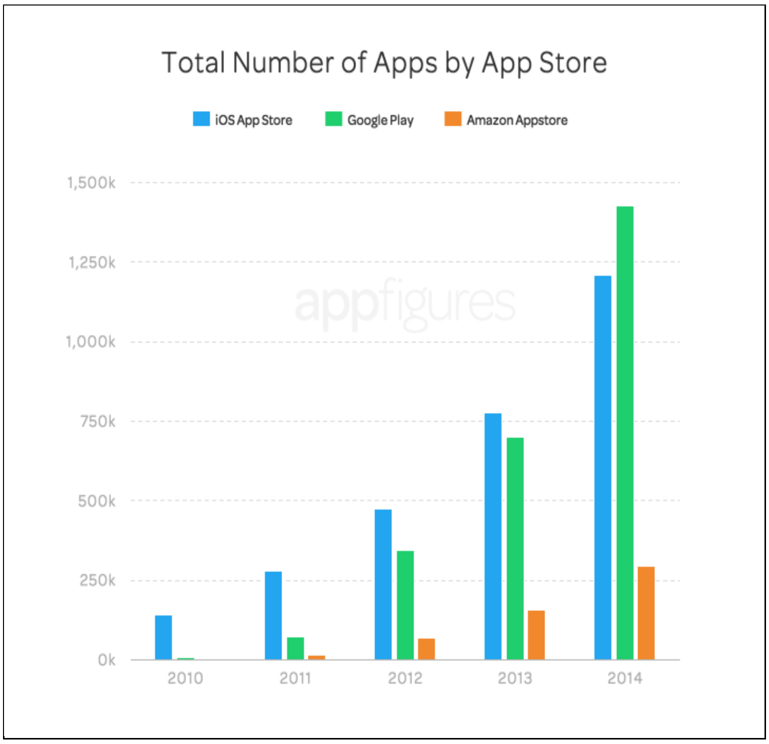


Figure 1.1 Total number of applications by store

Source: Michaeli (2015, p.1)

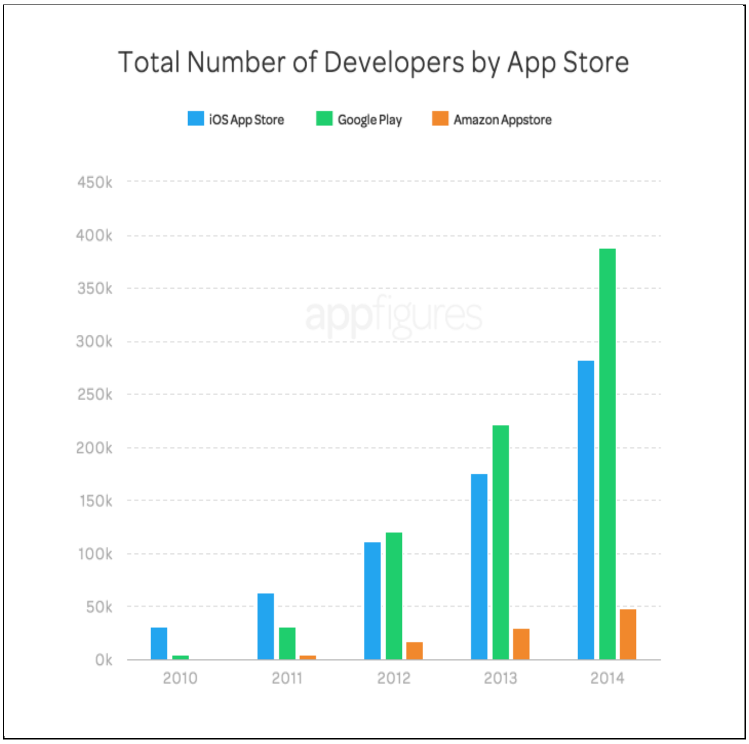


Figure 1.2 Total number of developers by store

Source: Michaeli (2015, p. 1)

The industry was expected to grow to reach $70 billion annual revenue by 2017 (Pettersen 2014). But according to 2018 statistics, the industry had exceeded this projection, achieving over $86 billion in consumer spending in 2017, which is a growth of 105% from 2015 (refer to Figure 1.3). These figures easily place mobile app stores among the largest e-commerce platforms in the world (App Annie 2018).

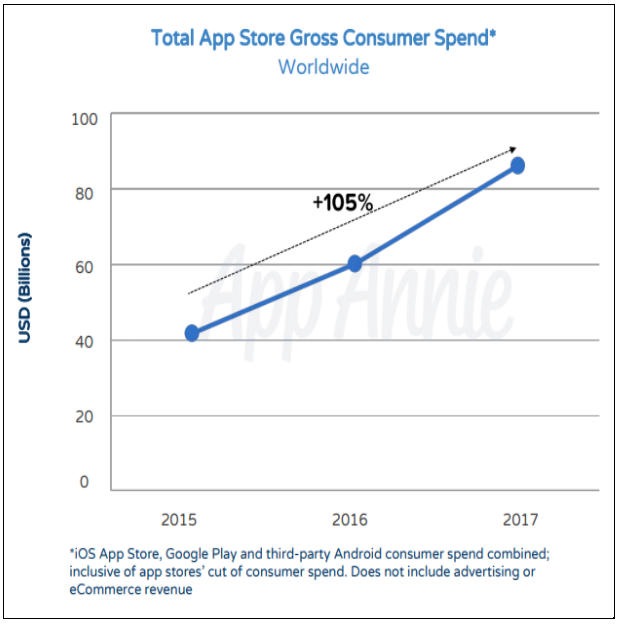


Figure 1.3 Total App markets gross

Source: App Annie (2018, p. 1)

This success prompted interest among academics to study the industry and prompted them to do so and to then publish research papers on mobile app consumer behaviour, app business models, and app success determinants in the market (Khalid et al. 2015; Kim, Lee & Son 2011; Lee & Raghu 2014; Lim et al. 2015; Liu, Au & Choi 2014; Zubaydi, Gide & Guo 2018).

The reasons the mobile application industry is of significance to academics are as follows:

1. The size of the consumer and developer communities are quite large. The consumer app store community size is over 250,000 developers, and Google Play community is approaching 400,000 strong (refer to Figure 1.2). Therefore, conducting research that helps this community to find ways to maximise their profit in the market would give stakeholders and developers significant financial advantages in the industry.

2. Developers sell apps on the same platform sharing the same business environment, customer traffic, and platform constraints; therefore, research findings and recommendations would be scalable and applicable to the whole community.

3. Because consumer behaviour is a key aspect of sound business modelling (Georgieva et al. 2015), research findings can be used to inform sound business modelling guidelines that are applicable to hundreds of thousands of developers working in a multi-billion-dollar industry.

In summary, this study aims to significantly add to existing body of knowledge and help improve app sellers' performance in the market.

1.4 Research Problems

The popularity and consumer base of mobile app stores have inspired hundreds of thousands of amateur and professional app developers to join the market and develop apps for Apple's operating system iOS, Android, and other platforms. While the financial success and growth rate of the app market remains very attractive for developers, the reality is that only a minority share in the financial rewards earned in the market. Figure 1.4 illustrates the app market problems for both developers and users.

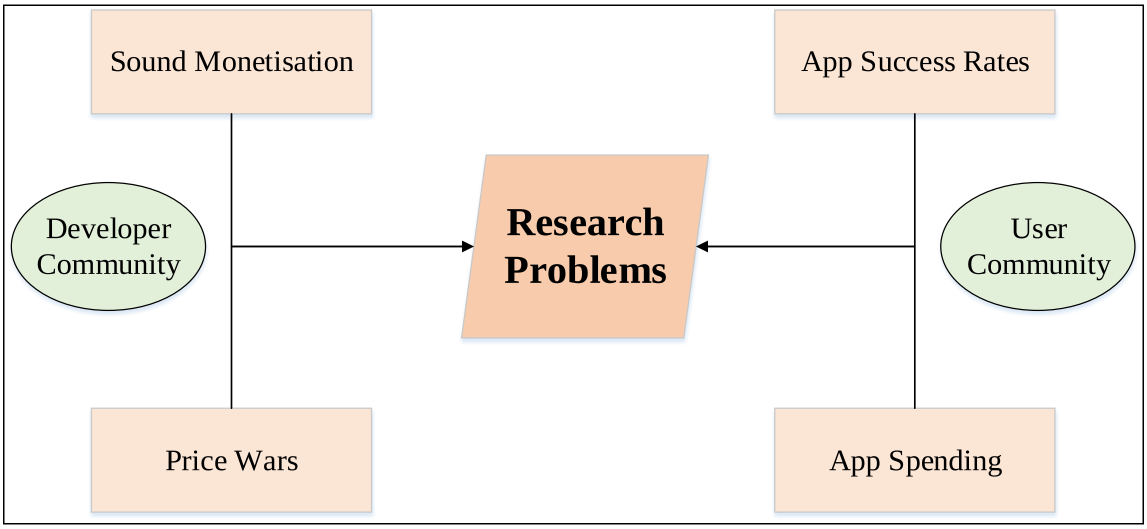


Figure 1.4 Research Problems

1.4.1 App Downloads and Success Rates

Early in 2011, market analysis company Distimo (now App Annie) published an in-depth review on app download volumes and found that 60% of apps in the App Store have no downloads; furthermore, 80% of paid apps on the Android platform have less than 100 downloads (Distimo 2011; Lim et al. 2015). Vision Mobile has also reported that 67% of developers earn less than 500 US dollars a month, not enough income to financially sustain them or their business (Vision Mobile 2013). Canalys (2012) also reported that only the top 25 developers make 50% of the total revenue in the US market, while the rest of the community shares the other half. New developers continue to face market penetration challenges, as customers' purchasing power often goes to apps owned by reputable developers (Arora, Ter Hofstede & Mahajan, 2017).

1.4.2 Spending on Apps

Future predictions regarding app seller prospects remain grim. Gartner research company predicted that through 2018, only 1% of mobile apps would be considered successful by their developers (Gartner 2014). The same company surveyed smartphone users regarding their spending and found that most of them never spend on mobile apps (Gartner 2017). Gordon's (2013) study showed that most consumers take advantage of free app offers in app stores. Mobile app analytics companies found that Android consumers spend less on apps than Apple consumers. Despite Android accounting for 70% of global app downloads in 2017, it only earned 34% of total consumer spending (Statista 2018; Sydow 2018a; Sydow 2018b) (refer to Figure 1.5).

1.4.3 Price Wars

Another reason for app failures is the price wars that app sellers started, due to the intense competition they face in app stores. Price wars often lead to a decline in income earned by all competitors selling similar products (Rao et al. 2000). For example, developer A creates a speed-reading app that helps users read text faster and prices that app at US$ 3. Competitor developer B creates a superior speed-reading app, but because they are unsure how to price it, they offer it for the minimum market price, US$ 1, to sell their product and to capture consumer traffic from A. The act of very low pricing can lead to price wars, and to an overall decline in profits earned by speed reading apps, harming all competitors including A and B.

Price wars do not necessarily stop at the market minimum price, Gordon's (2013) study stated that the rise of free apps often forces paid app developers to make their products free to survive free app competition in the market.

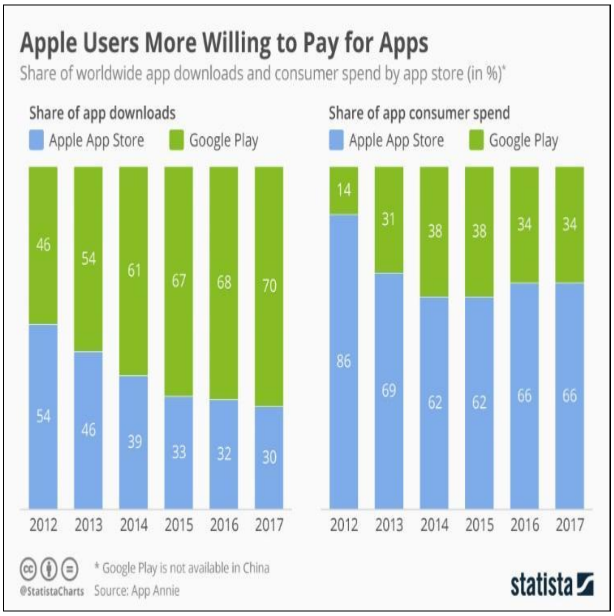


Figure 1.5 Share of app downloads vs share of app consumer spend

Source: Statista (2018, p. 1)

1.4.4 Monetisation

Monetisation models describe how businesses generate revenue. Successful models result in financial success, and unsuccessful models result in financial failure for apps. Unsuccessful models either fail to monetise the app or do not achieve the apps' highest earning potential. Mobile application earning potential is determined first by their appeal in the marketplace and secondly by their chosen business model. Google Play store offers several business models that developers can use in their products, and which can be classified according to their relative earning potential. Busines models with lower earning potential are as follows:

1. Freemium model: Used by applications that offer both free features and premium features that can be purchased with a one-time payment. This model has low earning potential because the application can only be monetised one time per customer.
2. Paid download model: Used by applications that can only be downloaded by a one-time purchase. This model has low earning potential because the application can only be monetised one time per customer.
3. Advertisement model: Used by applications that show advertisements to users based on the time spent viewing the video and banner ads, the benchmark for active users is estimated to be around $0.04 per user per month (Miller 2020). This model has low earning potential because the application can only generate a little income per customer,

especially when compared to higher earning models like subscription or in-app purchases.

Business models with higher earning potential:

1. Subscription: Used by applications that offer continuous use of their feature in exchange for a re-occurring fee. This model has high income potential because the application can be monetised more than one time per customer.
2. In-app purchases: Used by applications that offer an in-app shop to their users, the users can then purchase extra features and content from the application. This model has high income potential because the application can be monetised more than one time per customer.

Mobile apps can generate income by several monetisation models available in Google Play store and Apple's App store (listed in Figure 2.7, page 45). Some of the shown models have uncapped earning potential, like monthly subscription, and other models have capped earning potential, like one-time app product purchase. If an app seller chooses one-time product buy when her/his app could be monetised by subscription, then the app would have lost potential income for selecting a one-time purchase over a monthly recurring purchase.

An example of unsuccessful modelling is a game that went viral in 2014, called Flappy Bird. This game's developer used the advertisement model to monetise the game and was reported to be making US$ 50,000 in revenue every day, from advertisements shown on the app, before pulling it from the store for personal reasons (Macrumors 2014).

While US$ 50,000 in daily revenue is certainly very impressive for a mobile app, the developer would have generated much more revenue if the game's business model better captured the game's earning potential. This was showcased by a replica game, published after Flappy Bird was pulled from stores, called Clumsy Bird. The replica game developers added the in-app purchases model to the advertisement model adopted in the original game. Clumsy Bird had an in-game store where users could buy costumes and extra lives for the bird; if such features were offered by Flappy Bird, its seller would potentially have generated much more than US$ 50,000 a day from the game.

In summary, then, the main problematic issues discussed above are as follows:

- Most apps are not receiving downloads.
- Most developers are earning below US$500 a month.
- Half the market revenue is shared by the top 25 sellers only.
- Most smartphone users are resistant towards paying for mobile apps.
- Price wars occur among lead app sellers.
- App developers use unsuitable monetisation models.

1.5 Conceptual Foundation of the Study

This study addresses how mobile app products influence the spending behaviour of mobile app consumers. This premise is based on the framing effect paradigm that forms the conceptual basis of this research. The framing effect states that internal influences, such as biology, and external influences, such as culture and mass media, shape the frame (perspectives) by which people see and interpret the world. These frames remain in the individual's subconscious until triggered by a new influence that changes their frame, at such instances people become self-aware of the frame that shapes them (Tversky & Kahneman 1981).

To demonstrate the framing effect on decision making in social sciences, Tversky and Kahneman (1981) conducted an experiment that involved two groups of participants presented with a disease outbreak scenario that affected 600 people and requested to choose one of the two programs created to counter the disease. The first group were given a choice between program A that saves 200 people and program B, which guarantees that 33.3% of all 600 will survive and 66.6% will not survive. Seventy-two percent of group 1 participants chose program A. The second group were given a choice between program C in which 400 will not survive and program D which offers 33.3% chance that everyone survives and 66.6% chance that no one will survive. Seventy-eight percent of group 2 participants chose program C. Despite that programs A and C are identical, the way the choice was presented reversed the program preference.

Framing types, such as mental accounting and price anchoring, apply to consumer spending behaviour as they influence the way people perceive transaction deals. Mental accounting is the process in which consumers evaluate the economic outcomes of deals. This is shown by Thaler (1999), who stated that consumers' mental accounting subjectively influenced their evaluation of the transaction deal in terms of expected satisfaction with trade terms and expected benefit received by the trade. Price anchoring is a framing effect derived from psychophysics, it is the association of a response with a single stimulus or stimuli. It can be described as a cognitive bias, where consumers mistakenly predict future utility based on one aspect of an experience (Tversky & Kahneman 1981).

The anchoring effect was demonstrated in several studies by Tversky and Kahneman (1974). The earliest study asked a group of participants to estimate the product of numbers 1 to 8 within 5 seconds. Participants that were presented with the problem in ascending order (1x2x3x4x5x6x7x8) reported a median estimate of 512. Participants that were presented with the problem in descending order (8x7x6x5x4x3x2x1) reported a higher median estimate of 2,250. Because the initial numbers in descending order set a higher anchor, the participants were biased towards higher product estimates than participants who were presented with the lower anchor (Tversky & Kahneman 1974).

The framing effects researched in this study are a set of internal factors, such as pleasure and utility, and external factors, such as payment modes and peer influence. This study will investigate the effect of these factors on consumer spending behaviour measured by a psychometric variable called the pain of paying, which is the consumer's natural resistance to spending money on a trade that originates from activity in the brain region associated with bad odours and becomes activated whenever people are about to make payments. The level of pain of paying felt shapes the decision to make a purchase: the higher the sensation felt the more likely it will block the transaction and prevent the consumer from making the purchase, the lower the sensation felt the more likely that the consumer will go through with the transaction (Prelec & Loewenstein 1998; Rick, Cryder & Loewenstein 2007).

1.6 Research Objectives

Based on the research problems, this study addresses user resistance towards paying for apps. Consequently, understanding user spending behaviour is key to building a model that determines what drives customers to purchase a mobile app. Several academic studies have already identified factors that drive app purchasing (Arora, Ter Hofstede & Mahajan 2017; Hsu & Lin 2015; Kang 2014; Kim, Lee & Son 2011; Lee & Raghu, 2014; Lim et al. 2015; Liu, Au & Choi 2014). This study builds on this research and addresses a not yet tested quantifying association between mobile app attributes and app purchase factors.

Furthermore, because understanding consumer behaviour is essential to sound business modelling (Georgieva et al. 2015), the study's findings can help app sellers to further improve their monetisation models. Figure 1.6 illustrates the research objectives of this study.

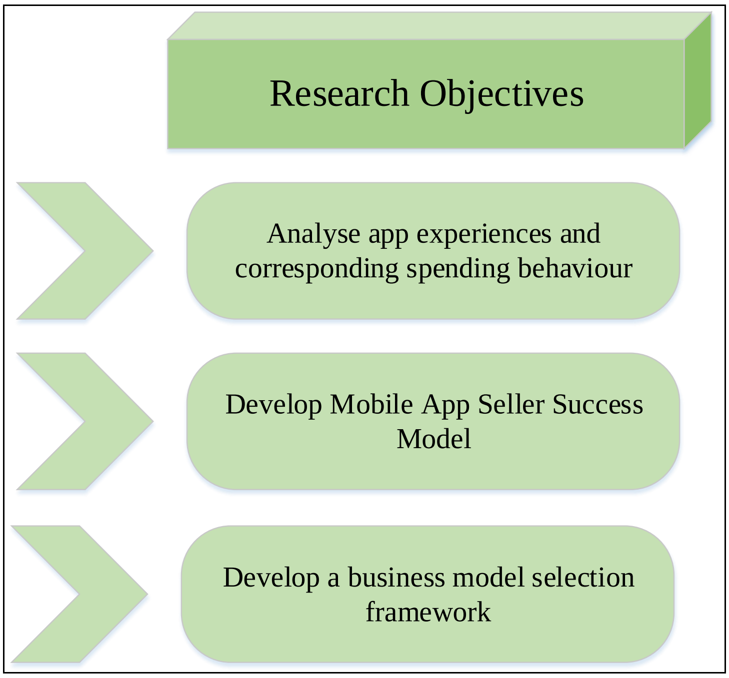


Figure 1.6 Research Objectives

This study aims to achieve the following:

- Analyse how different app product experiences influence consumer purchase behaviour.
- Develop a comprehensive model of factors of mobile app seller success based on previous literature and contributions of this study.
- Develop a monetisation-model selection framework to help app sellers select more optimal business models for their app products in the market.

1.7 Research Questions

Mobile apps are complex products with many different attributes and experiences that affect consumers' choice of spending money. To understand how users contemplate spending on these apps, it is important to understand the influence of each attribute or experience independently from the group that make up the mobile app: the first step to achieve this is to dedicate a separate research question to each of the researched attributes or experiences. Based on the literature on consumer behaviour and mobile app market, several attributes were explored as potential drivers of consumer purchasing, but not yet tested for correlation with user spending. Figure 1.7 illustrates the research questions of this research.

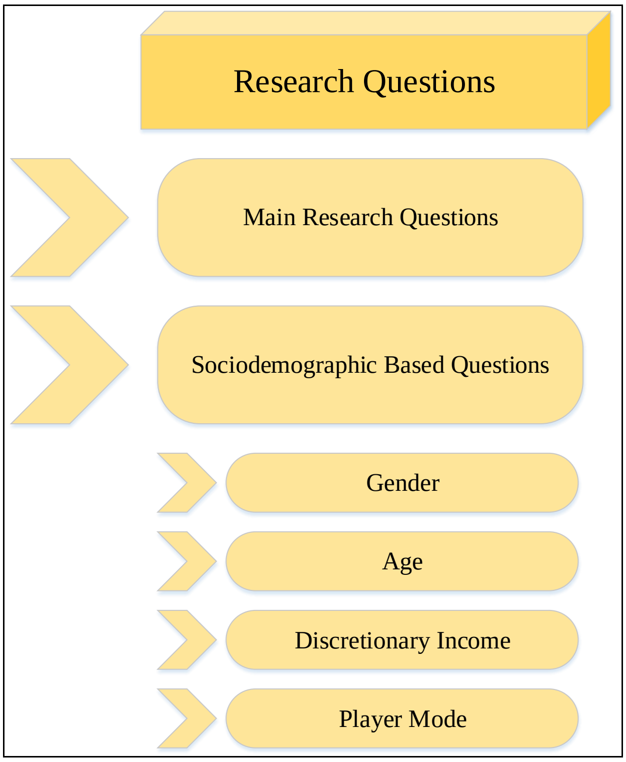


Figure 1.7 Research Questions

1.7.1 Main Research Question

The main research questions explore how app attributes and experiences influence consumer spending behaviour in the mobile app market.

Main research question: What are the attributes which influence consumers' spending on Mobile Applications?

The six sub-main questions are the derivatives of this study's main question, and they are given below:

RQ1. How does mobile game pleasure influence user spending on mobile games?

RQ2. How does mobile application functional benefit influence user spending on mobile applications?

RQ3. How does user spending on mobile applications compare with user spending on mobile games?

RQ4. Does buying native currency influence spending behaviour of consumers?

RQ5. Does peer admiration influence user spending on multi-player mobile games?

RQ6. Does competition among peers influence user spending on multi-player mobile games?

Similar research studies used spending related independent variables, such as intention to spend or sales performance of apps, to measure consumer spending behaviour; this study, however, used a more psychometric measurement from behavioural economics theory known as the pain of paying. Using this measurement opens the opportunity to study the statistical difference in pain of paying among different sociodemographic groups within the sample. Following the sub-main questions, then there are additional research questions to be considered:

Additional Research Question: What are the differences in consumer spending behaviours among different gender, age, income and player-mode groups?

And this question itself then gives rise to further research questions.

1.7.2 Gender

ARQ1: What is the difference in pain of paying between female and male gender groups?

ARQ2: What is the difference in overall app spending between female and male gender groups?

ARQ3: What is the difference in estimated percentage of income spent on discretionary goods between female and male gender groups?

ARQ4: What is the difference in the number of mobile applications used per week between female and male gender groups?

ARQ5: What is the difference in spending on mobile applications between female and male gender groups?

ARQ6: What is the difference in the number of mobile game play hours per day between female and male gender groups?

ARQ7: What is the difference in spending on mobile games between female and male gender groups?

1.7.3 Age

ARQ8: What are the differences in pain of paying among 18 and above age groups?

ARQ9: What are the differences in overall app spending among 18 and above age groups?

ARQ10: What are the differences in estimated percentage of income spent on discretionary goods among 18 and above age groups?

ARQ11: What are the differences in the number of mobile applications used per week among 18 and above age groups?

ARQ12: What are the differences in spending on mobile applications among 18 and above age groups?

ARQ13: What are the differences in the number of mobile game play hours per day among 18 and above age groups?

ARQ14: What are the differences in spending on mobile games among 18 and above age groups?

1.7.4 Discretionary Income

ARQ15: What are the differences in pain of paying among different discretionary income groups?

ARQ16: What are the differences in overall app spending among different discretionary income groups?

ARQ17: What are the differences in the number of mobile applications used per week among different discretionary income groups?

ARQ18: What are the differences in spending on mobile applications among different discretionary income groups?

ARQ19: What are the differences in the number of mobile game play hours per day among different discretionary income groups?

ARQ20: What are the differences in spending on mobile games among different discretionary income groups?

1.7.5 Player Mode

Mobile games have multi-players experience option, single-player experience option or both. The following additional research questions address consumer spending differences based on player-mode preference groups.

ARQ22: What are the differences in pain of paying among different player-mode groups?

ARQ23: What are the differences in the number of mobile game play hours per day among different player-mode groups?

ARQ24: What are the differences in spending on mobile games among different player-mode groups?

1.8 Research Scope

The focus of this study is to investigate app consumer spending habits on Google Play Store in Australia. Survey respondents are asked to rate their spending according to several experiences and expectations of apps created as primary products that consumers either buy or spend money to access premium features within the apps. Apps created by organisations to reach or service their user base are not considered by this study as primary products; therefore, they are not included in the survey questions of any other part of the study. Types of apps included or excluded in this study are listed in Table 1.1.

Table 1.1 Example of apps that are included and excluded from the research scope

Types of Included Apps	Types of Excluded Apps
Single or multi-player games	Social media apps (Facebook, Twitter)
eBooks	Communication apps (Messenger, WhatsApp)
Sketching and painting apps	Banking apps (NAB, CommBank)
Note taking and to-do apps	E-commerce apps (eBay, Amazon)
Photography and filter apps	Web Browsers (Chrome, Firefox)

1.9 Key Definitions

Apps. Software applications developed for handheld-touchscreen devices like tablets and smartphones. Apps run on two major operating systems designed for smartphones, iOS by Apple Inc. and Android by Google Inc.

Freemium. A set of business models that consist of free and premium components. Freemium apps have free basic features for users to experience and offer additional (premium) features for a price. An example of a highly successful game using this model is Clash of Clans; this game allows users to join and build their army base for free, and then attack and pillage enemy bases of the other players in the network. While players can experience the game entirely for free, they can also buy extra base assets or speed up building base structures..

Mobile app distribution platforms. Also known as mobile app stores or markets, these are platforms on which developers upload their mobile app products in order to make them available for smartphone users to download. The two biggest platforms are The App Store by Apple Inc. and Google Play Store by Google Inc. The App Store distributes applications that run on iOS and Apple smartphones and tablets exclusively, while Google Play distributes applications to all devices that run Android mobile operating system, which is not exclusive to any smartphone manufacturer.

Mobile app industry. Refers to all stakeholders or business entities that contribute and benefit financially from mobile apps. This term involves distribution platforms, mobile app developers and sellers, and smartphone manufacturers.

Mobile app sellers. Business entities that develop and sell mobile apps on app distribution platforms. Sellers can be large development studios or small independent individuals who develop and sell their own apps.

Mobile app users. Also referred to as mobile app consumers that use apps on smartphones or tablets. Mobile app users install apps from distribution platforms either for free or for a fee. They can review and rate apps based on their personal experience with them. In terms of spending, users are segmented into three segments: whales – users that spend the most money on apps, they are the major source of income for app sellers; dolphins – users who spend only when needed, they are the minor source of income for app sellers; and minnows – users who spend the least or no money on apps, they usually make money for app sellers through viewing advertisements.

Pain of Paying. A term coined in behavioural economics theory; it is related to consumer reluctance to spending money when making a purchase decision. The more pain of paying consumers experience when making a purchase decision, the more they are displeased about spending their money for the offered price; this is because they feel that they are spending more money than they would ideally like to spend on that purchase.

Store Ranking. Mobile apps are ranked within their category in the store, and they are displayed in sequential order (from the top ranking to bottom ranking). This means that apps with better ranking have better visibility in the market, and thus receive more user traffic.

1.10 Research Methodology

This study investigated Australian consumer spending behaviours in the Google Play store, particularly, how consumers' resistance to pay changes with multiple app attributes. To measure consumers' paying resistance, the study follows a measurable concept, drawn from behavioural economics theory, coined as the pain of paying.

A hypothesis based quantitative approach was selected in this study. A sample of 211 respondents completed a survey which mainly focused on their spending behaviours, app preferences, and app engagement habits. In total, 9 respondents did not complete the survey and were excluded from the study analysis. The respondents were sourced via a paid SurveyMonkey service that allows researchers to select the target population according to desired demographical and geographical characteristics, and then invites respondents of that population to anonymously participate in the research.

The study proposes several null and directional hypotheses. Each hypothesis describes an association between the pain of paying and one of the identified app attributes drawn from cited literature. The primary data collected was subject to one sample t-test and regression analyses; the results reflect the significance of correlations between the dependent variable (pain of paying) and several independent variables (app attributes).

1.11 Research Contribution

Chapter 2, section 1, of the thesis discusses the characteristics that influence buyers' pain of paying. Moreover, these characteristics offer a spectrum of potential variables that can either increase or decrease the pain of paying. This study has identified five variables taken from past exploratory research or other areas of commerce outside app markets, and based on quantitative analysis of primary data, determined the associativity of these variables with the pain of paying.

This study also contributes to the accumulating body of knowledge of consumer behaviour research within the relatively new, mobile app market. The results of this study add to both academics' and professionals' understanding of how mobile app users engage, and trade with mobile apps.

1.12 Research Limitations

1.12.1 Sample

Because consumer behaviour varies across Apple and Android mobile platforms (App Annie 2018) and across countries (Lim et al. 2015), this study was confined to sampling Australia based Android smartphone users. Accordingly, keeping the sample as homogeneous as possible allows more robust testing of theory and yields more precise theoretical predictions (Akinci, Atilgan-Inan & Aksoy 2010; Calder, Phillips & Tybout 1981). As a result, research findings may not be generalisable to the whole app market.

In addition, though the study took pace in a multicultural country, Australia, the study did not account for cultural factors that shape the respondents' consumer behaviours. Future studies could replicate this research on a sample of Apple smartphones users, yielding results that can be compared to this study's findings, and contribute to a body of knowledge that represents a bigger segment of the mobile app market.

1.12.2 Measurement

The pain of paying is the dependent variable that is measured in this study. The pain of paying is a hedonic sensation people experience when they are about to make a payment. This sensation occurs in the part of the brain that is associated with bad smells. The most accurate method of measuring the pain of paying is through experiments where subjects contemplate spending decisions while undergoing MRI scans.

Due to budget and research experience limitations, the study opted for a developed scale that measures the pain of paying using the survey method. While this method is not as accurate as MRI scans, it offers a more cost beneficial way of measuring buyer pain of paying (Rick, Cryder & Loewenstien 2007).

1.12.3 Apps

This study is also limited to investigating consumer behaviour of apps built for direct store monetisation by sellers. Apps designed by organisations only to reach their customers on mobile phones and apps that only sell advertisements are excluded from this research.

For example, mobile apps like games, e-book readers, and productivity tools that charge users money to install or access premium features are included in this study. In contrast, banking and government apps are built to service customers on their mobile device and not for direct monetisation. Apps of this kind are not concerned with their store ranking, or the number of downloads since they only wish to reach their customers and serve them via their mobile.

To make a clear distinction between included and excluded types, only apps that use Google Play Billing Service (Android Developers 2018) are included as they are presumed to be designated for direct monetisation. Excluded apps do not use this service and hence cannot charge Google Play Store user accounts, therefore they are presumed not to be designated for direct monetisation.

1.13 Thesis Structure

Chapter One Introduction: This chapter introduces consumer spending behaviour of mobile apps, discusses the topic’s background and problems, and states the plan and objectives of the thesis.

Chapter Two Literature Review: This chapter reviews relevant previous studies about consumer spending behaviour theories, the mobile app marketplace, and the factors that influence consumer spending on mobile apps.

Chapter Three Research Methodology: This chapter discusses the proposed App Seller Success Model and the six research hypotheses and research ethics. It outlines the data collection process and explains the data analysis techniques used to tests the hypotheses.

Chapter Four Analysis Results: This chapter executes the analysis explained in Chapter 3, section 6. Analysis output of each variable plus additional analysis is showcased and interpreted. Finally, the findings along with hypotheses tests are summarised.

Chapter Five Discussion: This chapter discusses the research findings and compares them to relevant literature findings and empirical observations of the market. Furthermore, the chapter discusses the additional analysis conducted to measure associations between different sociodemographic groups based on gender, income and age, and user behaviour and spending on mobile app.

Chapter Six Conclusion and Recommendations: This chapter summarises previous chapters and highlights the research findings regarding mobile app factors and user sociodemographic characteristics on spending behaviour.

1.14 Introduction Summary

This study investigates the mobile app factors that influence consumer spending on mobile app products. Thanks to smartphone technology and distribution platforms, third party developers can sell their software directly to consumers by developing mobile apps and selling them on market platforms. This has democratised the sale of software as it not only provided developers with an independent income avenue but also enabled them to compete with larger software companies.

Mobile app platforms like Google Play and the App Store have a set of defined monetisation models for app sellers to adopt for their products. Developers may adopt a single model and incorporate several models into their products based on their strategic business needs. Developers, however, need to adopt the most optimal model or mix of models to best monetise their products.

Small and independent app sellers face many challenges in mobile app markets; they face competition from bigger more experienced sellers, consumer perception of paying for mobile apps, price wars among sellers, and business modelling of products. Appropriate business modelling dictates that selection of the right mix monetisation models should be based on the product characteristics as well as the consumer behaviour of the product's target segment.

This study aims to investigate how multiple products' characteristics correlate with consumer spending behaviour to build a model of factors that impact mobile app sellers' success and produce a list of recommendations for mobile app seller success. The study will use data collected from mobile app users and analyse it using quantitative methods to test for correlations among mobile app characteristics and consumers spending.

CHAPTER 2 - LITERATURE REVIEW

This chapter explores the theoretical foundations of consumer spending that underpin consumer research in the mobile app market. Furthermore, this review will report studies made on the mobile app marketplace and highlight tested or proposed factors that drive app consumers to trade sellers for mobile app products.

Chapter Objectives:

Chapter 2's objectives are as follows:

- Review consumer behaviour theories.
- Discuss consumer studies of the mobile app market.
- Explain business models available on the app market platform.
- Discuss the theoretical foundation and factors investigated in this study.

2.1 Consumer Behaviour Theories

Consumer behaviour theories offer predictions on how consumers make decisions of purchase, as well as their capitalisation on these predictable or foreseen behaviours. These theories of consumer behaviour also look into 1) consumer purchase commodities as individuals and as groups, 2) emotions affect these purchasing decisions, 3) individual attitudes after purchases, and 4) the place of object utility in consumer behaviour. The theories of consumer behaviour are as discussed below.

2.1.1.1 Motivation-Need Theory

According to Abraham Maslow, there is a depiction of the hierarchy of human needs, in accordance with their ranks (Kaur 2013) (refer to Figure 2.1). The needs are psychological, safety, love/belonging, esteem and self-actualisation. The Maslow hierarchy of needs, as a theory, has been adopted in the marketing world to extrapolate on the need of explaining matters of marketing to the consumers. It is evident that consumers are motivated by the desire to own a certain commodity, as priority surpasses any other factors while making purchasing decisions. For example, if a student is required to sit a mathematical examination and they do not have a geometrical set, it would be categorised a commodity of urgency since it is mandatory for the specific situation. There are also artificial needs, whereby, consumers only purchase certain commodities to help with protection of other factors. For example, a sports car is considered as a luxury item, which offers safety and prestige to an individual as well as their family. Consumers should, however, understand that these luxury items are only purchased when they offer non-negotiable advantages. With this theory, consumers are inclined toward purchase of commodities that can fulfil and satisfy the diverse needs of a human being. It is no secret that individuals, after facilitating their basic needs, resort to spending a certain chunk of their monies to purchase luxurious commodities. Such an instance indicates the capability to fulfil all the needs without any form of strain or struggle. Maslow's theory does not offer any appeal to products or commodities that only selectively fulfil the needs of an individual, as it is only human enough to remain attached to products that give off positive experiences.

Figure 2.1 Maslow's hierarchy of needs

Source: Hopper (2019, p. 1)

2.1.1.2 Impulse Buying by Hawkins Stern

Stern and Hawkins (1962) investigated consumer behaviour from a different perspective, by eliminating any affiliations with rationality or logic. According to Stern, the average consumer has tendencies of impulse buying, regardless of their subscription to rationality or not. The theory posits a correlation between impulse buying and external stimuli, indicating that the latter is responsible for the former (refer to Figure 2.2). Traditional decision making cannot be aligned with the prevalence of impulse buying since it is mostly categorised as "responsible" rather than "irrational" and "irresponsible." In Stern's theory, there are different types of impulse buying, which include: 1) pure impulse buying, where a consumer picks an unwanted item on their way out of a store; 2) impulse buying, where consumers place certain commodities next to an item that they are purchasing; 3) impulse purchases that are suggested, where a consumer is forced to buy batteries after purchasing electronics; and 4) the planned impulse purchases, where consumers are unaware of the specifics of the products of their interest. Inasmuch as impulse buying has its advantages, it may be non-beneficial to both the marketers and consumers since they each incur certain losses; when consumers feel that buying would destabilise their financial situation, they reduce their spending, making it difficult for the marketers to accrue any profits. It is inevitable for consumers to avoid impulse buying, particularly due to the appealing nature of some products. For example, assuming there is a 50% off sale at one of the most prominent stores, individuals may be tempted to purchase items which were not in their budget in the first place. Even if impulse buying is inconsistent with consumer's purchasing decisions, it is a significant factor while looking into their buying patterns.

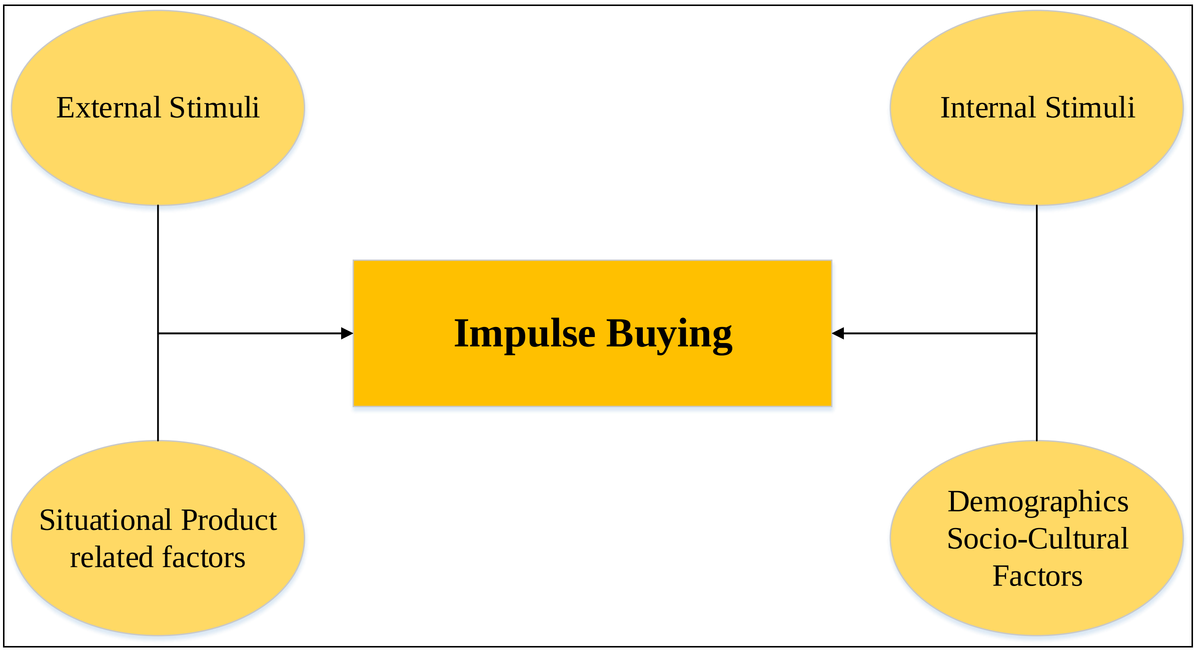


Figure 2.2 Factors of impulse buying

Source: Bhakat and Muruganantham (2013, p.156)

2.1.1.3 Theory of Reasoned Action

According to Vallerand et al. (1992), consumers make their decisions depending on the outcomes that follow. Based on concepts which are different from Stern's analogies of impulsivity, the consumers are driven by logic, rationality, and reason when making purchases. This theory does not explain irrational purchasing behaviours such as impulse buying. The theory explains that being aware of the product that an individual wants from the store depicts their ability to control their behaviours during purchase. The theory ensures that products are marketed in a positive light since the consumers do not condone any irrationality during purchases. Figure 2.3 illustrates the theory of reasoned action.

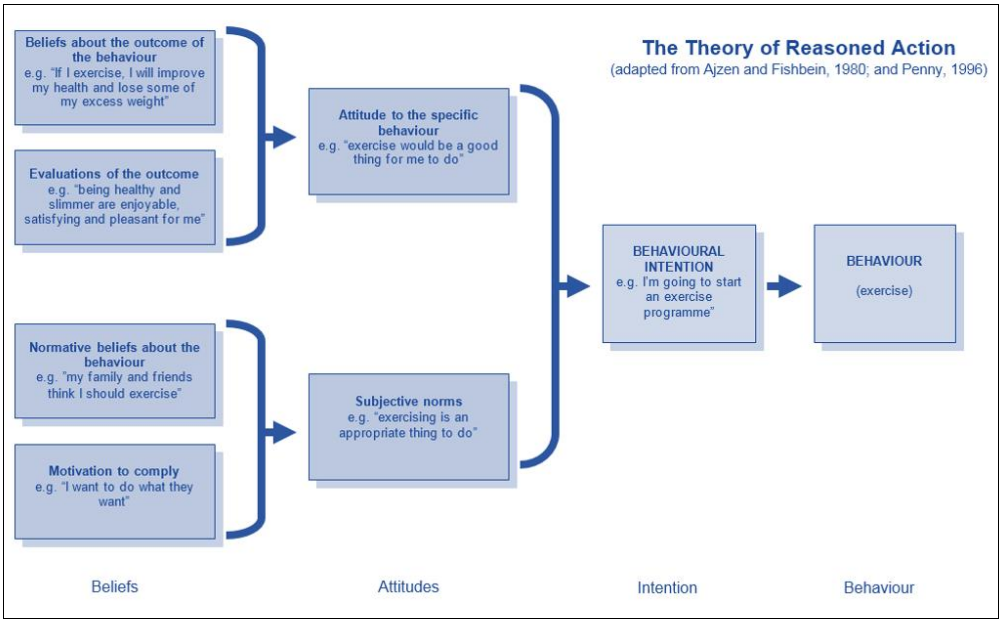


Figure 2.3 Theory of reasoned action

Source: AMAC Training (n.d., p. 1)

2.1.1.4 Engel, Kollet, Blackwell (EKB) Model

The Engel, Kollet, Blackwell (EKB) model extends the theory of reasoned action (Osei and Abenyin 2016). It describes the steps consumers take when making a purchase. In the first step, the consumers acquire information from the media before internalising them and making comparisons with previous experiences. Here, consumers do not transition to the decision-making stage right away rather, they maintain a thought transit, which assists them in maintaining rationality while making the purchases. Figure 2.4 shows the Engel, Kollet, Blackwell model.

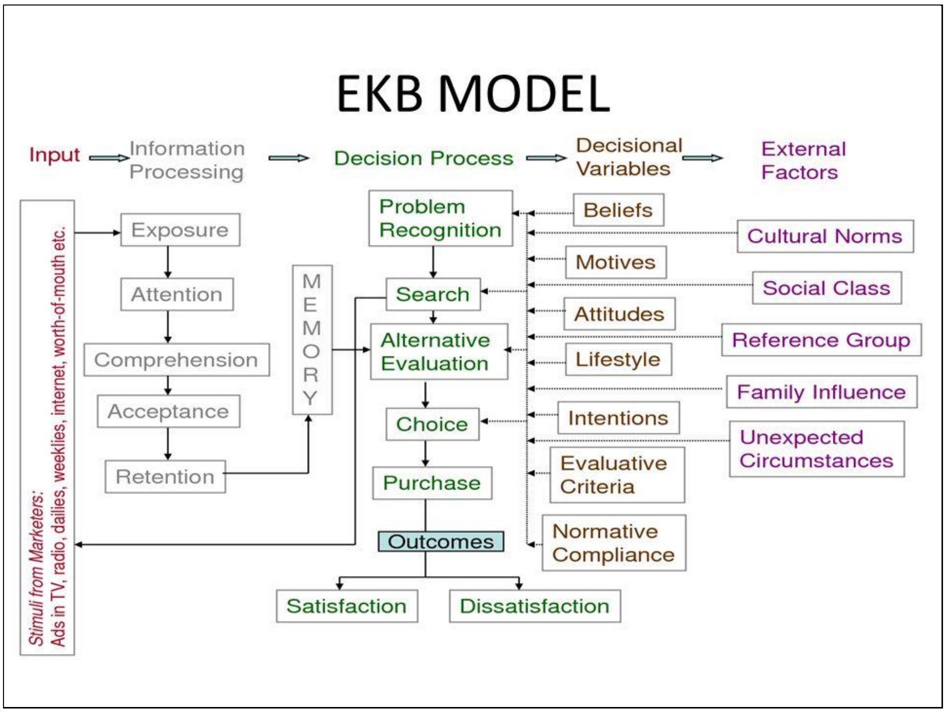


Figure 2.4 EKB model

Source: Tygoramar (2008, p. 1)

2.1.1.5 Theory of Consumption Values

This theory explains why consumers make the purchase decisions they make while shopping. The theory identified five consumption benefits that drive consumer shopping behaviour (Sheth, Newman and Gross 1991). The five consumption values are as follows:

- Functional value: Considered by the Marshallian economic model as the main driver of consumer purchasing behaviour. It refers to the perceived utility from buying a product or service like buying fuel for a car.
- Social value: The value received from associating with a specific socio-economic group because of purchasing a product or service like jewellery or sports cars that boosts the buyers' social status in their community.
- Emotional value: Refers to the positive feelings that arise because of a product or a service like buying a spa session or a music album for the emotional value they offer.
- Epistemic value: Refers to the value received from buying products or services that satisfy consumers' curiosity, novel experiences, or knowledge. This is believed to be

the main driver behind consumers breaking routine purchases to experience different or novel alternatives such as other brands of a product that consumers frequently buy.

- Conditional value: Refers to the value received from products or services because of a specific circumstance or situation. For example, the value of a wedding gown would be conditional on the presence of a wedding event, or the value of a birthday card is conditional on the presence of a birthday party.

2.1.2 Early Consumer Spending Theories

Economists were the first academics to produce theories that explain consumer behaviour. The most notable theories are the Marshallian economic model and the modern theory of consumer choice. These theories describe people as rational, emotionless, and calculating consumers who make rational purchase decisions determined by their income, the relative price of alternative products, excepted utility, and cost-opportunity analysis (Fisher 1930; Husson University 2018; Kotler 1965; Friedman & Neumann 1980). The Marshallian model suggests that consumer behaviour is based on three factors:

- Income: If the income of consumers is high, the consumed commodity will experience high sales.
- Price: If the price of a commodity is low, and its quality does not decrease, it will experience high sales.
- Utility: Consumers select commodities that offer the greatest utility to price ratio.

Another set of competing consumer behaviour theory was developed by psychologists and social scientists, and in direct contradiction to economic theories. They explain that people are in fact not rational but are emotional beings whose purchase decisions are influenced by habit and triggered by impulses or stimuli. A prime example of a behavioural theory was developed by the psychologist Ivan Pavlov.

Pavlov posits that people are creatures of habit, and that much of their behaviour is shaped through conditioning. The refined Pavlovian model (see Figure 2.5) suggests that consumer behaviour is based on four concepts (Kotler 1965):

- Drive: The compelling internal stimulus that induces an action.
- Cue: A weaker stimulus, relative to drive in the individual or environment; a collection of cues also induces an action.

- Response: The individual's reaction to a collection of cues.
- Reinforcement: The strengthening of a response if the experience for it was rewarding.

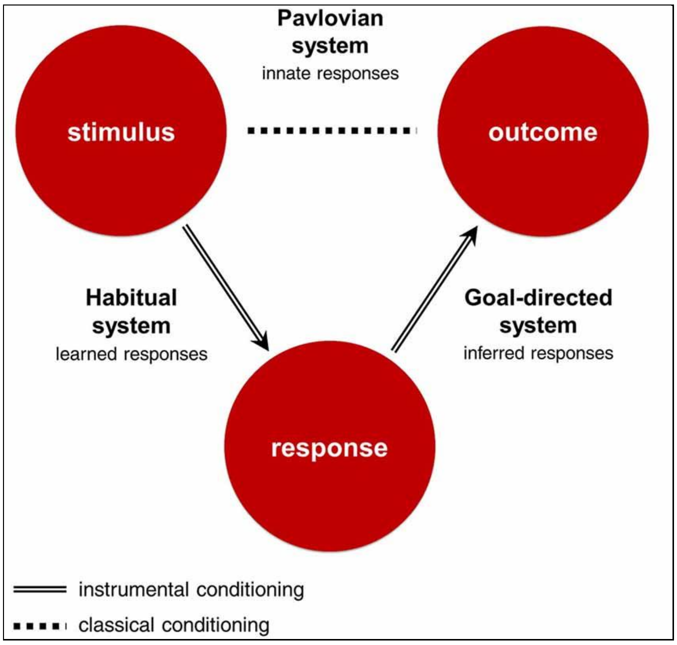


Figure 2.5 Pavlovian innate responses system

Source: Gęsiarz and Crockett (2015, p. 2)

The Marshallian model, compared to the Pavlovian model, is considered too simple, and not reflective of the complexities of the human mind. Moreover, the Marshallian theoretical view of how consumers make decisions has been disputed in a later study by Katona and Mueller (1955), who found that only a quarter of sampled consumers contemplate their options before buying. The consumer behaviour theory has since evolved, giving rise to a new scientific field known as behavioural economics.

Recent behavioural economics theory contradicts early economic models that characterised consumers as rational and calculating buyers. Behavioural scientists argue that consumers are generally irrational regarding spending, and do not always behave in their best economic interest because it is difficult for them to think about the opportunity cost involved with each purchase they make (Ariely 2013; Van der Horst & Mathhijsen 2013).

Opportunity cost refers to things that consumers cannot afford in the future if they buy something today. This concept is simple, yet according to behavioural economists, it is very difficult for consumers to rationalise opportunity costs while making a purchase. Zellermayer

(1996) cited three reasons that prevent consumers from considering the opportunity cost of purchases:

- People place more importance on the present relative to the future; therefore, resisting present consumption in favour of future consumption opportunities is difficult (Benzion, Rapoport & Yagil 1989; Laibson 1995).
- People experience loss when they give up current consumption, the present loss is harder to tolerate than the experience of future forgone gains (Nisbett & Ross 1980).
- People's cognitive limitations hinder their ability to calculate trade-offs between comparing utilities of current and future consumption opportunities (Simon 1955).

Many behavioural researchers found that consumers indeed do not think about opportunity cost while deciding to buy something (Becker, Ronen & Sorter 1974; Langholtz et al. 2002. Furthermore, in Dan Ariely's survey, customers were shown not to consider opportunity cost even while making high-value purchase decisions. Customers, who were about to buy a car, were asked what else they can buy later if they do not buy a car now; most of them replied that they had not thought about it at all (Psychology Today, 2018).

A question then arises: If we do not always calculate opportunity cost while shopping, how then do we control our spending?

The answer to that is an emotional force, within our psyche, that prevents us from overspending, it can be described as an immediate feeling of displeasure when we make a payment. This feeling is termed by behavioural economists as the pain of paying.

2.1.3 Behavioural Economics (Pain of Paying)

The pain of paying is a measurable concept in behavioural economics that reflects hedonic displeasure felt at the time of making a payment (Frederick et al. 2009; Philstar 2018; Prelec & Loewenstein 1998; Knutson et al. 2007; Zellermayer 1996). Generally, this emotional signal impedes excessive spending. However, it varies from one person to another, and its intensity also varies with different experiences, or mental states (Rick, Cryder & Loewenstein 2007). Measuring this emotional impulse can effectively ascertain irrational spending behaviour, and shopping habits of customers.

The following scenario demonstrates how the pain of paying can explain certain behaviours which are not addressed in the rational economic models, such as the opportunity cost analysis model. The scenario below was established in a consumer behaviour survey by Schindler (1989), whose respondents rated how they relate to the hypothetical subject's behaviour.

Zellermayer writes,

> Mr. A plays tennis twice a week. Recently he discovered a small crack in his racquet. Although the crack doesn't prevent him from playing, he feels that it impairs the level of his game, so last weekend he drove to the mall to buy a replacement. After spending more than an hour in each of two stores, and looking at several racquets that he would like to own, Mr. A was still unable to let go of the money. So, he left the mall without buying a racquet. (1996, p.1)

From the opportunity cost perspective, the tennis player had already decided to buy a new racquet the moment he travelled to the mall. However, this perspective cannot explain why he did not commit to the purchase at checkout time, especially after committing time and travel resources going to the mall.

The tennis player scenario describes people who shop for items they do not need but like to own yet end up not buying them at checkout time. This behaviour can be explained by behavioural economics, which argues that even though the tennis player had decided to buy a racquet and went to the mall, he resisted taking one to checkout, because at payment time, the displeasure he felt about making a payment prevented him from committing to the purchase (Zellermayer 1996).

An act of buying can be described by three main characteristics that determine the degree of pain associated with it: the characteristics are transaction utility, buffering and coercion. Figure 2.6 illustrates the characteristics of pain of paying.

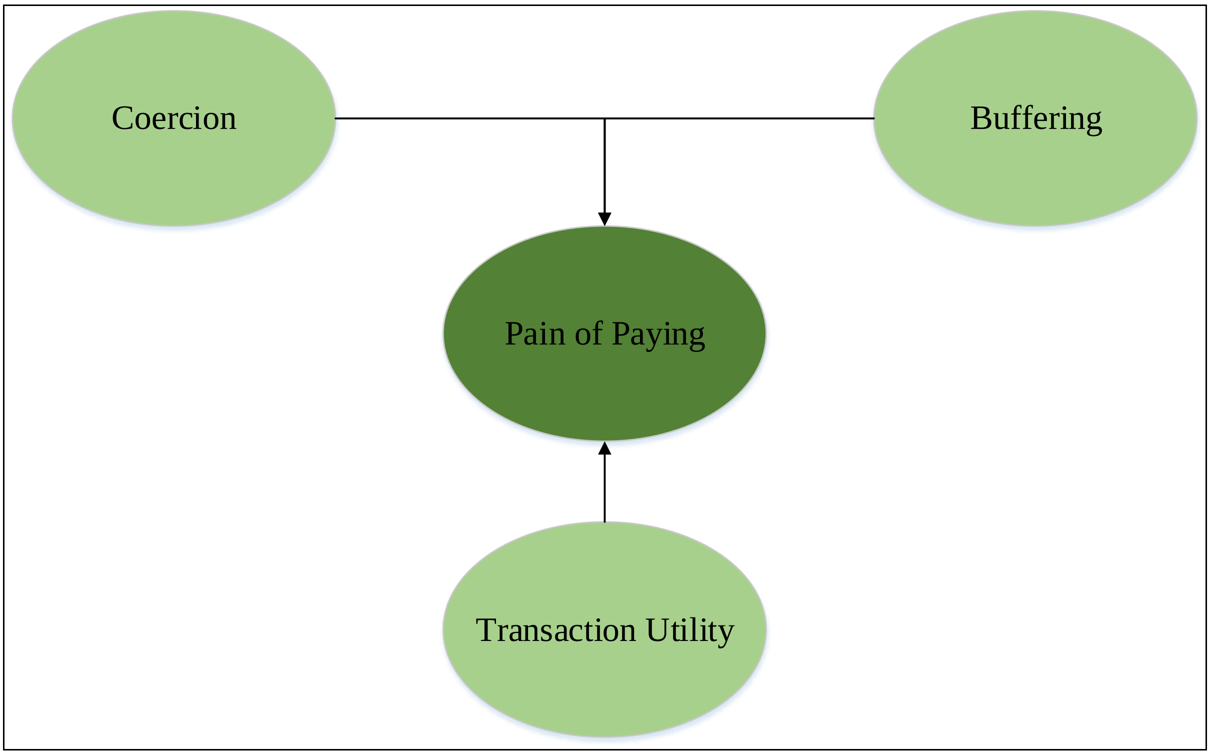


Figure 2.6 Characteristics of pain of paying

Source: Zellermayer (1996, p. 39)

2.1.3.1 Transaction Utility

Transaction utility refers to the customer satisfaction associated with the financial terms of the purchase. This implies that if customers feel they are getting a bad deal for an item, they will experience more pain of paying to buy it, regardless of whether the item itself was satisfactory or not (Thaler 1980).

This was demonstrated by Thaler's (1985) research on transaction utility theory. In his survey, he asked respondents to imagine themselves spending a day on a beach, thirsty for a cold beverage that their friend offered to get them from a nearby vendor. Half the respondents were told that the beverage is that of a five-star hotel vendor, and the other half were told that the vendor is a small convenience store. Respondents were found to be more willing to pay $2.65 for the hotel's drink, but only $1.50 for the same drink from the convenience store.

The explanation for this is that respondents realise that the hotel has higher running costs and are willing to accept a higher price to cover the hotel's high overhead to deliver that drink. However, they were not willing to pay the same price to a shop with lower overhead. Furthermore, respondents preferred to stay thirsty instead of paying over $1.50 at the convenience store. The pain of paying they would experience conceding to being overcharged outweighs the consumption utility of vanquishing their thirst.

This shows that the perception of the deal's fairness is correlated with the pain of paying; that is, the more customers feel that the deal terms of an item favours them, the less pain of paying they experience purchasing it.

2.1.3.2 Buffering

Buffering refers to the interdependence of consumption experience and payment; that is, the extent to which payment spoils consumption experience, and the extent to which a consumption experience softens the pain of paying (Prelec & Loewenstein 1998). The effect of payment on consumption experience varies according to time duration and coupling between payment and consumption.

The time duration between consumption and payment, and which part of the deal comes first, determines the level of the pain of paying felt. For example, customers experience less pain paying for a vacation cruise three weeks before the trip than paying for it three weeks after; in the first instance, the excitement of going on cruise softens the pain of payment; but in the second instance, the cruise experience becomes only a memory that cannot soften paying for it after it was already consumed and enjoyed. The payment will even be more painful if consumers had to pay one year after the trip, even though it is economically a better deal, because the experience is long gone, and consumers can no longer associate it with the payment.

Coupling reflects how closely payment is linked with consumption. That is, how strongly can consumers associate a payment with a consumption. In strongly associated (coupled) consumptions and payments, customers can easily justify the amount paid, resulting in low pain of paying felt. However, when customers cannot justify the payment, they feel more pain of paying (Arkes & Blumer 1985). For example, customers who pre-pay for electricity (credit top-up) can see how their electricity credit dwindles with every use of an electrical appliance, allowing them to associate what they pay with what they use in their house. Post-pay customers who get a bill at the end of every quarter will experience more pain because they cannot associate a single bill with electricity, they have been using for the past three months. Customers feel more pain of paying if they pay for past experiences that have depreciated at the time of payment, because they can no longer associate what they are paying with what they consumed.

2.1.3.3 Coercion

Refers to the control customers have regarding a payment decision associated with consumption. Generally, the less control they have over the decision, the more displeasure, or pain of payment, they experience when making that payment. That is, consumers who voluntarily pay for something feel less pain of paying than consumers who must pay for it (Zellermayer 1996).

For example, residents that choose to upgrade their medical insurance to a better premium tier will experience less pain of paying than residents who must upgrade their medical insurance to meet their visa conditions. This is because the latter group had less control in the matter than the first group.

Together, transaction utility, buffering, and coercion explain why purchases like luxury cars or jewellery are favourable, while paying for insurance or taxes are disliked, despite the latter payments being more essential to individuals' well-being in society. This is because when consumers pay for luxury items, they accept the deal terms (understanding why the cost of luxury items is high), they can directly associate what they pay with what they get, and they have full control over the choice of buying items they desire. On the other hand, consumers who pay for insurance or taxes, usually consider the deal terms unfair (favouring the insurer or government), cannot directly associate what they pay with what they get (potential accidents that may never happen, or government services that do not serve them directly), and yet have no choice but to pay for them.

These three characteristics provide a whole spectrum of factors that affect the pain of paying. Furthermore, this provides an opportunity for future research to explore new factors and measure their correlation in accordance to the pain of paying (Zellermayer 1996).

2.2 The Mobile App Marketplace

Mobile app markets are digital distribution platforms for software applications that run on mobile operating systems like Android or IOS. This service started with Apple back in July 2008, one year after the release of their first iPhone. Initially, the iPhone intended to run web applications that users can access via iPhone's web browser Safari. However, developers were not excited about that proposition and demanded the ability to develop native applications on the iPhone as they did on Apple MacBooks. This is because developing native applications allows developers to make better use of an iPhone's hardware resources and offers them more ways to monetise their applications with advertisement revenue (iMore 2018).

Apple responded by promising to release a software development kit (SDK) for developers, by February 2008, and a distribution service later that year (iMore 2018). That same year, Google Inc., Apple's biggest competitor in mobile software, released their own distribution service known as The Android Market, which was later consolidated with Google eBookstore and Google Play Music to form Google Play Store. Google also provided developers with an SDK to develop native applications on the Android operating system that runs on most non-Apple smartphone brands, like Samsung and HTC.

By 2015, the industry grew to attract a net worth of around $100 billion. The mobile app marketplace and industry has led to the continuous spread of smartphones and other digital devices that have established the fields of social media networking and electronic gaming as well as online retailing and businesses (Rakestraw, Rangamohan & Rammohan 2013). Amidst the growth of popular brands, such as Apple, others, such as Blackberry, have delineated their prowess in the mobile app markets, as a way of seeking loyalty from existing consumers.

Apart from Blackberry, other brands like LG, Samsung, and Motorola joined the mobile apps industry, gaining loyal customers and eventually being inclined toward competition as well as competitive markets. These apps are useful in facilitating various capabilities, such as games, sending and receiving emails, tracking one's spending and networking, among others.

When Research in Motion (RIM) made an announcement of the Playbook tablet computer, running on Android platforms. RIM is part of Blackberry's App world, which works as the marketplace for both Blackberry and Android apps. There, however, is a discrepancy as the apps that function on the Playbook are unavailable on any other platforms other than the Blackberry App World. Logically speaking, therefore, any apps from the Android marketplace or other third-party marketplaces are incompatible with the device.

If the Android apps are supposed to function well with RIM's Playbook, they should be configured with certain rules, permissions and packages that will promote compatibility. Following such a direction appears inevitable, for example, since 2011, the Blackberry App World only had about 20,000 applications, while the Android marketplace was equipped with more than 250,000 apps, indicating the effectiveness of the latter (Rakestraw, Rangamohan & Rammohan 2013). A software development kit (SDK), like with the Google apps on iOS phones, was introduced to ensure that the operating system of the Playbook was well-programmed to allow the functioning of other apps apart from those in the Blackberry's App world.

Third-party marketplaces, also known as niche marketplaces, have recently penetrated through the mobile apps industry. The developers of these marketplaces are quite smaller than Apple or Google; therefore, it is well in their mandate to deal with app users with specific needs (niches). It, however, has been a good market since 2009, when there was an increase in niche app stores and a decrease in general app stores. After 2009 and into 2010, the general app stores started to increase before drastically undergoing a decline in 2011 (Rakestraw, Rangamohan & Rammohan 2013). Subsequently, companies were encouraged to focus on niche marketplaces, as they offer a solution for penetration into the mobile apps industry.

With these niche marketplaces, users are exposed to applications that target their precise needs. Such an approach makes it easier for them not to indulge in the different apps just to find their preferred ones. The increasing number of apps and developers leads to confusion as they may fail to tend to the specific needs of these users. The three constituents of niche mobile markets include:

- Platform-oriented markets. They deal with applications for a targeted operating system (like Android or IOS).
- Target segment-oriented markets. These are marketplaces that offer the provision of apps to a specified group of these app users.
- "Carve out" markets. These are niche stores that exist under "full catalogue stores" such as "@work" from Apple's platform.

By 2010, the mobile app marketplace/industry was quite congested, as there were new developers and competitors who introduced different apps. There were still certain apps that were preferred by the consumers and some of them included Facebook, Google Maps, and LinkedIn, among others. These third-party apps and developers acted as complementors to Apple and Google, who provided SDKs and development environments for developers to develop applications for their smartphone devices. Observably, without the assistance from these third-party app developers, customers will shift and direct their loyalties to more popular platforms (Rakestraw, Rangamohan & Rammohan 2013).

2.2.1 Google Play Store Product Categories

App stores offer plenty of categories that cater to the increasing variety of needs of their billion-plus users. Today, Google Play Store offers products categorised into 33 mobile application and 17 mobile game categories, respectively (Google Play 2015). Refer to Table 2.1 for the list of mobile applications in Google Play Store.

2.2.1.1 Games

Google Play Store offers games in categories, such as action, adventure, arcade, board, card, educational, music, puzzle, racing, role playing, simulation, sports, strategy, trivia, and word.

2.2.1.2 Applications

Table 2.1 Google Play Store Application Categories

Category	Examples
Art & Design	Sketchbooks, painter tools, art & design tools, colouring books
Auto & Vehicles	Auto shopping, auto insurance, auto price comparison, road safety, auto reviews & news
Beauty	Makeup tutorials, makeover tools, hair styling, beauty shopping, makeup simulators
Books & Reference	Book readers, reference books, textbooks, dictionaries, thesaurus, wikis
Business	Document editor/reader, package tracking, remote desktop, email management, job search
Comics	Comic players, comic titles
Communications	Messaging, chat/IM, diallers, address books, browsers, call management
Dating	Matchmaking, courtship, relationship building, meeting new people, finding love
Education	Exam preparations, study-aids, vocabulary, educational games, language learning

Entertainment	Streaming video, movies, TV, interactive entertainment
Events	Concert tickets, sporting event tickets, ticket resales, movie tickets
Finance	Banking, payment, ATM finders, financial news, insurance, taxes, portfolio/trading, tip calculators
Food & Drink	Recipes, restaurants, food guides, wine tasting & discovery, beverage recipes
Health & Fitness	Personal fitness, workout tracking, diet and nutritional tips, health & safety, etc.
House & Home	House & apartment search, home improvement, interior decoration, mortgages, real estate
Libraries & Demo	Software libraries, technical demos
Lifestyle	Style guides, wedding & party planning, how-to guides
Maps & Navigation	Navigation tools, GPS, mapping, transit tools, public transportation
Medical	Drug & clinical references, calculators, handbooks for health-care providers, medical journals & news
Music & Audio	Music services, radios, music players
News & Magazines	Newspapers, news aggregators, magazines, blogging
Parenting	Pregnancy, infant care & monitoring, childcare
Personalisation	Wallpapers, live wallpapers, home screen, lock screen, ringtones
Photography	Cameras, photo editing tools, photo management and sharing
Productivity	Notepad, to do list, keyboard, printing, calendar, backup, calculator, conversion
Shopping	Online shopping, auctions, coupons, price comparison, grocery lists, product reviews
Social	Social networking, check-in

Sports	Sports news & commentary, score tracking, fantasy team management, game coverage
Tools	Tools for Android devices
Travel & Local	Trip booking tools, ride sharing, taxis, city guides, local business information, trip management tools, tour booking
Video Players & Editors	Video players, video editors, media storage
Weather	Weather reports

Source: Google Play Console Help (2018, p. 1)

The massive success and market data availability of mobile app stores, have generated much interest among academic researchers. Over the past decade, numerous published research papers have explored multiple facets of the industry, for example, software design, app store metrics, app consumers, and threats like spam and data privacy.

Breaking down the apps into different categories makes it simpler to understand their ranks in the Google Play Store. From the list, it is quite evident that lifestyle apps are quite popular, as they receive more reviews from the users. As Sefferman (2016) observes, ratings make it easier for consumers to discover apps, and accentuate the brand image, while exposing them to the existing global markets. Studies indicate that about 59% of consumers often check out the app's ratings before downloading it. Assuming one app has a 3-star rating and another one has a 4.5-star rating, it is inevitable for the users to be interested in the latter. According to users, the belief is that highly rated apps will be more effective than the ones with lower ratings. The ratings are quite influential to the point where users remain oblivious of other app characteristics, while maintaining their "fixation" on the former (Sefferman, 2016). These reviews are also quite useful for developers since they require the feedback to make amendments (and improvements) on their platforms.

Sefferman (2016) explains that even with negative reviews/scrutiny, there is a need for developers to accept positive criticism, which helps with fixing any loopholes within the app. It is much better to deal with users that fall under the category of the "majority" using a certain app since they give more detailed reviews. The minorities are quite vague and often only end up saying that "the apps simply work", and they do not give any underlying reasons to explain further the effectiveness of these apps. Whether it is from the majority or minority customers, these users and customers are the developer's "backbone" since, without them, they are incapable of improving their app experiences. As mentioned, while it is encouraging to have positive feedback, identifying the weaknesses of these apps is plausible enough to ensure that the markets have better-developed applications.

Developers should understand that individuals who give 1 star or 2 stars ratings are not necessarily disparaging their work, rather they are giving feedback with the hope of acquiring a better (and more improved) platform from them. Wanting more development of the apps, therefore, means that the customers are interested in exploiting the full potential of these developers. In such cases, it is necessary for developers to avoid being subjective and maintain all forms of objectivity while handling customer feedback. Integration of any personal feelings will affect the developers negatively, making it impossible for them to make any of the required amendments.

It works in favour of the developers if they reroute the development of their platforms. The customers not only leave their reviews in the Google Play Store but also on social media platforms such as Facebook and Twitter. On these public platforms, it is possible for the message to reach a wider audience; thereby, either making or breaking the name of these developers' apps. Sefferman (2016) further explains the necessity of sharing feedback to these platforms as it becomes much easier to interact with the customers from a personal perspective. The Google Play Store's review provision appears quite useless since it is only a one-way platform that does not offer any room for much interaction. Even if the developer manages to verbally react to a review or feedback, their interaction is quite limited in the app stores.

Failure to communicate with one's users or customers limits the likelihood of improving their experience (Sefferman, 2016). Since developers are inclined toward creating more apps when there is the success of one, the feedback will help them with their consequent projects. In case customers complain about a certain glitch in these apps, the developers ensure efficiency while developing their new platforms.

2.2.2 Literature Related to the Mobile App Market

Minelli and Lanza (2013) explored the software engineering of mobile apps from source code, third-party APIs, and historical data perspectives, highlighting the differences between mobile apps and traditional software systems.

Hassan, Shang and Hassan (2017) researched the scenarios that lead to emergency app updates on Google Store, resulting in the identification and examination of 1,000 emergency updates that occur due to deployment problems or source code changes. They found that emergency updates hardly ever include update notice description, are rarely followed by a second emergency update, and the updates preceding them cause a user backlash manifested in negative reviews.

Amalfitano, Amatucci and Memon (2017) compared all developed online testing methods for the Android platform and produced a general framework that describes the most common testing techniques found online and in literature.

Eskandari et al. (2017) investigated mobile app compliance with European Union data protection regulations that restrict personal data of European users from being transferred outside Europe. They analysed 1,498 apps and found that 16.5% of them transfer user data outside Europe and that 51% do not provide any privacy policy for European users.

Syer et al. (2011) compared Android and BlackBerry micro-apps along three dimensions: source code, code dependencies, and code churn. They found that BlackBerry micro-apps are larger and more reliant on third-party libraries. Syer et al. (2013) also compared mobile apps to large and small desktop applications along two metrics: code size and debugging time, to identify software engineering challenges unique to mobile apps.

Ruiz et al. (2012) studied the reuse of software, by inheritance or class reuse; they found that, on average, 61% of classes in every store category occur in more than one app.

Seneviratne et al. (2017) developed an automated spam app detection mechanism that can detect spam apps with over 95% accuracy; the detection tool was then applied on Google Play Store and found that 2.7% of 180,000 tested apps to be potential spam.

Atkinson et al. (2018) investigated inadvertent personal information leaked from mobile apps via wireless networks. They found that information related to religion, age, and gender can be broadcasted by mobile apps despite WiFi encryption being used.

The mobile app market cannot be fulfilled without an improvement in any of the hardware related to these mobile devices. If they appear incompetent (and ineffective), the developers often have a difficult time selling them to interested users. Hardware to be improved may include an expanded network bandwidth (wireless) or more effective and better processing capabilities.

As indicated, the mobile app market has a mobile application portal, which is essential in facilitating the distribution process of these mobile applications. Portals are useful in this line of action as they have a role in creating a connection/link between developers and consumers of the apps. Though there are debates about either increasing or decreasing the number of portals, the constant element is their indisputable changes. There are centralised and decentralised portals, each of which performs their specific duties.

Discussing the mobile app market includes talking about the mobile application distribution process, which involves the development (or creation) of an application, linking it with the markets, selling and purchase of the apps and finally, their utilisation on mobile devices. There is a need to explore this concept, which allows users to have a grasp of the underlying concepts surrounding the markets.

Tao and Edmunds (2018) investigated the popular nature of these mobile applications, by exploring the number of users that are active on a monthly basis, to make conclusions about their frequency on the apps. These mobile apps are designed, created, and developed for global markets that are supposed to attract different consumers.

While talking about the necessity of these apps in the lives of mobile users, offering an exploration on the scope of in-app ads is useful in understanding the technological narrative. Ads are quite annoying and inconveniencing, but ironically their prevalence does not affect the place of mobile apps, as consumers continue to purchase and indulge in them. These ads have their usefulness as developers have a role to play in advertising marketers and ensuring they are well-connected to their target audience (or market).

Previously, there has been a mention of SDKs, and their roles in these mobile app markets. These kits work together with third-party developers to ensure the building of applications that run the specific platforms. These platforms are designated to offer the provision of integrated development environments (IDE) to propel the process of development, and exposure to the application markets.

Developers are tasked with the idea of playing around with certain features, as this accentuates device variety. When dealing with a feature that appears compatible with most devices, it is the developer’s role to maintain compatibility with at least a single device. These underpinnings indicate an increase in freedom for developers while looking into this variety of devices. For instance, while features such as Bluetooth did not appear in the earlier iPhone platforms, they were readily available in the other devices that competed heavily with IOS.

Even though iPhones have maintained that Bluetooth is a “standard” feature on their recent devices, this may have been due to the pressure imposed on them from their competitors.

App adoption is particularly affiliated with the fact that they are easy to use and allow consumers to attract the desired content. For instance, when one needs to sign into a website, using the mobile app appears faster and more effective. With apps such as Facebook, it may be difficult for users to access all the actions and experiences while using the website via mobile phones. If one is to sign into Facebook using a website, it makes better sense to use a computer or laptop. In comparison, mobile apps such as those for banking, shopping and ordering food, are quite useful as they lessen the burdens of these users.

Understanding the mobile app market delineates the inevitability of competition between different platforms is indicative of the pressure experienced by developers. Perhaps if there was only one existing developmental platform, there would be no need to borrow or replicate the technologies from other sectors.

2.2.3 Business Models Adopted in The Mobile App Market

When looking at the term ‘‘business model”, there is an explanation that the term represents a deviation from any traditional business to digital/online business. Up until 2000, the business model was used to extrapolate further on the “Internet boom-bust cycle.” Baghbaniyazdi and Ferdosara (2016) understand that business models refer to the logicalities surrounding the valuable nature of either products or services. Right from the 20th century, the “business model” was classified as a versatile concept, as it shifted from IT-related matters to a framework for analysing various market structures (Baghbaniyazdi & Ferdosara, 2016). The business model framework consists of the following: 1) the assessment of value position, 2) internal competencies, 3) revenue logic, 4) customers, 5) competitive strategy, and 6) future factors, such as organisational size and scope. These business models have been adopted into the mobile app market.

According to Osterwalder et al. (2011), business models explain how businesses develop, deliver, and capture value, as well as determine how technological developments are transformed into economic value. E-commerce, social media, and mobile apps have changed conventional ways of business. As a result, new business models were needed to generate value from these new concepts (Yen, Drinka & Kanamori 2013). Comparing a variety of categories of mobile applications, it is evident that games are seen to portray the “widest range of revenue models” (Baghbaniyazdi & Ferdosara 2016). Basing these business models in the mobile app market offers a delineation that they can be placed into six categories: 1) premium, 2) free, 3) freemium, 4) in-app purchase, 5) in-app advertising, and 6) combination model.

First, when it comes to premium, it is not difficult to understand the logic surrounding this business model. The users are charged for both downloads and installation of an app that happens via a one-off purchase. Afterward, the developers are paid using these revenues, while the app store retains its share of the transaction. The prices of these paid apps, however, varies throughout different countries as each one of them had their specific quotes. In Australia, Canada, South Korea, Germany, the U.S., the U.K., Russia, France and China, for example, the prices were about US$ 0.99 to US$ 1.99. The case was different in Japan as apps were priced at about US$ 18 (Baghbaniyazdi & Ferdosara 2016). Furthermore, the free model offers free access of apps to the users or consumers. Due to its nature, it is one of the most popular models, as users are built to enjoy free apps. Before 2014, most of the apps were categorised under the premium model since users had to pay for it to have any form of access. Now, there are numerous apps in app stores that are downloaded free of charge, making it easier for users to download and install them.

Also, there are similarities between the free and freemium" models. However, for better experiences, it may be advisable for consumers to pay for the apps (Baghbaniyazdi & Ferdosara 2016). As per its title, freemium is a blend of free and premium models, meaning there are some instances where users would be required to make purchases. The model is quite common in the categories of games since there is no upfront fee charged. In such a case, the users become more interested in downloading the app, due to their benefits.

According to Baghbaniyazdi and Ferdosara (2016), in-app purchase (IAP) is an extension of the freemium model, which offers the provision of personalised features, such as higher game levels or acquiring an upgrade within the game apps. There is no individual/personalised upgrade to the premium version (Baghbaniyazdi & Ferdosara 2016). When it comes to in-app advertising, developers offer the provision of product advertisements to acquire some form of revenue. These in-app advertising models are known as ads, videos, interstitials, and offer walls. A good example are the gaming apps, which require users to watch advertisements and acquire native currency in return. From 2013 to 2014, Baghbaniyazdi and Ferdosara (2016) state there was about a 56% growth of in-app advertising.

The combination model is a blend of different business models apropos of the largest profits and conditions of markets that would be employed by developers. Specifically, the freemium model plus in-app advertising and IAP are some of the most feasible combination models.

Evidently, mobile app distribution platforms have adopted business models that are established in e-commerce and the video gaming industry. Table 2.2 briefly explains the business models adopted by the mobile app market.

Osterwalder et al. (2011) described business models as a composition of four components: value proposition, user segmentation, distribution channels, and revenue streams. They studied the implementation of the freemium model in the gaming industry and determined that tracking, analysing, and predicting consumer spending behaviour is essential for successful implementation of the freemium model and business models in general. This view was supported by Georgieva et al. (2015), who stated that analysing consumer spending behaviour is instrumental to developers because it enables them to optimise freemium, in-app purchases and native currency models designed for video gaming products. Figure 2.7 categorises monetisation models in terms of earning potential per user: lower earning models are marked in red, high earning models are marked in green and finally, models that are out of the thesis study’s focus are marked in grey.

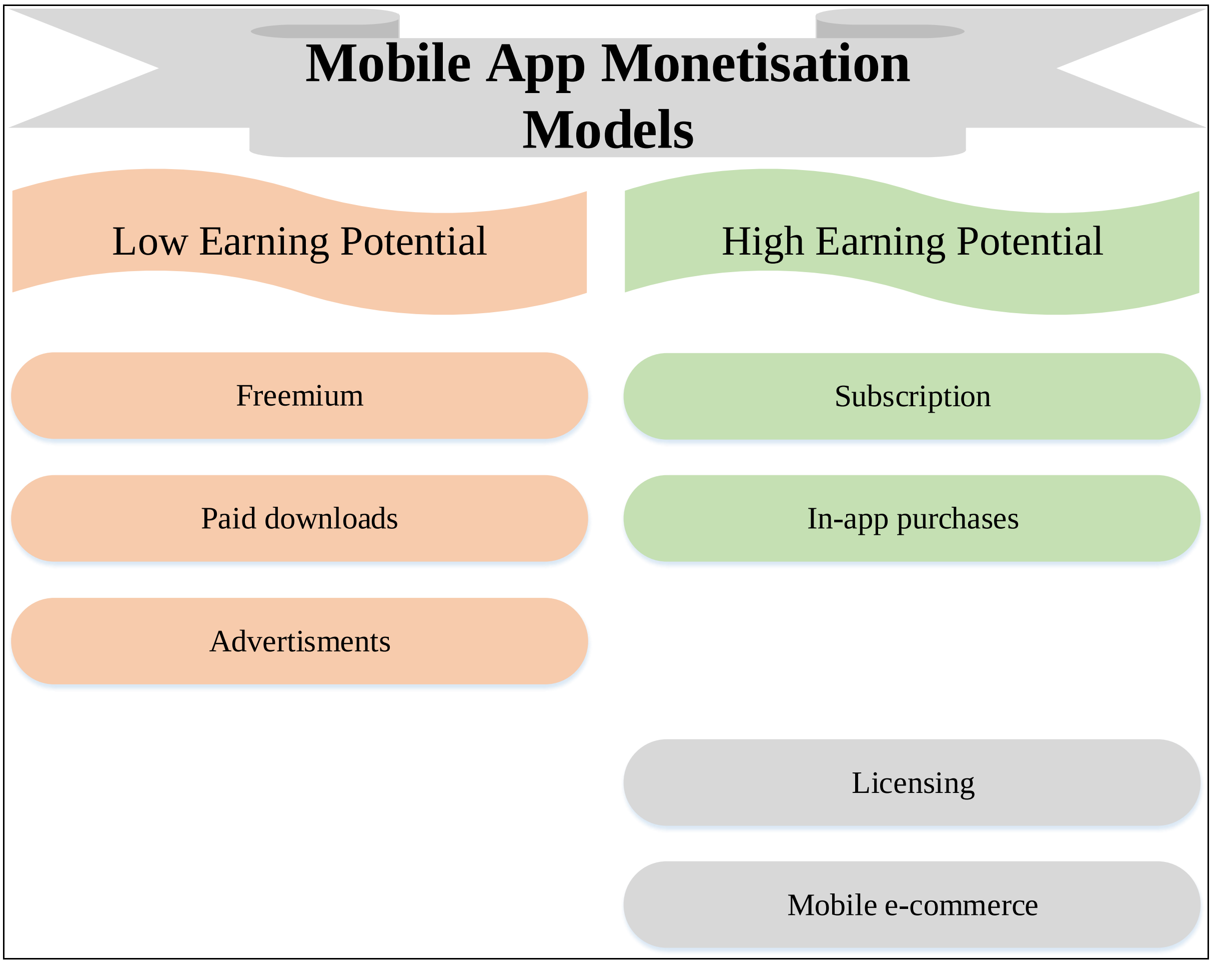


Figure 2.7 Classification of Android monetisation models in terms of earning potential per customer

Table 2.2 Description of business models in the mobile app market

Business Model	Description
Mobile e-commerce	Based on the selling of physical or virtual of goods and services through mobile apps.
Licensing	Mobile apps can be licensed to smartphone distributors; licensed apps are preinstalled on devices sold by distributors. Mobile app developers receive a royalty payment for each sold device.
Subscription	Mobile apps that provide digital content like movies, music, books, and magazines charge consumers a regular subscription fee in exchange for content consumption.
Advertisements	Developers can sell advertisement space and time on mobile apps. Third-party services pay developers to show ads to users while interacting with mobile apps. Mobile developers either generate revenue from impressions or installs depending on the ad model used. The two ads models are: ● CPM (Cost per thousand impressions): Developers earn a fee per every thousand ad views. ● CPI (Cost per Install): Developers earn a fee per every app install directed by an ad view.
Freemium	One of the most popular models in the market. Users can download freemium mobile apps and enjoy basic features for free but need to pay to unlock premium features or remove ads.
In-app purchases	Often referred to as freemium. This model offers uncapped earning per app to developers by offering virtual goods that can be sold repeatedly to users.
Native currency	Often referred to as freemium. Mobile apps can offer virtual currency (in-app credit) for users to buy virtual currency and premium features. Virtual currency is purchased with real currency. This model is like in-app purchases, the difference is users first purchase virtual currency to then purchase virtual goods and premium features.
Paid downloads	Developers can charge users upfront for downloading mobile apps. In pure paid downloads model, users cannot experience paid apps before purchasing them.

Source: Noort (2015, p. 1)

2.3 Consumer Spending Behaviour of Mobile App Users

Relative to desktop software, mobile app prices are quite affordable. The average app price of paid apps in the App Store and Google Play is US$4.37 and US$4.86, respectively (Statista 2018). Despite the low pricing, consumer spending behaviour in the mobile app market has been shown to be generally conservative (Gartner 2017; Statista 2018). Ariely argued that customers do not like paying for apps because of the mass availability of free alternatives; apps of any category are likely to have free substitutes that users can obtain without paying. He explained that by offering apps for free, stores have created a pain of paying for paid apps, even ones priced for US$ 1 (Heyman & Ariely 2004). This is known as price anchoring (Help Scout 2018) that is where consumers evaluate a deal based on an initial reference price, which in the case of mobile apps, is zero dollars.

Consumers are willing to spend on apps that offer them satisfaction and fulfillment compared to the ones categorised as plain or bland. Apps purchased by consumers often appear less painful when they offer some form of satisfaction and fulfilment to them. A good reason that consumers prefer free apps is that even if they end up not liking its content, there is no pain experienced for spending any money on the purchase. In terms of consumer spending, among the largest online markets is Apple, as a huge number of these spenders utilise the iOS platform. Any of the users that place their money on different categories apropos of these mobile apps are known as "big spenders."

Moreover, Apple users higher spending on mobile apps can also be attributed to their better financial situation compared to Android users. A survey by Slick Deals online shop has found that the average salary of iPhone users is $53,251 per annum compared to Android users, who earn $37,040 per annum. In that survey, iPhone users reportedly spend more on clothes, technology and beauty products than Android users (Schmall 2018).

According to Kooti et al. (2017), the following are some of the general findings while looking at consumer spending behaviour of mobile app users:

- Most of these big spenders are older individuals, most likely to be males, and less likely to originate from the U.S. These spenders are often of Turkish, Romanian or Greek descent. Due to the financial disparities, it is quite possible to delineate a comparison between these big spenders and other ordinary users.

- The big spenders are seen to avoid app repurchases, while their rates of spending increase and decrease, consecutively.
- Heterogeneous spending is rampant. Only about 1% of the spenders are responsible for about 59% of the finances used on in-app purchases.
- Even if these big spenders avoid a specific app for a period, they are more likely to impose their spending behaviour on another new app, in comparison with any other random users.

Based on literary research on big spenders, it is evident that out of all the consumers, only a selected group are interested in spending. Not all users delineate their spending behaviours. Patterns of in-app spending are diverse and do not match all the consumers. Understanding the distinct features of these big spenders, helps to identify the consumer spending behaviour of mobile app users.

It is impossible to shun any prevalence of online shopping as consumers have come to trust these online payment platforms (Kooti et al. 2017). As with big spenders, who are mostly older individuals, there is a category of online shoppers that are younger. These consumers also possess more wealth as well as education, in comparison with other shoppers, who are often known as mundane and average online users (Kooti et al. 2017). It is somewhat difficult to distinguish either male or female shoppers because they each have a role to play in the delineation of consumer spending behaviour in mobile app users.

Users in the Apple app store spend more than the users dealing with Android's Google Play Store. There are real-life statistics indicating that the around $20 billion that was spent in the Apple App Store was four times more than the amount spent by Android users in 2015. With these characteristics of high spending, it would be plausible enough to keep track of any of the constant and frequent consumers inclined toward these in-app purchases (Sydow 2018b).

Even if big spenders are known to change brands, while remaining loyal to the new ones, the ordinary spenders have a pattern of buying the same and specific item numerous times, especially if it influenced them positively. Such patterns, however, do not interfere with the fact that users tend to easily get bored of apps, thus reducing their purchasing threshold. Kooti et al. (2017) note that app adoption eventually leads to abandonment when the users are no longer interested in the mobile application.

While investigating the concepts of app adoption and abandonment, there is also a need to investigate the reasons for these users to switch to other applications. About 8.6% of the buyers within a certain app have been seen to abandon their current apps, while now switching to the new apps to make these in-app purchases. The truth is that consumers cannot have similar consumer behaviour patterns because, according to the Marshallian and Pavlovian models, consumer behaviour can never be the same. Each of these consumers solicits for different features in the apps, thus their explaining their refined tastes and preferences.

Facebook has consumers of different age groups and thus cannot be compared to Snapchat, which mainly includes the millennials and children from a younger age group. Gaming applications are also quite universal as they are categorised as among the most downloaded apps in mobile app stores. According to Rakestraw, Rangamohan and Rammohan (2013), consumers spent more time on these apps, as each session lasted longer than the others. Since there are some games within the Facebook platform, numerous users end up signing into the app, before engaging in the games. For instance, games such as Candy Crush or Words with Friends are often played against one’s Facebook friends, making the social networking app a necessity in the lives of these gamers.

However, other academics have since conducted more in-depth app consumer behaviour studies and provided more understanding of the complex purchase decisions made by app consumers (Rakestraw, Rangamohan & Rammohan 2013). This section starts with an overview of literature related to mobile app spending, in chronological order.

2.3.1 Literature Review of Consumer Spending on Mobile Apps

Kim, Lee and Son (2011) explored what drives consumers to purchase apps. They identified variables and ranked them, from most dominant to least dominant, across four app classifications. They found that word of mouth, usefulness, and pleasure were among the most dominant purchase drivers across different app classes.

Harman, Jia and Zhang (2012) utilised data mining techniques to analyse 32,108 apps in the Blackberry App Store. They found a strong correlation between customer ratings and store ranking but found no correlation between price and customer rating, or price and number of downloads.

Liu, Au and Choi (2014) studied the effects of the freemium strategy in the mobile app market and analysed 711 high ranking apps on Google Play. They found that trial performance (rating of free app version) and app ranking variables were positively associated with higher app sales.

Lee and Raghu's (2014) research focused on how app developers could succeed in the market by examining apps in top store charts. Their research indicated that offering apps across multiple categories and investing in less competitive categories had a positive effect on surviving in top store charts and receiving more consumer traffic.

Hsu and Lin (2015) examined what drives purchasing intention for paid mobile apps (paid download business model), surveying 507 mobile app users regarding factors that influence their intentions to buy apps. Their research concluded that app rating, value for money, and social influence were positively associated with user intention to buy apps.

Khalid et al. (2015) qualitatively analysed 6,390 low-rated customer reviews on the App Store, and found that technical errors, and app crashing, feature requests were among the most frequent reasons behind negative reviews.

Lim et al. (2015) investigated country differences in app user behaviour and mobile app software engineering challenges, analysing survey data gathered from 4,824 respondents. They found that the UK and Canada were more price sensitive, and that Japan and Australia were less likely to submit app ratings, while packaging requirements and quality expectations were among top app development challenges.

Liu et al. (2017) identified consumer behaviour patterns based on the app management activities (app installs, updates, and uninstalls) of 17 million users over a 5-month period. They found that the number of installs of an app did not indicate its quality or how users perceived it. They also found that users maintained a routine schedule to managing apps on their smartphones.

Arora, Ter Hofstede and Mahajan (2017) analysed Google Play market data to measure how factors like availability of free version, developer reputation, and app rating correlate with the speed of paid app adoption. They found that developer reputation and app ratings were positively associated with adoption speed and that the availability of a free version of the paid app reduced adoption speed.

Kang (2014) investigated mobile app purchasing on tablets and surveyed users regarding proposed factors that influence their continued intention to use mobile apps. The research found that performance expectancy, social influence, and effort expectancy had a positive effect on user intention to purchase mobile apps.

2.3.2 Drivers of App Consumer Spending

Kim, Lee and Son's (2011) exploratory study is one of the earliest studies on customer spending behaviour in the mobile app market. Their study on the determinants of mobile apps purchase was the foundation for future researchers to test hypotheses regarding app consumer spending behaviour. Kim, Lee and Son (2011) interviewed thirty app users about their purchasing habits of apps belonging to four classifications: productivity, entertainment, information, and networking. They found that word of mouth (user ratings, user reviews, critics' reviews, and friend recommendations) was one of the most dominant drivers of mobile app purchases. Their findings are summarised in Table 2.3.

Table 2.3 Determinants for the purchase of mobile apps

App category/ Purchase driver (ranked from most dominant to least dominant)	Productivity	Entertainment	Information	Networking
1	Usefulness	Word of mouth	Usefulness	Word of mouth
2	Word of mouth	Pleasure	Word of mouth	Usefulness
3	Trial performance (for apps that offer a trial version)	App Ranking	Monetary value	Monetary value
4	Monetary value	Trial performance (for apps that offer a trial version)	Trial performance (for apps that offer a trial version)	App Ranking
5	App Ranking	Monetary value	App Ranking	Trial performance (for apps that offer a trial version)
6	Ease of use	Usefulness	Ease of use	Pleasure
7	Pleasure	Ease of use	Pleasure	Ease of use
8	Other	Other	Other	Other

Source: Kim, Lee and Son (2011, pp. 7-9)

2.3.2.1 User Rating

Mobile app stores enable consumers to rate their user experience and provide feedback to apps they download via user ratings and reviews. User rating is a 5-star based summary evaluation that app users conduct to reflect their experience and perceived quality of the app, the system is designed to award 1 star for terrible, to 5 stars for excellent. App rating is very important to sellers because it allows developers to be aware of consumers' concerns about the app and make the necessary changes which will consequently influence future consumers' decision to buy the app. A survey by Apptentive has shown that 79% of consumers checked ratings and reviews before downloading apps, 53% checked before updating apps, and 55% checked before making in-app purchases (Wilson 2019).

Store algorithms use ratings and reviews to adjust app store rankings and discoverability (App Store 2018). The significance of user ratings and reviews on purchase decision has been established by previous research of other industries, such as eBook stores, video gaming, and cinema (Bawa & Shoemaker 2004; Jiang & Sarkar 2009; Johnstone & Dodd 2000).

Furthermore, a user survey by Apptentive found that 59% of users often checked ratings before installing new apps (Medium 2017).

Liu, Au, and Choi (2014) analysed the association between user ratings and app sales and found a positive association between them. This finding is also supported by Hsu and Lin (2015), and Arora, Ter Hofstede and Mahajan (2017), as both studies found positive associations between paid app user rating and intention to buy apps or adoption speed of the paid app. Refer to Table 2.4 for the summary of findings.

Because of the importance of app ratings, mobile app sellers implement several strategies to keep their scores high, ranging from constant updates and quality maintenance to proactively asking their users to consider granting them 5-star ratings (Zolotareva 2017).

Table 2.4 User rating cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Liu, Au and Choi, 2014	The revenue of the paid version of a mobile app is positively associated with the rating of its free version	Supported
Liu, Au and Choi, 2014	The importance of paid app rating is reduced when a free trial app is offered.	Supported
Liu, Au and Choi, 2014	Rating of free trial version of app is positively associated with higher sales.	Supported
Liu, Au and Choi, 2014	The importance of free app version rating increases for hedonic apps.	Supported
Liu, Au and Choi, 2014	For apps without a free version, rating is more important for lower-ranked apps than for higher-ranked apps.	Not Supported
Hsu and Lin, 2015	App ratings positively affects consumer intention to buy paid apps.	Supported
Arora, Ter Hofstede and Mahajan, 2017	Higher paid app user rating is associated with higher adoption speed of paid app.	Supported

Arora, Ter Hofstede and Mahajan, 2017	The positive association between paid app user rating and adoption speed of paid app becomes more positive with time.	Supported

Sources: Arora, Ter Hofstede and Mahajan (2017, p.64); Hsu and Lin (2015, p.54); Liu, Au and Choi (2014, p. 345)

2.3.2.2 Reviews

Alongside ratings, users may justify their evaluations using reviews. Users use reviews to explain their opinions of mobile apps. Users usually use reviews to recommend or warn against downloading apps, but sometimes they use them to request new features and report bugs. Reviews influence app download decisions as well as affect apps' visibility on mobile app stores: the better the reviews are, the higher the app ranks on relevant keyword searches in Google Play and The App Store. Many industries implement reviews to give consumers a public voice. Vasa et al. (2012) found that reviews have a profound influence on businesses' sales and rate of growth; their findings are also supported by Zhao et al. (2015) who found that higher ratings of reviews average correlates with higher sales and that lower ratings of reviews have a negative effect on sales.

2.3.2.3 Free App Trial Version

Apps that offer free trials implement the try-before-you-buy selling technique; free trials' primary aim is to entice consumers into buying the premium version of a product and to continue using after the free trial period expires. There are several ways in which free trials are offered in the mobile app market depending on the monetisation model used.

Premium (buy to install) apps often make available a free trial version of the premium app with limited functionality for users to sample. If they enjoyed the app or found it useful, they can buy the premium version and get access to the complete functionalities of the app. Freemium apps combine both free and premium feature in the same software download, users are free to install the app but the premium features remain locked, if users wish to unlock the premium features they can buy and access them within the app. Subscription model offers a limited time trial, in which users enjoy the full features of apps for a limited time only, and afterwards they are reverted to a free basic version or to no access. If users wish to continue using the full version, they keep paying a regular subscription fee charged every month or year depending on the subscription agreement.

Academics contest whether developers should offer a free trial version of paid apps (use a freemium business model) or stick with paid versions only (Arora, Ter Hofstede &Mahajan 2017; Liu, Au & Choi 2014). Kempf (1999) argued that customers who personally sample and experience products display more confidence and determination in their intention to buy the products than customers who do not personally sample them. Anderson (2009) argued that products without free versions risk lower interest and awareness from customers, which lowers their sales. Kim and Morris (2007) demonstrated that customers who experience free trials of low involvement products display better cognitive responses to the products compared to high involvement products. However, Dey and Lahiri (2013) warned that time-limited trial versions could cannibalise the paid versions for short, or one-time customers because by the time they need to upgrade to premium, they no longer need the product. Faugère and Tayi (2007) also warned that customers with technical skills crack trial versions to unlock paid versions free of charge.

Both Liu, Au and Choi (2014) and Arora, Ter Hofstede and Mahajan (2017) tested free trial versions offering association with app sales and reported conflicting results. Liu, Au and Choi (2014) found that offering a free trial version of paid apps, also identified by Kim, Lee and Son (2011), was positively associated with higher paid app sales. In contrast, Arora, Ter Hofstede, and Mahajan (2017) found that offering a free trial app version had a slowing effect, that grows with time, on the adoption speed of paid apps. Both studies, Liu, Au and Choi (2014) and Arora, Ter Hofstede and Mahajan (2017), used dependent variables that reflected app sales performance, and used similar methodologies (analysing Google Play Store secondary data). Therefore, it is difficult to ascertain which finding is more conclusive.

As for free alternatives to paid apps, the reviewed disadvantages of free versions do not apply to free app alternatives; this was shown by Hsu and Lin (2015) who found no evidence that free alternatives negatively affected consumer intention to buy paid apps. Refer to Table 2.5 for a summary of findings.

Table 2.5 Free app trial version cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Liu, Au and Choi, 2014	Offering a free app version is positively associated with higher sales of paid version	Supported
Liu, Au and Choi, 2014	For apps without a free version, rating is more important for lower-ranked apps than for higher-ranked apps.	Not Supported
Hsu and Lin, 2015	Free alternatives to paid app negatively affects consumer intention to buy paid apps.	Not Supported
Arora, Ter Hofstede and Mahajan, 2017	Free version presence associates with lower adoption speed of paid app.	Supported
Arora, Ter Hofstede and Mahajan, 2017	The negative association between free version presence and adoption speed of paid app becomes more negative with time.	Supported

Source: Arora, Ter Hofstede and Mahajan (2017, p.64); Hsu and Lin (2015, p. 54); Liu, Au and Choi (2014 p. 345)

2.3.2.4 Social Influence

Social influence is the change in people's thoughts, opinions or behaviours as a result of interacting with a person or group of influence that is perceived to be charismatic or experienced (French & Raven 1959; Graf-Vlachy Buhtz & König 2018; Kelman 1958). Villota and Yoo (2018) have demonstrated group influence in an experiment design to recreate an experiment by Solomon Asch in 1952 (Bond & Smith 1996) but in a designed media sphere; they recruited a group of 60 subjects to participate in a visual quiz posted on Facebook that displayed an image of three lines of different lengths. Subjects were required to state which line was the longest in the comment section. Fifty-five of the 62 participants were accomplices, instructed to write the wrong answer in the comments section. As a result, 71.34% of the 7 subjects (intended for experimentation) selected the wrong choice despite the right answer being obvious, and the subject who got it right reported confusion and anxiety as they selected the right answer.

Social influence was also found to be a contributing factor in technology adoption and is incorporated into adoption theoretical models like the theory of planned behaviour (Ajzen 1991; Graf-Vlachy Buhtz & König 2018). In the mobile app marketplace, social influence is another contributing factor because it is the consumers' belief that other people's preference is important in purchase decision making (Ajzen 1985). Jiang and Sarkar (2009) argued that word of mouth, peer pressure, and social surroundings increased the likelihood of customers adopting a new product. A study by Lim et al. (2015) ranked survey responses and found that app recommendations by friends/family was the third most dominant reason why users downloaded mobile apps (refer to Figure 2.8).

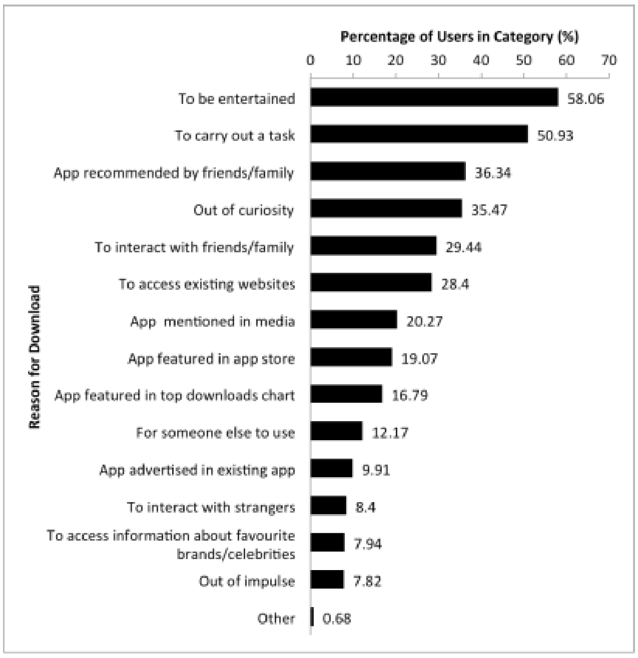


Figure 2.8 Reasons for downloading apps

Source: Lim et al. (2015, p. 49)

However, social influence is not always the antecedent of product adoption; it is sometimes the expected benefit of buying products. Hsu and Lin (2015) have demonstrated that users buy apps to make a positive impression on, or win approval of, other people. Kang's (2014) study supports Hsu and Lin's (2014) assertion; it found that social influence does have a positive effect on consumer adoption of mobile apps. Refer to Table 2.6 for a summary of findings.

Table 2.6 Social influence cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Hsu and Lin, 2015	Social value (receiving social approval from others due to using apps) positively affects consumer intention to buy paid apps.	Supported
Kang, 2014	Social influence will have a positive effect on intention to purchase tablet computer applications.	Supported

Sources: Hsu and Lin (2015, p. 54); Kang (2014, p. 34)

2.3.2.5 Networking with Strangers

Many successful social media platforms are built around networking with friends and family; however, networking with strangers also proved profitable for developers. In fact, most of the top grossing app designs are primarily based on users interacting with strangers. Games like Clash of Clans enables their users to play against each other online, and dating apps like Tinder allow strangers to meet and chat online; both examples reside in Google Play's highest grossing apps (Google Play 2018).

Despite the abundance of empirical evidence of successful apps built on connecting strangers online, academic studies' findings undermined the importance of this factor. In Georgieva et al.'s (2015) survey on online gaming, most respondents considered the option to interact with other users as not an important satisfaction factor for them. Furthermore, in Lim et al.'s (2015) survey, only 8.4% of respondents ticked stranger interaction as an option as a reason to download apps.

Interaction with strangers remains a key element of the value proposition of many highly profitable mobile apps dominating app stores. This conflict, between theoretical research and empirical evidence, presents an opportunity for researchers to address with more in-depth studies than the ones reviewed.

Today, it has become quite prominent for individuals to meet other people and interact with them online. Apart from Tinder, interactions also take place in ordinary apps—which are not solely for dating—such as Twitter and Facebook. Technological advancements have coerced human beings to remain fixated on the digital and internet lifestyle. In fact, statistics indicate that out of four adolescents, one of them makes and maintains friendships on social media networks.

Even if adolescents use these social media apps to network with individuals they already know, it is inevitable for them to have conversations with strangers. Statistically, it is expected that boys make more friends than girls. Another commonality noted is that adolescents from dysfunctional backgrounds—such as single parenthood—immerse themselves in these sites to network with strangers. Adolescents with married parents are not placed in this category of dysfunction; therefore, they are rarely seen networking and making online friends.

According to Lenhart and Madden (2007), "16% of teens are connected to 'friends' on social networking sites who they have not met in person". However, networking goes two-ways, where an individual only resorts to conversing with these strangers on their timelines or public profile and never in their direct messages. Making online friends only suffices when the energies between both parties are reciprocated to the point of them planning to network in real life, as well. The numbers of fake accounts that exist online have not stopped individuals from making friends or lovers from these social media platforms. Most adolescents, according to the study by Lenhart and Madden (2007), talk about the ease of making friends online, particularly if their school has a large population.

2.3.2.6 Store Ranking

Mobile app consumers use store search or general browsing to discover apps based on preferences they express in searches via keywords. App visibility on storefront or by search depends on its ranking. Therefore, the higher the app ranking, the more likely a user will see, and select it (Play Console Help 2018). Due to the importance of rankings, app marketers conduct continuous app store optimisation to boost or maintain their apps' ranking within app stores (Patel 2018). When apps have a high ranking, they acquire more exposure while attracting more traffic, which inevitably increases downloads. Saccomani (2017) extrapolates further on some of the features that are useful in ensuring that an app is ranked at the top. The factors include the app title, targeted keywords, number of downloads, and positive ratings. Furthermore, it is important for developers to maintain workable titles for their apps that are neither short nor limited (Saccomani 2017). The constant denominator is that developers should have app titles that are wholly related to their brand. If one is developing a taxi app, for instance, it would be inevitable for them to use transport related terms.

Furthermore, using targeted keywords means that the app will attract substantial traffic while maintaining low competition. The users often have search intent, therefore, with the correct keywords, they achieve their goals (Saccomani 2017). These keywords, in both the Google Play store and App store, are quite crucial in determining app , thus they should be chosen carefully. Also, the number of downloads is an inevitable indication that an app is functioning successfully due to its exposure to high traffic. If more users and consumers are interested in a developer's app, they attract others. The age of an app, in this case, does not matter because a recent app may garner more traffic than an older one. Download velocity is also an important feature when it comes to ranking apps in the stores. Finally, positive app ratings influence the extent to which consumers download the apps. The users are driven by reviews and feedback; therefore, when it is positive, the app gains more traffic.

Kim, Lee and Son (2011) assert that consumer interviews placed store ranking in the top five app purchase drivers. On the other hand, Liu, Au and Choi (2014) found that despite free app version ranking being important for hedonic apps, it did not lead to higher sales. They concluded that consumers did not necessarily think that free version app ranking indicated paid version quality or sale attraction. Refer to Table 2.7 for the summary of findings.

Table 2.7 App ranking cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Liu, Au and Choi, 2014	Rank of the free trial version of the app is positively associated with higher sales.	Not Supported
Liu, Au and Choi, 2014	The importance of free app version rank increases for hedonic apps.	Supported

Source: Liu, Au and Choi (2014, p. 345)

2.3.2.7 Pleasure

Favourable emotions like pleasure or joy play a significant role in product purchase and consumption. As Levy (1959) stated, "people buy products not only for what they can do but also for what they mean".

Personalisation of these apps to meet the consumers' needs facilitates their extent of enjoyment, pleasure, and satisfaction. There is a correlation between consumers' ability to enjoy a product during the purchase as well as the stage of consumption. If individuals lean toward experiencing insightful talks and debates, for example, they will install similar applications to meet their emotions, wants, and desires. If a consumer feels any negative emotions on purchasing a product, they become less interested in paying as this increases their pain. No matter the extent of personalisation, if the commodity or app does not fulfil a consumer's needs, they will experience pain during the purchasing process.

App enjoyment serves as a motivational force for users to continue purchasing and downloading certain apps. Soodan (2016) extrapolates further on the idea of motivation by looking into emotions, and their roles in-app enjoyment (or lack thereof).

Soodan (2016) argued that the reasons people buy products or services are to either experience a desirable emotional state or achieve emotional goals. Consumers experience an initial sense of joy when they acquire a product and a subsequent sensation as they consume it. In the case of products that have little or no functional value, like concert or cinema tickets, emotions are the primary motivation for purchase, as customers buy them for the emotions the products will induce, not their utility.

Emotions associated with the product itself are not the only drivers of purchasing; studies have shown that a pleasant shopping environment also drives consumerism. Store and shops that provide joyful surroundings increase consumers' consumption as shoppers are more likely to spend more time in the stores and to revisit them again (Baker, Levy & Grewal 1992; Donovan et al. 1994).

Kim, Lee and Son (2011) found that word of mouth, pleasure, and ranking are the most dominant purchase drivers of entertainment apps. If one's friend recommends a certain app, this makes it easier for them to believe in the app's effectiveness; thereby, increasing downloads. It is much easier to trust a close party rather than a stranger because the former is much more likely to give truthful reviews. Even if an app had a certain shortcoming, friends or family can discuss this with a potential purchaser, who would then be able to make an informed decision. Despite pleasure coming second to word of mouth, users whom they interviewed expressed that the primary reason behind buying entertainment apps was fun, and if their friends or family recommend apps to use for fun, they would download them. Kang (2014) also indicated that people use mobile apps to alleviate boredom or occupy leisure time and found that perceived pleasure had a positive effect on customer intention to buy tablet computer applications. Arora, Ter Hofstede and Mahajan (2017) also found that the adoption speed of paid mobile games was higher than mobile applications. Refer to Table 2.8 for the summary of the findings.

Table 2.8 Pleasure on app spending cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Kang, 2014	Perceived pleasure will have a positive effect on the continued intention to use mobile apps.	Supported
Lu, Liu and Wei, 2016	Enjoyment has a positive effect on the continued intention to use mobile apps.	Supported

Source: Kang (2014, p. 34); Lu, Liu and Wei (2016, p.8)

2.3.2.8 Price

Price is one of the earliest identified factors of consumer spending, starting with early consumer behaviour models that base consumer purchase decision almost entirely on pricing, to more recent models in which pricing is one aspect of decision making (Kotler 1965). However, ultimately, pricing remains a huge factor of consumer decision making and overall profitability (Hinterhuber 2008; Kannan & Kopalle 2001). The effect of price is most impactful when it undergoes a sudden reduction; Alvarez and Vázquez Casielles (2005) found that immediate price reduction significantly influences brand choice. Liao, Shen and Chu (2009) found that price discount promotions trigger impulse shopping behaviour.

Consumers are often lured into purchasing items that have huge discounts. The mentality is that it saves them a lot of money to buy an item that is on offer compared to waiting to purchase it on a typical day. Some sellers even give discounts of over 50%, making it more tempting for the buyers to engage in impulse shopping. Even if it appears that the sellers are making a loss during these discounts and promotions, they can benefit due to the increased number of buyers for the commodities.

Price can also have a negative effect on product purchases if consumers perceive the product to be overpriced; this is determined by comparing product price to a reference price, of similar products in the market, that consumers learn by experience or word of mouth (Ariely 2013;

MintLife Blog 2018). In such a case, consumers may completely shy away from these products, making it difficult for the developers to acquire any form of revenue. When items are too overpriced, they demoralise consumers; therefore, no sales occur. The significant impact of price anchoring on consumerism has led many retailers to increase the discount frequency from seasonal sales to almost all-year round sales, and often employing fake discount tactics by inflating products' prices then selling them at discounts that reset their products' prices back to the intended price (Ngwe 2017). For example, with price anchoring, the secret is to show clients that instead of buying commodities for $150, they receive a discount, making the product retail at around $75.

On mobile app pricing, Kim, Lee and Son (2011) found monetary value was a purchase driver of mobile apps, especially entertainment and networking apps. Furthermore, Hsu and Lin (2015) found that value-for-money had a positive effect on consumer intention to purchase apps and argued that consumers pay for apps that offer them value-for-money. None of the consumers were interested in purchasing sub-standard products. Therefore, in cases where a developer wants to sell an app at a high price, they should ensure that the opportunities and experiences enjoyed from the app are equally worth it. Alternatively, even if consumers are uninterested in high prices, they are often willing to spend on goods (and services) that bring equally elevated rewards. The concept of price may be tied back to that of app enjoyment; whereby, consumers are unwilling to spend on a product that offers them more pain than pleasure. It is not a preferential matter since all consumers are only attracted to apps that give them fulfilment throughout. Pricing, therefore, should be handled accordingly to ensure that the developers do not chase away their customers. Refer to Table 2.9 for a summary of the findings.

Table 2.9 Effect of user rating on app spending literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Hsu and Lin, 2015	Value-for-money positively affects consumer intention to buy paid apps.	Supported

Source: Hsu and Lin (2015, p. 54)

2.3.2.9 App Usefulness

Utility (usefulness) is the product's ability to meet customer needs and expectations. Useful products drive positive consumer perception and commercial success (Cooper 1979; Szymanski, Kroff & Troy 2007; Voss, Spangenberg & Grohmann 2003). Perceived usefulness, as extrapolated by Cho (2015), explains that new technologies play a role in influencing an individual's performance. It is a more in-depth concept than the idea of purchases, as the study attempts to explain the usefulness of the Internet as a medium to improve performance and enhance the consumers' experience of shopping (Cho, 2015). With these apps, therefore, if individuals can achieve all their goals via online means, they do not necessarily need to visit the physical stores. The apps offer individuals the luxury of having a detailed description of the product information, provision of visual guides, as well as independent choices of products, which would affect the consumers in a positive manner. Usefulness of the app may also be inclined toward understanding its quality and its ability to offer services to the respective consumers. Since these consumers are reliant on online reviews, usefulness of an app is affiliated with the fact that an app garners positive reviews from other customers (Kim et al. 2016). Offering quality service to the consumer means, therefore, that they are satisfied and fulfilled by these mobile apps.

Moldovan, Goldenberg and Chattopadhyay (2011) studied the effects of product originality and usefulness on generating word of mouth. They measured the quantity and valence of word of mouth of 226 participants regarding 20 new functional products, finding that people primarily buy to use rather than enjoy (non-hedonic products). They also found that while originality generates more word of mouth, usefulness dictates the positiveness of the word of mouth content. With this platform, it is impossible to meet face-to-face; therefore, these word of mouth reviews are useful in drawing consumers closer to the products (Cho 2015). If the customers offered negative reviews and feedback, it would be obvious that the apps were not useful.

Li, Zhang and Wang (2015) studied the effects of product usefulness to consumers' intentions to adopt new products. They analysed data collected from 560 potential consumers and found that usefulness was positively associated with adoption intention of new products. Even if a product is new, the ability of consumers to maintain their want for these commodities is linked with the extent of satisfaction and fulfilment felt by them. For new products, however, usefulness will only be realised if there is maintenance of buyer-customer trust during the shopping experience. Consumer trust in online spaces, however, proves quite absent unless there is a continued relationship with the online stores (Cho 2015). There is no room for usefulness if the consumer cannot maintain any form of trust with the retailers.

Usefulness is a significant driver of mobile app purchase, especially in the case of non-hedonic apps that consumers buy for utility reasons rather than pleasure. Kim, Lee and Son (2011) found that usefulness was rated as either the most or second most dominant purchase driver of productive and information apps. However, this was not case with entertainment apps as usefulness was ranked sixth of the eight drivers. This, however, does not dismiss usefulness relevance in hedonic apps. Kim, Yoon and Han (2016) found that usefulness of entertainment and information category apps also had a positive effect on mobile app usage.

2.3.2.10 Native Currency

Some mobile game sellers develop their own native currency (like coins or jewels) that consumers buy with real money to later trade with desired products or services inside the game. The use of native currency is prevalent among the highest grossing apps in the market (Google Play 2018) and is attributed to increasing the revenue they generate because this feature allows app sellers to reward consumers with free native credit to keep them invested and to incentivise loyalty (Nazario 2014).

Another explanation for the success of native currency is that users perceive that they have only converted their money into a different currency, and thus did not actually make a purchase. This explanation is supported by Yamaguchi (2004) that argued that users technically still held the monetary value and can later purchase whatever goods within the app whenever they wish. But regardless, the users should still maintain at the back of their minds that native currency still means that they are spending their monies. It should be noted that irresponsible credit card use may cause bankruptcy. Therefore, consumers should recognise that native currency transactions increase their overall spending.

Finally, this study provides its own explanation that is extrapolated from Zellermayer's (1996) and Ariely's (2013) research. It suggests that the native currency adds an extra layer between app products and money, which reduces the coupling between goods and payment, which in turn causes consumers to feel less pain of paying. When they feel less pain during paying, they indulge more in a product compared to when the pain is elevated. Some shoppers often feel guilty after making certain purchases, especially when they spend more money than what they had in their budgets. Such feelings, therefore, lead to dissatisfaction, which may force these persons to avoid depending on the product in question. If it is a mobile app, for example, the users may either permanently boycott the platforms or shift to other apps. As a result, consumers spend more money via native currency than via real money.

2.3.2.11 Usability

Software usability refers to a collection of quality standards that control interface design, user satisfaction, learnability, response, and execution times. Users spend more time on useable applications, and the more time spent means greater monetisation opportunities for the applications (Abran et al. 2003).

Usability in mobile apps is more difficult to achieve than in desktop software due to the wide variety of mobile devices in the market. Developers should account for different hardware specs, screen densities, and screen resolutions so that their apps can serve as many customers as possible and compete in a saturated marketplace, where customers have many options to choose from in every category (Mobithinking 2011; Nayebi, Desharnais & Abran 2012). Moreover, Khalid et al. (2015) who studied 6,390 negative app customer reviews, found that functional problems and crashes are among the most frequent reasons behind negative reviews. In such a case, they should work toward ensuring that all the functional issues are handled so that customers easily utilise the applications. The goal is to ensure that users only leave positive reviews that in turn increase the extent of traffic to these mobile apps.

It is necessary for developers to maintain constant documentation of their source code, which will assist in capturing the specifications of their platforms. With this, it also becomes easier to separate the customers depending on their preferences. Since most of the developers are swamped with different projects/assignments, it may become difficult for them to handle all their customers' needs. In addition, developers should consider drafting different rules that expose them to consumer expectations under app building and creation. Developing apps that cannot be used by the consumers appears useless as there will be no returns or revenues. The developers are often urged to somewhat borrow from already existing apps to ensure they are at par with their competition.

When these developers receive the adequate and required material to create their applications, the process becomes much easier, smoother and faster. Offering the developers application programming interfaces (APIs), for instance, reduces their workload when it comes to creating these mobile applications. As a library of codes, these APIs are useful in facilitating the efficiency of programming, simplifying difficult tasks as well as reducing any prevalence of bugs. Cooperating with these third-party developers, therefore, makes room for the achievement of successful and effective business models. For them to create a suitable environment for their users, they should also be given similar treatment, as effective usability requires their full attention.

Kim, Lee and Son's (2011) study ranked ease of use among the dominant purchase drivers of apps across all categories. Kang (2014) found that effort, performance, and perceived expectancies had a positive effect on customer intention to buy tablet computer applications.

In contrast to Kang's (2014) finding, Hsu and Lin (2015) found no association between performance and consumer intention to buy paid apps; this could be due to users examining paid apps prior to purchasing them, causing them to consider other factors, like ratings or reviews, when buying apps. Refer to Table 2.10 for a summary of the findings.

Table 2.10 Effect of usability on app spending cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Kang, 2014	Performance expectancy has a positive effect on continued intention to use mobile apps.	Supported
Kang, 2014	Effort expectancy has a positive effect on continued intention to use mobile apps.	Supported
Kang, 2014	Perceived mobility has a positive effect on continued intention to use mobile apps.	Supported
Hsu and Lin, 2015	Performance positively affects consumer intention to buy paid apps.	Not Supported

Source: Hsu and Lin (2015, p. 54); Kang (2014, p. 34)

2.3.2.12 Developer Reputation

Reputation is quite an important factor in the success of an app seller. Customers often commit to buying based on the seller's reputation if the quality of a product or service cannot be verified prior to purchase. Reputable sellers recognise the advantage of their reputation and endeavour to maintain it in all transactions with their customers (Bar-Isaac & Tadelis 2008).

App sellers can build their reputation on app stores by constantly upgrading their products and responding to customer complaints and queries, which later reflects in their apps' ratings, reviews and ranking in the store. The importance of reputation to apps' success was asserted by Arora, Ter Hofstede and Mahajan (2017), who analysed 460,000 apps and found that developer reputation was positively associated with user adoption of paid apps. However, the older the app listing becomes, the less impact reputation has on app adoption speed because more information about the app, like ratings and reviews, become available to users to make their choice.

For developer reputation to influence the importance of apps, it is necessary for developers to maintain aspects of uniqueness in their technology. There are numerous similar apps today that exist in both Google Play Store and App Store. Inasmuch as there is a variety to choose from, there remain those quality apps that offer impeccable services to the consumers. For example, assuming two consumers download food application apps, the in-built features are not necessarily considered to be similar, apart from the fact that both technologies deliver food to their consumers. While one may require consumers to only pay via cash, another app may give leeway for cash, mobile and credit card payments, making it more convenient for the consumers. These small differences in the apps create differences as regards the customer ratings and reviews from consumers, for example, maybe a consumer may have been unable to make cash payments and the provision of other options made it easier for them to offer a 5-star rating to the specific service.

Creating such a rapport with the consumers will work in the developer's favour as the former will trust them more than before. Therefore, personalisation of one's apps influences the developer's reputation, as the customers have a different experience while using them. Once a developer creates rapport with their consumers, they end up having a ready market their newly developed applications; thus, they will not struggle to advertise and market their mobile apps.

Developers that do not have positive reviews cannot influence their consumers as they are not trusted enough to develop workable technologies. Hence, they should strive to build their ratings in either the Google Play Store or App Store, as this influences the consumers and informs them about the usefulness (or lack thereof) of these mobile apps. Refer to Table 2.11 for a summary of the findings.

Table 2.11 Effect of developer reputation on app spending cited literature findings

Source	Predictions of cited literature	Outcomes of cited literature
Arora, Ter Hofstede, and Mahajan, 2017	Developer reputation associated with higher adoption speed of the paid app.	Supported
Arora, Ter Hofstede, and Mahajan, 2017	The positive association between developer reputation and the adoption speed of paid app becomes more positive with time.	Not supported

Source: Arora, Ter Hofstede and Mahajan (2017, p. 64)

2.3.2.13 Other Tested Factors

Hsu and Lin (2015) also tested the impact of several more factors on user intention to buy paid apps but found no evidence of associativity among them. Refer to Table 2.12 for a summary of the findings.

Table 2.12 Effect of satisfaction and habit on app spending cited literature findings

Predictions of cited literature	Outcomes of cited literature
Satisfaction (resulting from global performance evaluation based on experience using mobile apps) positively affect consumer intention to buy paid apps.	Not Supported
Feelings resulting from using apps positively affects consumer intention to buy paid apps.	Not Supported
Free alternatives to paid app negatively affect consumer intention to buy paid apps.	Not Supported
Habit (the extent to which consumers use mobile apps based on past learned behaviour) positively affects consumer intention to buy paid apps.	Not Supported

Source: Hsu and Lin (2015, p. 54)

2.4 Synthesis

The chapter reviewed previous scholarly research on factors that are associated with app consumer spending and mobile app sales. The review highlighted several conclusions with the most notable being the realization that there are many such factors which do influence consumers' spending behaviours. In addition, consumers do not solely base their spending on pre-set budgets or value-for-money of products.

Most reviewed studies used a quantitative approach, but their data collection methods fit into two distinct types. First, there are studies that surveyed consumers regarding their intention to buy, or continue to use, mobile apps (Hsu & Lin 2015; Kang 2014). Second, there are studies which harvested app store data that potentially factor into apps succeeding and overcoming competition in the marketplace (Arora, Ter Hofstede & Mahajan 2017; Liu, Au & Choi 2014).

Several studies have researched app ratings and social influence, and they agree regarding the importance of both factors to an apps' success in the marketplace (Hsu & Lin 2015; Kang 2014). However, reviewed studies yielded opposing findings regarding offering free trial versions as leading to an apps' success or not (Arora, Ter Hofstede & Mahajan 2017); therefore, the review remains inconclusive on the free trial factor.

Another interesting finding is the disparity between the literature and empirical evidence regarding the value of networking with strangers to an app's success in the market. However, this can be attributed to the fact that both studies that surveyed this factor used basic descriptive analysis (frequency analysis) to produce their findings (Georgieva et al. 2015; Lim et al. 2015). Hence, more in-depth analysis of this factor is needed to confidently address this disparity.

The present study will compare consumer spending behaviour of hedonic versus non-hedonic variables and will also test variables supported by empirical observation but that have not been thoroughly tested by previous studies.

Most of the reviewed studies had developed their own independent variables to represent consumer behaviour in the mobile app marketplace. This study adopted a variable from behavioural psychology and the psychology of money; this variable (the pain of paying) reflects consumer spending behaviour at a deep psychobiological level that can more accurately measure consumers' behaviour. Realising the importance of the pain of paying concept to behavioural economics research, Rick, Cryder and Loewenstien (2007) developed a way to measure it (Spendthrifts - Tightwads [ST-TW] Scale) to make it accessible for a wider range of research methods. The research model is presented and further discussed in Chapter 3, section 3.1.

CHAPTER 3 - RESEARCH METHODOLOGY

Based on the research objectives and questions listed in Chapter 1, sections 4 and 5, this chapter discusses the hypotheses and the study's model. The later sections explain and justify the methodology used to quantify factors that influence consumer spending and test them for associativity with consumer spending.

3.1 App Seller Success Model

The thesis' proposed seller success model was developed based on investigating current research on factors of consumer behaviour and marketplace app success. The model in Figure 3.1 below shows the variables that are positively associated with app seller success in the marketplace.

This study introduces a new dependant variable, drawn from behavioural economics theory, coined as the pain of paying. Independent variables include pleasure and utility (Kim, Lee & Son 2011) as well as three new independent variables: peer recognition, peer competition, and virtual credit (refer to Figure 3.1).

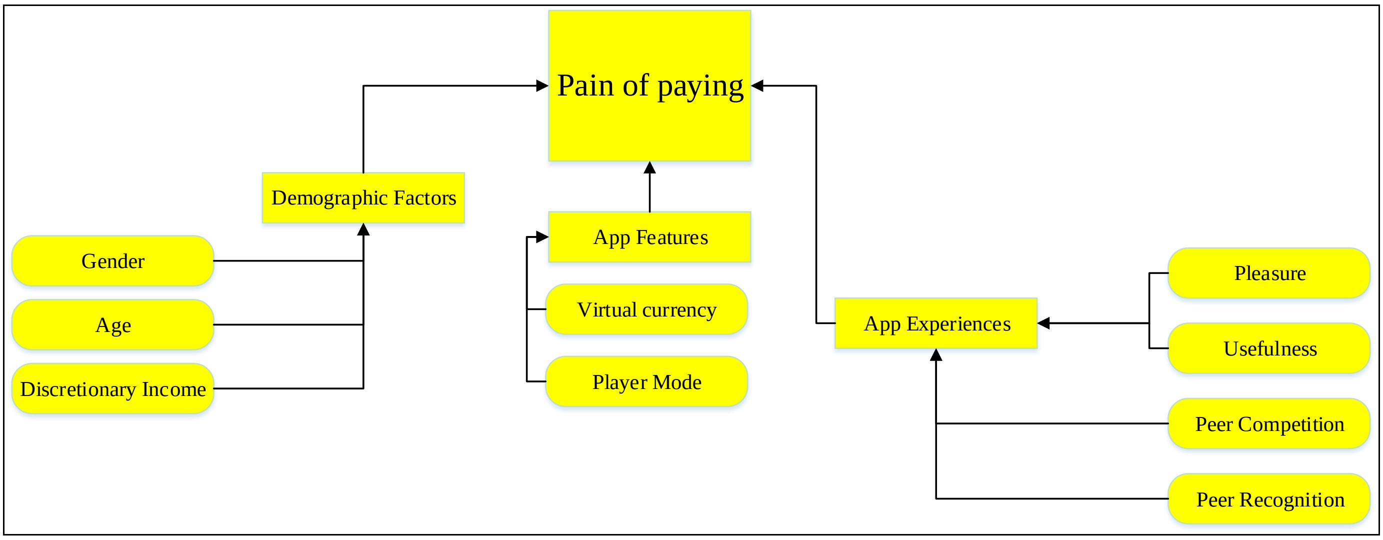


Figure 3.1 Proposed conceptual research model of factors that affect user spending behaviour in the Australian market

3.1.1 Independent Variables

Mobile app stores classify apps into two major groups, games and applications. Mobile games' core value preposition is pleasure (entertainment). Users play games to experience pleasant emotions. On the other hand, mobile applications' core value preposition is usefulness. Consumers use applications for reasons that include improving work productivity, monitoring health, and learning.

Both value prepositions have been identified by previous exploratory study as drivers of mobile app purchasing (Kim, Lee & Son 2011). Furthermore, pleasure was further tested and found to be positively associated with continued intention to use mobile apps (Hsu & Lin 2015). This study tests and compares both variables: app usefulness (also referred to as utility in this study) and app enjoyment (also referred to as pleasure in this study) for associativity with perceived pain of paying of users.

Social influence and social value variables were both tested and were found to be positively associated with intention to buy apps and continued intention to use apps, respectively (Hsu & Lin 2015; Kang 2014). Social influence represents the effect of family's and friends' recommendations on users' app purchase decision making, and social value represents the status gained from using apps in users' social circles. Since the literature results indicate that social factors outside user-app experience itself do affect app purchase decision making, this study tests other social factors that involve interacting with strangers. The social influence variable that will be tested in this study are competition with peers in mobile games, and recognition by peers in mobile games.

Many high grossing games are in fact network games that allow strangers to meet and play together in game environments. Despite empirical evidence of the attraction of network games for users, descriptive research found that interaction with strangers is not enough incentive for users to buy apps (Georgieva et al. 2015; Lim et al. 2015). This disparity warrants more investigation; therefore, this study proposes two variables, peer competition, which represents the value of enabling players to compete with one another, and peer recognition which represents the value of allowing players to buy non-functional purchases, like collectable items and character skins, that have no value other than making a player "look good" to other players in the game environment.

Finally, the association of demographic variables (gender, age and discretionary income) with spending behaviour will also be tested to determine how these factors correlate with consumer behaviour in the mobile app market.

Player mode and native currency are the remaining variables whose association with spending behaviour will be tested. Reviewed research argued for apps offering native currency (Yamaguchi 2004), but none tested the factor for association with any dependent variable relating to app sales or purchase incentives. This study recognises the importance of native currency based on empirical evidence of most high-grossing games offering native currency for their players to buy and shop with. Therefore, this study proposes and tests native currency variable's association with consumer perceived pain of paying.

3.1.2 Dependent Variable

The pain of paying (also defined in section 1.3) is the dependent variable measuring consumer spending behaviour in the model. It refers to the undesirable feelings people experience when they are about to make a purchase, or in other terms, let go of their money (Prelec & Loewenstein 1998). The pain of paying is measured using Rick, Cryder and Loewenstien's (2007) Spendthrifts - Tightwads (ST-TW) Scale that they developed specifically to measure individuals' perceived pain of paying, using the survey method.

Ideally, the pain of paying is measured using an MRI brain scan that records brain activity by detecting blood flow changes inside the brain (Rick, Cryder & Loewenstien 2007). When people experience the pain of paying sensation, a region of the brain, that is also associated with experiencing bad smells, is activated (Knutson et al. 2007); that activity is measurable using MRI scans. However, because of the cost associated with conducting scans to collect data, the ST-TW Scale was developed, and its validity tested to enable researchers to measure pain of paying using survey questionnaires instead of brain scans.

3.1.3 Main Research Hypotheses Illustration

Research hypotheses of the sub-main and additional research questions are illustrated in the study's proposed model shown below (refer to Figure 3.2).

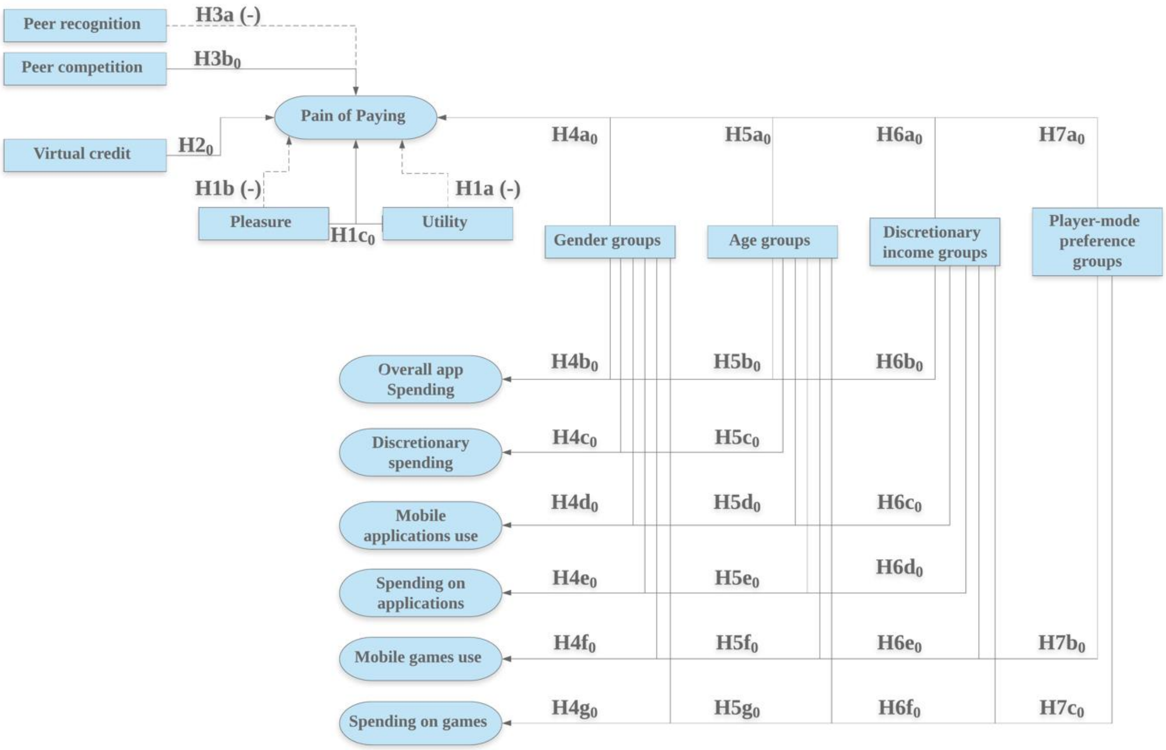


Figure 3.2 Research model shows the proposed associations between the independent variables and dependent variables

3.2 Research Hypotheses

There are two types of hypotheses proposed in this study, directional and null hypotheses. Directional hypotheses describe the relationship between two variables as positive or negative, greater than, or less than; thus, predicting the effect of the predictor variable on the criterion variable. For example, a company that needs to investigate the effects of work stress on employee productivity, would predict the relationship with the following hypothesis:

The greater the stress experienced at work, the lower the productivity of employees.

The hypothesis predicts a negative relationship between the variables, where stress and productivity are assumed to move in different directions.

The second type of hypotheses proposed in this study are the alternative and null hypotheses. The alternative hypothesis predicts a difference between the comparison value (proposed by the researcher) and true mean of the analysed sample, whereas the null hypothesis predicts no difference between them (McLeod 2018).

Researchers propose null hypotheses with the aim to disprove them, or in technical terms, reject them. Alternative hypotheses assume the opposite of null hypotheses and have three variations. If the researcher aims to measure any difference between the values, then a two-tailed hypothesis is proposed, if the direction of difference is also of interest, then either an upper or lower tail hypothesis is proposed (Sekaran 2003; Surbhi 2016). Refer to Table 3.1 for a summary of null/alternative hypotheses.

Table 3.1 Definition and representation of hypotheses

Formal Definition	Mathematical Representation
The null hypothesis (H0) assumes that the difference between the true mean (μ) and the comparison value (m0) is equal to zero.	H0: $\mu = m0$
The two-tailed alternative hypothesis (H1) assumes that the difference between the true mean (μ) and the comparison value (m0) is not equal to zero.	H1: $\mu \neq m0$
The upper-tailed alternative hypothesis (H1) assumes that the true mean (μ) of the sample is greater than the comparison value (m0).	H1: $\mu > m0$
The lower-tailed alternative hypothesis (H1) assumes that the true mean (μ) of the sample is less than the comparison value (m0).	H1: $\mu < m0$

Source: Statistics Solutions (2018c, p. 1)

In this study, the predictor variables are hypothesised to correlate with the criterion variable, the pain of paying. The predictors are pleasure, utility, virtual credit, peer recognition, and peer competition.

Because the reviewed literature argued that both app pleasure and usefulness are relevant factors of mobile app adoption, the study makes two proposals. First, the study proposes that the more gratification consumers experience playing games, the less cognitive resistance (pain of paying) they feel while spending money on them. Second, the study proposes that the more benefit consumers receive using mobile applications, the less pain of paying they feel while spending money on them.

H1a: *The more pleasure users experience while consuming a mobile app product, the less pain of paying they experience while deciding to purchase it.*

H1b: *The more utility users receive from a mobile app product, the less pain of paying they experience while deciding to purchase it.*

The third hypothesis compares the pain of paying means of pleasure and usefulness; the study proposes that consumers on average feel less pain of paying spending on games than applications. This assumption is supported by empirical evidence of app stores, in which nine of the 10 highest grossing apps are games.

H1c: *The mean of pain of paying for pleasure (gaming) apps (μP) is equal to mean pain of paying for utility apps (μU);* $\mu P = \mu U$

The fourth hypothesis compares the pain of paying means of using app-native credit and real money. The study proposes that consumers feel less pain buying via app-native credit than paying via real money. The null hypothesis assumes that the two means are equal. Therefore, if the hypothesis is rejected, the alternative hypothesis is concluded to be true, with 95% confidence. Failing to reject the hypothesis means that no evidence is found that native currency is associated with pain of paying.

H2: *The mean of pain of paying for virtual credit (μV) is equal to mean pain of paying for in-app items (μR);* $\mu V = \mu R$.

The last two hypotheses compare the pain of paying means of social value variables: peer recognition and peer competition. The study proposes that consumers feel less pain spending on in-app game purchases that either boost their status among other players or help them compete against other players. The null hypotheses assume that the paired means are equal. Therefore, if the hypotheses are rejected, the alternative hypotheses are concluded to be true at 95% confidence. Thus, failing to reject the hypothesis means that no evidence is found that social value is associated with pain of paying.

H3a: *The mean of pain of paying for appearance items that grants users social recognition from their peers within the app network (μI), is equal to the mean of pain of paying on items or features in single-player mode (μP); μI = μP.*

H3b: *The mean of pain of paying for purchases that grant users a competitive advantage against their peers (μC) is equal to the mean of pain of paying for purchases that grants users a competitive advantage against mobile app AI (μI); μC = μI.*

Additional hypotheses assume the differences in pain of paying and consumer behaviour on mobile apps among different sociodemographic and player-preference groups. The first set of additional hypotheses test differences between female and male gender groups:

H4a: *The mean of pain of paying of women is equal to the mean of pain of paying of men.*

H4b: *The mean of overall app spending of women is equal to the mean of overall app spending of men.*

H4c: *The mean of estimate percentage of income spent on discretionary goods of women is equal to the mean of estimate percentage of income spent on discretionary goods of men.*

H4d: *The mean of the number of mobile applications use a week of women is equal to the mean of the number of mobile applications use a week of men.*

H4e: *The mean of spending on mobile applications of women is equal to the mean of spending on mobile applications of men.*

H4f: *The mean of the number of mobile games play hours a day of women is equal to the mean of the number of mobile games play hours a day of men.*

H4g: *The mean of spending on mobile games of women is equal to the mean of spending on mobile games of men.*

The second set of hypotheses test sociodemographic and player-preference differences among respondents' age groups:

H5a: *The means of pain of paying of all age groups are equal.*

H5b: *The means of overall app spending of all age groups are equal.*

H5c: *The means of estimate percentage of income spent on discretionary goods of all age groups are equal.*

H5d: *The means of the number of mobile applications use a week of all age groups are equal.*

H5e: *The means of spending on mobile applications of all age groups are equal.*

H5f: *The means of the number of mobile games play hours a day of all age groups are equal.*

H5g: *The means of spending on mobile games of all age groups are equal.*

The third set of hypotheses test sociodemographic and player-preference differences among respondents' discretionary income groups:

H6a: *The means of pain of paying of all discretionary income groups are equal.*

H6b: *The means of overall app spending of all discretionary income groups are equal.*

H6c: *The means of the number of mobile applications use a week of all discretionary income groups are equal.*

H6d: *The means of spending on mobile applications of all discretionary income groups are equal.*

H6e: *The means of the number of mobile games play hours a day of all discretionary income groups are equal.*

H6f: *The means of spending on mobile games of all discretionary income groups are equal.*

The last set of hypotheses test sociodemographic differences among respondents' gaming player-mode preference:

H7a: *The means of pain of paying of all player-mode preference groups are equal.*

H7b: *The means of the number of mobile games play hours a day of all player-mode preference groups are equal.*

H7c: *The means of spending on mobile games of all player-mode preference groups are equal.*

3.3 Research Design

Research methods are generally classified into two distinct approaches: qualitative and quantitative methods. Qualitative methods were originally developed to investigate cultural phenomena in social sciences, whereas quantitative methods were developed to investigate natural phenomena in natural science, but later were adopted for social science research (Myers 1997). In the social sciences, researchers use a qualitative approach to explore and identify variables in new areas of research, while a quantitative approach is best used for previously explored research to measure dependences among explored variables (Sekaran 2003).

Researchers usually adopt one of the two approaches but can also mix them into a quantitative-qualitative hybrid approach if it satisfies their research objectives. This study is a correctional research that measures relationships between variables using statistical analyses and is purely quantitative (Sekaran 2003; Neuman 2014).

The survey questionnaire targets mobile app users to gather information about their spending behaviour in the mobile app marketplace. The spending drivers model is then tested using regression and paired t-test analyses to determine the effect of mobile app spending drivers on consumer perceived pain of paying. Because the survey sample size is representative of the target population, the results can be projected to the entire populace (Sekaran 2003).

3.4 Data Collection

Among the most common methods used in quantitative research are survey methods, formal methods, and lab experiments (Myers 1997). Survey methods refer to gathering data from respondents by inviting a representative group of them to respond to a questionnaire that contains a uniform set of closed or open-ended questions (Sekeran 2003). Using the same survey instrument to survey a group of different respondents allows for more accurate comparisons of responses because all respondents answered the same group of questions (Joppe 2005). Nevertheless, researchers should be careful with determining the nature and length of the questionnaire to minimise respondent bounce off rate (Burns et al. 2008; National Research Council 2013). Questionnaires that are invasive or too lengthy will cause respondents to abandon the survey before completing it, resulting in less complete (usable) responses for the researchers (Burns et al. 2008; National Research Council 2013).

There are two main types of survey questions: open-ended and closed questions. Open-ended questions allow respondents more freedom in writing their answers, while closed questions restrict them to a predefined set of answers. Closed questions are preferable because they are easier for respondents to answer and for researchers to prepare for analysis (Sekaran 2003).

The survey method offers many advantages for this kind of research: it is easy to administer, it predicts behaviour, and its responses are generalisable to the targeted population (Newsted, Munro & Schwarz 1998). This method, however, has weaknesses because surveys cannot provide in-depth understanding of phenomena or prove causality among surveyed constructs (Newsted, Munro & Schwarz 1998). Despite the above-mentioned weaknesses, the survey method remains an effective data collection method that offers higher validity and reliability than other techniques (Joppe 2005).

The low cost and advantages of survey methods for social scientific research make it the appropriate data collection method of choice for this research.

3.4.1 Sample Size

Researchers generally agree that the 200-respondent survey sample size is representative of a targeted population (Diamantopoulos & Siguaw 2000) as a reliable and representative sample of targeted community. Tabanchnick and Fidell (2003) also confirmed that the 200-sample size is acceptable for statistical research analysis.

3.4.2 Sample Criteria

The target sample of the questionnaire is Android mobile app consumers based in Australia, one of the world’s biggest English-speaking markets for mobile apps. The study used the SurveyMonkey tool to collect responses; the target population characteristics were as follows: based in Australia; adults, 18 years or older; and Android smartphone users. The respondents were informed of the purpose of the questionnaire upon invitation. Refer to Figure 3.3 for a summary of the target population criteria.

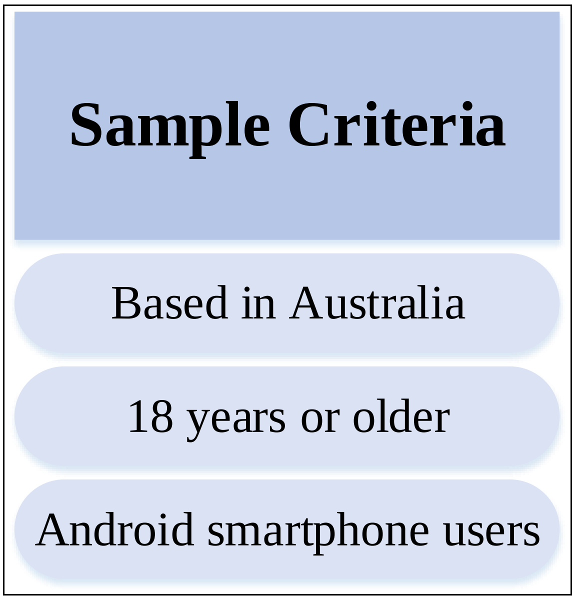


Figure 3.3 Research survey target

The population targeted in this study consists of adult mobile app users based in Australia. The rationale for restricting the sample population to a single country is to homogenise the socio-economic-cultural status of respondents as much as possible and eliminate unaccounted external variables that can influence responses (Amine & Tamer Cavusgil 1986). For example, in countries where online payment solutions are unavailable, consumers cannot purchase mobile apps regardless of budget or spending preferences. Therefore, if surveyed, their responses would be merely hypothetical and not based on real experiences.

In 2014, Google Play and Apple signed agreements with the US Federal Trade Commission that requires them to refund all store charges incurred by minors without their parents' consent. This decision come because of an investigation into the practices of Google Play and the App Store, that allowed minors to make in-app purchases using their parents' credit card details without authorisation. Both stores agreed to refund purchases conducted by minors but paid for by adults without authorisation (Neowin 2018). In addition, consumers that do not use their money to pay for products are technically consuming for free and not likely to feel pain of paying. Furthermore, minors cannot consent to purchases on app stores, and often do not use their own money; hence, this study excludes them from the age sociodemographic of the target population.

The smartphone and mobile app industries are dominated by two major rival technologies: Google's Android and Apple's iOS. Android and iOS consumers differ in their overall spending and brand devotion. Apple is culturally perceived as a creative powerhouse by consumers (Kunz, Schmitt & Meyer 2011), and this has triggered an immense sense of brand loyalty among Apple users to a scale that was described by Belk and Tumbat (2005) as cultish behaviour. Apple users are also bigger spenders than Android users.

The final criterion of sample selection dictates that the surveyed app consumers use Android-powered smartphones. Sydow (2018) compared Google Play and App Store downloads and earnings in the first quarter of this year; results showed that despite Google Play apps receiving 135% more downloads than App Store apps, global consumer spend in Google Play lags behind App Store consumer spending by 85% (refer to Figure 3.4).

Because of the cultural and spending differences between Android and iOS customers, this study targets Android consumers only so as to keep the sample population as homogenous as possible.

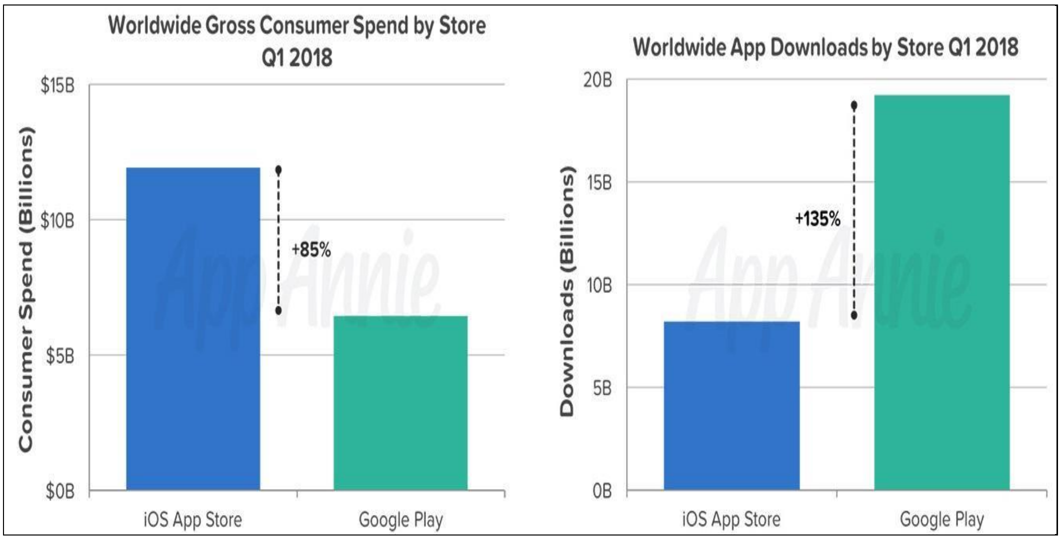


Figure 3.4 Total number of applications by store (Adapted from Sydow 2018, p. 1)

3.4.3 Respondent Profile

Survey respondent sociodemographic are not part of the core analyses of this study but are reported for additional statistical analysis purposes and to supplement knowledge about the relationships among sociodemographic groups and spending. Respondent information is reported in terms of gender, age, percentage of income spent on discretionary consumption, and average spending. This information was also used for descriptive analysis purposes (refer to Table 3.2 for profile of respondents who participated in this study's questionnaire).

Table 3.2 The research study questionnaire respondent profile

Sociodemographic	Frequency	Percent
Gender		
Female	102	50.5
Male	100	49.5
Age		
18 – 24	20	9.9
25 – 34	49	24.3
35 – 44	51	25.2
45 – 54	34	16.8
55 – 64	29	14.4
65 or older	19	9.4
Percentage of income spent on discretionary consumption		
5% or less	42	20.8
10%	46	22.8
20%	61	30.2
30%	37	18.3
40% or more	16	7.9

3.4.4 Survey Design

Studies that adopt survey methods must carefully design and execute surveys to obtain usable and reliable data (DeFranzo 2012). Good surveys should offer a professional, friendly, and accessible experience to participants by providing a welcoming message, using familiar formats, colours, white space, and most importantly, keeping questions simple and interesting (Garson 2007; Kitchenham & Pfleeger 2002).

According to Sekeran (2003), sound questionnaire design is based on three principles: wording of questions, categorising of variables, and the overall appearance of the questionnaire. Sekaran (2003) provides a comprehensive set of guidelines that were considered by this study during the survey design stage, and these are given below.

Guidelines for phrasing questionnaire items (Sekaran 2003):

1. Language sophistication and choice of words depends on respondents' educational background and expertise. Questions should be simple to read and understand by respondents.
2. Open-ended questions can cause survey fatigue or confusion to respondents. Thus, should be used only when applicable and necessary.
3. Questionnaires that contain both positively and negatively worded questions keep respondents alert and reduce their tendency to automatically select the end of the scale for every answer without carefully reading the questions.
4. Double-barrelled questions can lead to mixed responses and therefore should be broken into separate questions.
5. Ambiguous questions do not convey clear meaning to respondents. They confuse respondents and often lead to inaccurate responses.
6. Questions that require recalling experience create bias as respondents who had that experience more recently, or simply have better memory, are more likely to provide more accurate answers than other participants.
7. Leading questions are phrased in ways that lead respondents to favour certain answers from the options list and therefore, they should be avoided.
8. Loaded questions are worded in ways that trigger emotions of respondents, causing them to provide biased and polarised responses, they also should be avoided.
9. Questions should not be phrased in ways that pressure respondents into providing socially desirable responses. This can cause respondents to provide answers that contradict their beliefs in order not to disclose socially undesirable opinions.

Previous research has shown that survey length is negatively correlated with lower response rates, which means the more time a survey requires to be completed, the lower the response rate achieved (Steele, Schwending & Kilpatrick 1992; Yammarino, Skinner & Childers 1991). Garson (2007) stated that while there is no specific length advised for questionnaires, they should preferably be completed in 10 to 60 minutes. As for item length, Garson (2007) recommended that items should be from 12 to 22 words long. Other studies recommend that, as a rule of thumb, items should not exceed 20 words or a full-line length (Horst 1968; Oppenheim 1992; Sekaran 2003).

3.4.5 Cost

One of the main advantages of the survey method for research is its low cost compared to other data collection methods, especially online surveys that save print and postage costs (Roy & Berger 2005). But the low cost is not without drawbacks: surveys that do not incentivise potential respondents to participate may not collect enough usable responses for research. Besides lack of interest to participate, potential respondents often do not participate due to privacy concerns, timing of follow-up messages, and misidentification of survey invitations as spam (Sills & Song 2002).

This study opted for incentivised survey participation to collect enough usable responses in a timely manner. Consequently, the study used a SurveyMonkey paid service that collects the required number of responses from participants within set criteria in a short amount of time. Using this service, this study paid A$ 2,171.4 to SurveyMonkey for 200 responses that were collected within 15 minutes of submitting the order.

3.4.6 Measurement of Constructs

Scale development is an important aspect of survey design, as it aims to produce scales that effectively measure unobservable subjective constructs (latent variables) such as feelings and opinions (DeCoster 2000; DeVellis 2016). Scale type selection shapes the data collected in the survey, and this should be carefully considered to control method bias (Pearson Assessments 2006; Podsakoff et al. 2003).

McDaniel and Gates (2002,) state that one of the most important considerations of scale selection is its length (number of points on scale). Several studies investigated the effectiveness of multiple scale points in terms of validity and reliability and concluded that there is no ideal specific length that works for all survey measurements (Cox 1980; Preston & Colman 2000). Nevertheless, researchers offer two recommendations for scale selection:

1. Using the same scale to measure all predictor and criterion variables in a survey leads to method bias. To overcome this, surveys should employ a mix of different scale types to measure predictor and criterion variables and a mix of negative and positive wording of survey items (Podsakoff et al. 2003).
2. Many researchers support the use of (2-11)-point scales for survey measurement, specifically (5-7)-point scales that are the most commonly used in studies (Colman, Norris & Preston 1997; Malhotra et al. 2006; Preston & Colman 2000). However,

> Babakus and Mangold (1992) argued in favour of 5-point Likert-type scale because it boosts response rate quality, reduces survey fatigue, and does not confuse survey participants. In contrast, Cox (1980) concluded that scale-points should be not less than 5 points and not more than 9 points, with preference for 7-point scales.

Based on the above recommendations, this study employed a mix of 5-, 7-, and 11-point scales to measure constructs of consumer habits, preferences and spending behaviour. However, due to researchers' preference for 5- and 7-point scales, most questionnaire items used 5-point and 7-point scales for measurement.

3.4.6.1 11-point Scale

The questionnaire starts with a measurement of respondents' overall pain of paying using an 11-point scale developed specifically to measuring this construct. The Spendthrift-Tightwad (ST-TW) Scale was developed and tested for validity by Rick, Cryder and Loewenstein (2007) to enable the measurement of pain of paying using survey questionnaires. Ideally, the pain of paying is most accurately measured via brain scanning (functional magnetic resonance imaging, (fMRI)) because when consumers experience the pain of paying, a region associated with experiencing a range of bad odours and pain stimuli is activated in their brains (Knutson et al. 2007; Wicker et al. 2003) that fMRI can capture. However, due to the high cost associated with using fMRI method for measuring pain of paying, Rick, Cryder and Loewenstein (2007) developed the ST-TW Scale as an economic, yet effective, alternative.

To establish the validity of ST-TW measure, Rick, Cryder and Loewenstein (2007) administered the scale items to 13,327 respondents over a 31-month period, confirmatory analysis showed 0.99 goodness-of-fit, 0.97 normal fit, and 0.97 Bentler's comparative indices. The scale's reliability test scored a Standard Cronbach's alpha of 0.75 and inter-item correlation of 0.42.

Reviewed research concerning scales did not recommend scales above 7 points and argued that longer scales are more confusing to respondents. One 11-point scale was used because it was specifically developed to measure the independent variable of this study (refer to Figure 3.5). Nevertheless, due to research concerns with long scales, the study used it only in one item. The rest of items measuring pain of paying used a 5-point Likert scale and 7-point scale.

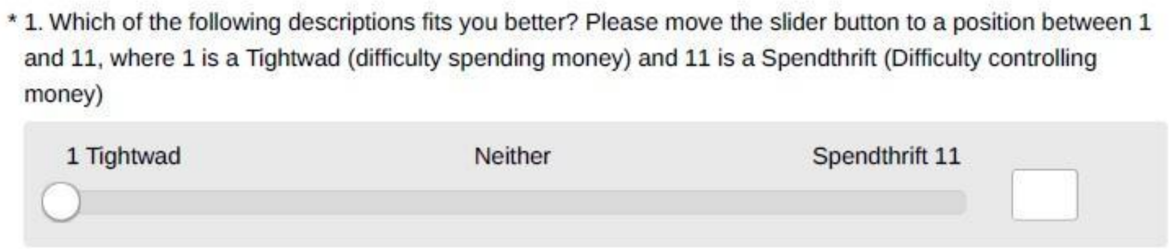


Figure 3.5 Questionnaire item 1, Spendthrift-Tightwad (ST-TW) Scale

Source: Rick, Cryder and Loewenstein (2007, p. 5)

3.4.6.2 7-point and 5-point Scales

Most psychometric studies that measure constructs such as attitudes, opinions, or feelings used 5- and 7-point rating and Likert scales (Colman, Norris & Preston 1997; Preston & Colman 2000). Therefore, this study used 7-point scales to measure predictor variables, while a 5-point scale was used to measure the criterion variable for all survey questions except the first item. For examples of 5- and 7-point scales being used in this study's questionnaire, refer to Figures 3.6 and 3.7 below.

Figure 3.6 Questionnaire item 8, measurement of number of days respondents use mobile applications per week

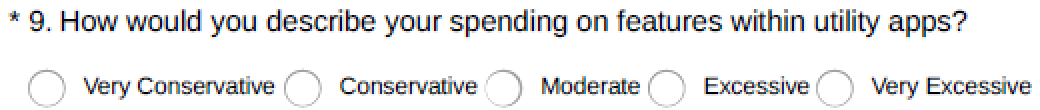


Figure 3.7 Questionnaire item 9, measurement of pain of paying associated with mobile applications

3.5 Goodness of Measures

To establish goodness of measures, two procedures are conducted:

1. Validity analysis to assess measures' ability of measuring constructs.

2. Reliability analysis to determine the ability of measures to produce consistent results.

3.5.1 Validity Analysis

Validity refers to the extent of a measure's accuracy in measuring the intended variable. In other words, validity refers to how well a survey instrument represents the variable it is supposed to measure (BC Campus 2018; Malhorta et al. 2006).

Both validity and reliability are assessed to establish the goodness of measures in this study. This study assesses validity before reliability, because measurements cannot be reliable if they are not valid (Ikmund & Babin 2007). Several types of validity tests are available to establish an instrument's goodness of measure, and these tests fall under three main groups (Sekaran 2003), which are discussed below.

3.5.1.1 Content/Face Validity

Content validity assesses the adequacy of a measure's items in measuring a latent concept (Sekaran 2003). This type of validity is established via focus groups, pilot surveys, or a panel of expert judges (Hair et al. 1998; Kitchenham & Pfleeger 2002; Sekaran 2003). While the assessment of content validity is subjective, it is nonetheless a systematic approach that evaluates the survey contents in terms of accuracy in representing variables and comprehensiveness in terms of representing all variables of the study (Kitchenham & Pfleeger 2002).

3.5.1.2 Criterion-Related Validity

Criterion-related validity refers to two validity types. The first type is concurrent validity, which compares a new test with previous pre-validated tests or compares tests running on two different groups at the same time. Common uses of concurrent validity are in two-part theory/practical tests in schools: if students who achieve high scores in practical tests also do so in theory tests, then concurrent validity of the tests is established (Malhorta 2006; Sekaran 2003; Statistics How To 2018).

The second type is predictive validity, which assesses how well a measure can predict future events. Common uses of predictive validity are student admission tests that predict their success at university: if students who pass enrolment tests also do well and graduate successfully from their university, then predictive validity of the tests is established (Malhorta 2006; Sekaran 2003; Statistics How To 2018).

3.5.1.3 Construct Validity

Construct validity compares the scores obtained by two different measures and assess how well the comparison fits the predictions proposed for the test. The nature of prediction determines which type of construct validity is used. The first type, convergent validity, is used when the scores of two measures are predicted to be correlated: if the scores have significant correlation, then construct validity is established. The second type, discriminant validity, is used when the scores of two measures are predicted to be uncorrelated: if they are found to be uncorrelated, then construct validity is established (Kitchenham & Pfleeger 2002; Malhorta 2006; Sekaran 2003).

3.5.2 Reliability Analysis

Reliability refers to the ability of a measure to produce accurate results consistently over time and over repeated use throughout the survey (Sekaran 2003; SPSS 1998). Along with validity, reliability is an important aspect of assessing the goodness of measures of latent variables (Laerd Statistics 2018b; Sekaran 2003; SPSS 1998).

Measurement scale reliability is determined by the consistency and stability in which the scale measures a latent variable (Sekaran 2003). Scale reliability can be measured using stability and consistency tests.

3.5.2.1 Test-Retest Reliability

Test-Retest is a stability test that produces a reliability coefficient obtained by surveying the same group of respondents twice in two consecutive questionnaires, and then measure the correlation between scores, obtained by the tested measure, from the two questionnaires. The measured correlation is the test-retest coefficient; the higher the coefficient, the more reliable the measure is (Malhorta et al. 2006; Sekaran 2003). This test is not possible to administer in studies where the respondents are invited to participate anonymously.

3.5.2.2 Parallel-Form Reliability

Parallel form is an alternate stability test that measures correlation between the scores of two questionnaire sets that use the same measure but differ in the wording and ordering of question items. A strong correlation between the two sets of scores indicates that the measure has minimal error variance resulting from phrasing or ordering and is therefore reliable (Sekaran 2003). Parallel-form is a suitable alternative to test-retest because it is often difficult or impractical to recall the same respondents for a second survey weeks or even months after the first survey (Kitchenham & Pfleeger 2002; SPSS 1998).

3.5.2.3 Split-Half Reliability

Split-half test divides a questionnaire into two halves and measures the correlation between the scores of each half. The resulting correlation is the reliability measure of the scale used in the divided questionnaire (Zikmund & Babin 2007). Sekaran (2003, p. 205) stated that "Split-half reliabilities could be higher than Cronbach's alpha only in the circumstance of there being more than one underlying respond dimension tapped by the measure and when certain other conditions are met as well". Therefore, Cronbach's alpha inter-item consistency reliability method, used in this study, remains the most suitable and the most common assessment of survey instrument reliability in research (Malhorta et al. 2006; Sekaran 2003; Zikmund & Babin 2007).

3.5.2.4 Inter-Item Consistency Reliability

Also known as internal consistency test, this measures the inter-correlations among all questionnaire items that use the same measure (Malhorta et al. 2006; Sekaran 2003). The most used test of inter-item consistency is the Cronbach's coefficient alpha used for scale-type measures (Cronbach 1946). This study assesses survey measure reliability using Cronbach's alpha internal consistency analysis because the survey was conducted only once, and all participants received one standard form of the questionnaire.

Cronbach's alpha coefficient ranges from 0.00 to 1.00, and the stronger the inter-item correlations the closer the coefficient is to 1.00 (Malhorta et al. 2006; University of Virginia 2018). A high coefficient indicates strong correlation among measurement items within the questionnaire and recommends keeping them. On the other hand, a low coefficient indicates weak correlation among the questionnaire's measurement items and recommends removing them from the questionnaire.

According to several researchers, acceptable Cronbach's alpha coefficient values should not be less than 0.60 (e.g., Malhorta et al. 2006), but other researchers disagree and recommend that 0.70 should be the minimum acceptable coefficient value (Gliem & Gliem 2003; Sekaran 2003; SPSS 1988).

Zikmund and Babin (2007) evaluated the reliability of a range of Cronbach's alpha coefficient values. They also recommend that 0.60 values can be accepted but offer only fair reliability (refer to Table 3.3).

Table 3.3 Cronbach's alpha coefficient range reliability evaluations

Range	Evaluation
0.80 – 0.95	Excellent reliability
0.70 – 0.80	Good reliability
0.60 – 0.70	Fair reliability
Less than 0.60	Poor reliability

Source: Zikmund and Babin (2007, p. 322)

3.5.2.5 Thesis Validity and Reliability

For this study, questionnaire items' content validity was evaluated by the thesis supervisors as expert judges, who evaluated questionnaire items in terms of representativeness and relevancy. The process went through multiple iterations where draft items were written by the researcher and presented to the supervisory panel for review and to provide feedback. The feedback received was used to refine questionnaire items and produce a further draft until the content validly of the questionnaire was satisfactory.

Cronbach's alpha coefficient analysis is used to test for inter-item consistency reliability of survey measures. The survey used the same 5-point scale to measure respondents' spending behaviour and only items scores 0.70 or over were accepted for this study.

The Cronbach's alpha scores shown in Table 3.5 reflect excellent reliability of measures. Therefore, none of the analysed items were removed from the survey (refer to Table 3.4 for item statistics).

Table 3.4 Research study questionnaire Item Statistics

Item Statistics			
	Mean	Std. Deviation	N
How would you describe your spending on apps you use for gaming or utility purposes?	.965	1.036	202
How would you describe your spending on features within utility apps?	1.014851485148515	1.021926557456272	202
How would you describe your spending on items or features within mobile app games?	.920792079207921	1.087126909410757	202
How would you describe your spending on items that would impress other players in a mobile app game network?	.816831683168317	1.062927892353339	202
How would you describe your spending on items or features that would help you beat other players in a mobile app game network?	.812	.997	202
While playing alone, how would you describe your spending on items or features that would help you beat an app game engine?	.807	.999	202
How would you describe your spending on games that offer credit units (like gold coins or jewels) that you later exchange for premium goods?	.916	1.057	202
How would you describe your spending on gaming apps that offer premium goods in exchange for real money only?	.777	1.017	202

Table 3.5 Cronbach's Alpha Reliability Score

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
.964	.964	8

3.6 Data Analysis

Data collected from the survey was analysed using SPSS to measure constructs and test hypotheses proposed in the spending drivers model reported in section 3.1 of this chapter. This section explains the analyses conducted in Chapter 4; the procedure consists of the following functions:

- Frequency analysis to provide descriptive data summaries.
- Paired-sample t test to test null hypotheses.
- Regression analysis to test directional hypotheses.

3.6.1 Frequency Analysis

Frequency analysis is an aspect of descriptive statistics that presents data in a tabular format that shows the number of occurrences (frequency) of data sets. This analysis shows the central tendency, percentile values, and dispersion of data. Central tendency represents the value on which the entire data set clusters around. The mean (average) is the common measure of central tendency when the data set is normally distributed; if the set is skewed, then the median (middle score of an ordered data set) becomes the more adequate central tendency measure. Mode is the third (most occurring score in a data set) and least effective central tendency measure (Laerd Statistics 2018a; Research Optimus 2018).

3.6.2 T-Tests

T-tests are hypothesis testing methods that determine if the difference between the means of two groups is statistically significant; this group of tests are also described as parametric tests because they are applicable to metric data (Malhorta et al. 2006; Social Research Methods 2018).

The type of t-test analysis selected depends on the number of samples and their interdependence. T-tests analysis procedures consider sample size and variability when comparing sample means together, or to a comparison value to produce the T value and its corresponding P value. The T value is the ratio of variance between groups to variance within groups, or in other words, the difference between two groups; whereas the P value represents the probability that there is a real difference between the groups (Minitab Blog Editor 2018b).

T values range between 0 to (+/-) 2; 0 indicates that there is no difference, while 2 indicates that the difference is double size of data variability. Acceptable P values are 0.05 and below, typically 0.05 and 0.01. $p = .5$ indicate that there is a 5% chance that there is no real difference between the sampled groups, and $p = .01$ indicates that there is 1% chance that there is no real difference between the sampled groups (Minitab Blog Editor 2018b).

3.6.2.1 One Sample t-test

One sample t-test makes inferences about the population-mean value of normally distributed data and compares them to the hypothesised value. For example, an electronics company needs to test if the new device they are producing weighs 100 grams, they collect a sample of already produced devices, weigh them and compare their mean value with the hypothesised mean (100 grams). The hypothesis made in this case is that the difference between the measured true mean and the comparison value (100 grams) is zero; if that is the case then the hypothesis is accepted, and the company has determined that the new device weighs 100 grams (Statistics Solutions 2018a). Equation 1 shows the formula used to perform one-sample t-test calculations.

Equation 1 One-sample t-test formula

$$t = \frac{(x_1 - x_2)}{\sqrt{\frac{(s_1)^2}{n_1} + \frac{(s_2)^2}{n_2}}}$$

There are different variations of the one-sample t-test determined by the proposed hypothesis. Using the same example, if the company suggests that the difference between the true mean and comparison value is not equal to zero, then a two-tail t-test analysis is conducted to test this hypothesis. However, if the company suggests that the true mean can only be greater or less than comparison value, then a one-tail t-test is conducted. In cases where it is unclear which t-test variation is appropriate, a two-tailed t-test should be used because it provides a more comprehensive comparison than the one-tailed test (Zikmund & Babin 2007, p. 536; Statistics Solutions 2018a).

3.6.2.2 Two Sample t-tests

Two sample t-tests compare the mean value of two samples gathered from two independent groups or from within the same group. An independent-sample t-test is used to compare the difference between means of two populations to determine whether the difference is statistically significant or not (refer to Figure 3.8).

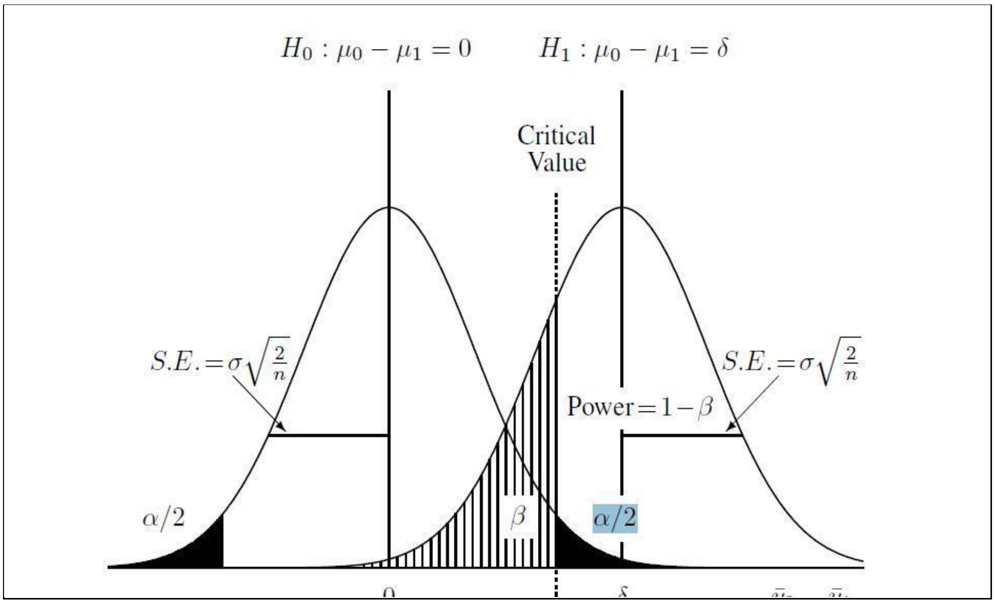


Figure 3.8 Two Sample T-Test

(Source: Stack Exchange 2018, p. 1)

A paired t-test compares difference between means of paired observations collected from the same group. A common use for this analysis is to compare before and after observations to determine if the mean difference between the sets is equal to zero. This analysis is suitable for repeated-measure studies that test null or alternative hypotheses.

This study uses paired t-tests to compare four paired sets of observations:

1. The mean of pain of paying for applications with the mean of pain of paying for games.
2. The mean of pain of paying with app virtual credit with the mean of pain of paying with real money.

3. The mean of pain of paying for items that award social recognition in multi-player games with the mean of pain of paying for items in single player games.
4. The mean of pain of paying for items that award a competitive advantage against other players with the mean of pain of paying for items that award a competitive advantage against mobile app artificial intelligence.

The analysis procedure is commonly done automatically using SPSS; however, it can be calculated manually according to the following steps (Statistics Solutions 2018c):

1. Calculate mean.

2. Calculate standard deviation.

3. Calculate test statistic.

4. Calculate probability of observing the test statistic under the null hypothesis.

5. Determine if the results constitute enough evidence for rejecting the null hypothesis or failing to reject it in favour of the alternative hypothesis.

Interpreting paired sample t-test results, from a statistical significance standpoint, depends on the P value which represents the probability of outcome proposed in the tested hypotheses. When testing a null hypothesis, a 0.05 (or less) indicates a low chance (5% or less) of obtaining a result that matches the observation expected if the null hypothesis was true. Therefore, a low P value indicates that the null hypothesis can be rejected (Statistics Solutions 2018c; Ugoni & Walker 1995).

3.6.3 One-way ANOVA

Survey respondents were classified into multiple disposable-income and age groups; the study analysed differences among the means of pain of paying and spending behaviours among different sociodemographic groups. To analyse statistical differences among two or more means, one-way ANOVA analysis can be used. However, one-way ANOVA is often used to compare three means or more. To ensure that the collected data can be analysed using this type of analysis, six assumptions must be met; otherwise, other variations of one-way ANOVA test are used (Laerd Statistics 2018b). The six assumptions are as follows:

1. The dependant variable must be measured at interval or ratio level.

2. The independent variables must consist of more than one independent group.
3. Observations must be independent of each other. This means that respondents can belong to one and only one of the groups with no overlap.
4. No data points whose values are far off the rest in a way that breaks the usual pattern.
5. The dependant variable must be normally distributed across every group of the independent variable.
6. The variances across different groups must be homogenous.

The first stage of one-way ANOVA analysis categorises participants into six age groups based on their answers to the age-group question and compared means of pain of paying, overall spending on apps, discretionary income percentage, number of application uses a week, spending on applications, number of games play hours a day, and spending on mobile games among the different age groups.

The second stage analysis categorises participants into five discretionary income groups based on their answers to the income-groups questions and compared means of pain of paying, overall spending on apps, number of application uses a week, spending on applications, number of games play hours a day, and spending on mobile games among the different discretionary income groups.

The last stage analysis categorises participants into three player-mode groups based on their answers to the preferred player-mode on mobile games and compared means of pain of paying, number of games play hours a day, and spending on mobile games among the different player mode groups.

3.6.4 Regression Analysis

Regression analysis measures the relationship between two or multiple variables. It is used to find significant relationships between criterion and predictor variables as well as the strength of influence of the criteria on the predictor. This analysis compares the effects of variables measured on continuous scales and is used by researchers to build predictive models (Analytics Vidhya 2015).

Linear regression is the modelling technique used in this study. It the most common form of regression analysis that measures relationships between one criterion (dependant) variable and one or more predictor (independent) variables using best fit line (Statistics Solutions 2018a). Equation 2 shows the regression analysis formula.

Equation 2 Linear Regression Equation

$$\overset{\text{Dependent Variable}}{Y_i} = \underbrace{\overset{\text{Population Y intercept}}{\beta_0} + \overset{\text{Population Slope Coefficient}}{\beta_1} \overset{\text{Independent Variable}}{X_i}}_{\text{Linear component}} + \underbrace{\overset{\text{Random Error term}}{\varepsilon_i}}_{\text{Random Error component}}$$

Source: Towards Data Science (2018, p. 1)

3.6.4.1 Five Key Assumptions of Regression (*Statistics Solutions 2018a)*

The five key assumptions of regression are as follows:

1. The relationship between predictor criterion must be linear; this can be checked using a scatter plot.

2. Variable data must be normally distributed; this can be checked with a goodness of fit test.

3. The analysis assumes no or little correlation among predictor variables (multicollinearity) and can be checked with a correlation matrix analysis.

4. There must be no or little inter-dependence among the residuals (autocorrelation).

5. The residuals must be equal across the regression line; in other words, the data must be homoscedastic.

Linear regression analysis is used in this study to measure the correlations of pleasure and utility variables that were measured on continuous scales, on the criterion variable (pain of paying).

3.7 Research Ethics

Research in Australia that involves humans is under the oversight of The National Health and Medical Research Council (NHMRC). This governing body determines the risk of ethical reviews based on three risk levels: harm, discomfort, and inconvenience. Human research ethics are based on values of respect, merit, integrity, justice, and beneficence; these values dictate that the relationship between researchers and human participants be that of trust, mutual responsibility, and ethical quality (NHMRC 2018).

Because this study requires human participation in an online survey, the researcher applied for CQU ethics clearance from the ethics committee prior to commencing data collection.

The researcher recognises the importance of conducting ethical research, and that research outcomes must be only achieved through ethical means, and in compliance with the ethics committee's instructions, this study has done the following:

1. Informed participants of the purpose of the study, and how to reach the researchers.

2. Informed participants of their option to withdraw from the survey at any stage for any reason including inconvenience.

3. Informed participants that if they elect to withdraw at any stage during the survey, their already collected data will not be analysed or used in any way in this study.

4. Informed participants that their personal information is not collected in any capacity by the questionnaire.

The study used SurveyMonkey tool that collected data anonymously from users. Furthermore, no questions in the survey asked the participants to disclose their personal information. All incomplete responses were omitted from the sample before analysis.

CHAPTER 4 - DATA ANALYSIS AND RESULTS

The data obtained from survey respondents were analysed using the SPSS tool. The results, and their implications on the thesis hypotheses are discussed briefly in this chapter. The survey collected 211 responses of which nine responses were not usable because the nine participants did not complete all survey questions.

4.1 Descriptive Statistics

Respondents' overall pain of paying was measured on the 11-points Spendthrift-Tightwad Scale, mean and standard deviation were calculated for the entire sample first, then for separate gender, age, and discretionary income groups. Refer to Tables 17.1-17.4 for details.

The ST-TW Scale measures consumers' spending behaviour, where 1 represents tightwads (resistance to spend money) and 11 represents spendthrifts (difficulty controlling spending). The result in Table 4.1 shows that the average spending of the surveyed sample is 6.14 which represents moderate spending.

Table 4.1 Sample pain of paying mean and standard deviation

Pain of paying	Sample	Mean	Std. Deviation
ST-TW Scale 1-11	202	6.14	2.111

Table 4.2 shows the ST-TW Scale respondent measurements by gender: the spending behaviour means are 6.25 for women and 6.02 for men; these figures represent moderate spending behaviour.

Table 4.2 Pain of paying statistics by gender

Gender		Statistic	Std. Error
Female	Mean	6.25	.226
	Median	6.00	
	Variance	5.202	
	Std. Deviation	2.281	
Male	Mean	6.02	.193
	Median	6.00	
	Variance	3.717	
	Std. Deviation	1.928	

Table 4.3 shows the ST-TW Scale respondent measurements by age; the spending behaviour means are 6.35 for age group 18-24, 5.92 for age group 25-35, 6.14 for age group 35-44, 6 for age group 45-54, 6.39 for age group 55-64 and 6.37 for age group 64 or older. All measured means of the different age groups represent moderate spending.

Table 4.3 Pain of paying statistics by age

Age		Statistic	Std. Error
18 to 24	Mean	6.35	.310
	Median	6.00	
	Variance	1.924	
	Std. Deviation	1.387	
25 to 34	Mean	5.92	.376
	Median	6.00	
	Variance	6.910	
	Std. Deviation	2.629	
35 to 44	Mean	6.14	.302
	Median	6.00	
	Variance	4.641	
	Std. Deviation	2.154	
45 to 54	Mean	6.00	.340
	Median	6.00	
	Variance	3.939	
	Std. Deviation	1.985	
55 to 64	Mean	6.39	.376
	Median	6.00	
	Variance	3.951	
	Std. Deviation	1.988	
65 or older	Mean	6.37	.392
	Median	6.00	
	Variance	2.912	
	Std. Deviation	1.707	

Table 4.4 shows the ST-TW Scale respondent measurements by discretionary income groups; the spending behaviour means are 5.26 for discretionary income group of 5% or less, 6 for discretionary income group of 10%, 6.25 for discretionary income group of 20%, 6.73 for discretionary income group 30% and 7.13 for discretionary income group of 40% and more.

This shows that the consumers' spending behaviour means are higher for groups with higher discretionary income.

Table 4.4 Pain of paying statistics by discretionary income

Estimate percentage of income freely spent on discretionary goods		Statistic	Std. Error
5% or less	Mean	5.26	.311
	Median	6.00	
	Variance	4.052	
	Std. Deviation	2.013	
10%	Mean	6.00	.300
	Median	6.00	
	Variance	4.133	
	Std. Deviation	2.033	
20%	Mean	6.25	.274
	Median	6.00	
	Variance	4.589	
	Std. Deviation	2.142	
30%	Mean	6.73	.304
	Median	7.00	
	Variance	3.425	
	Std. Deviation	1.851	
40% or more	Mean	7.13	.631
	Median	6.00	
	Variance	5.981	
	Std. Deviation	2.446	

Respondents were asked to check all the types of mobile applications they use from a list of app categories. Results show that personalisation apps were the most used, while medical apps were the least used (refer to Figure 4.1 for details).

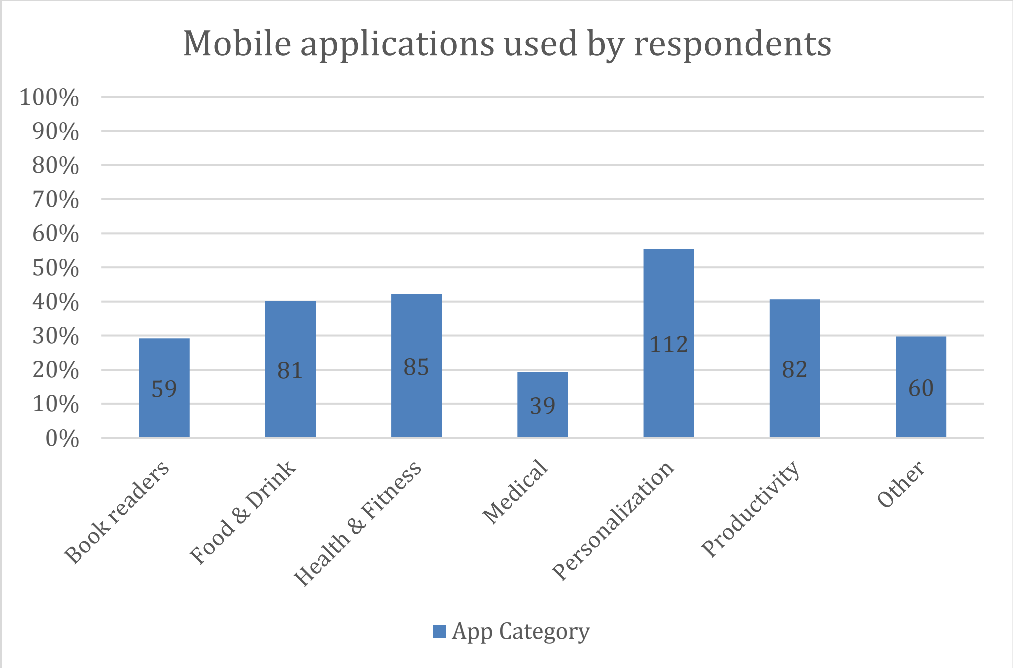


Figure 4.1 Number of mobile applications users by category

Respondents were also asked to check all the types of mobile games they play from a list of app categories. Results show that puzzles are the most played, while sports and racing games are the least played (refer to Figure 4.2 for details).

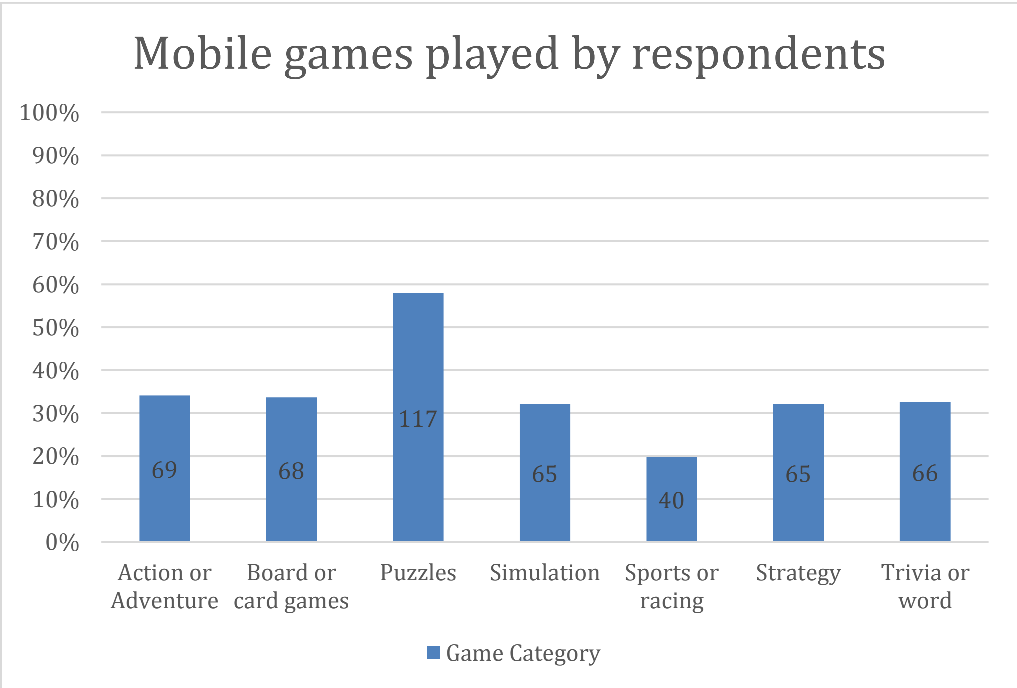


Figure 4.2 Number of mobile game users by category

While playing network games, respondents were asked about the kind of mobile games in-app purchases they make to improve their image or to compete with other players. Most players believe that premium and rare items are most impressive to others. However, 39 respondents reported in the “other” option box that they do not make purchases to impress other players in the network (refer to Figure 4.3 for more information). When competing with other players in mobile games networks, most respondents buy performance items or features to best compete with other players. However, 36 respondents reported in the “other” option box that they do not make purchases to compete with other players in the network (refer to Figure 4.4 for more information).

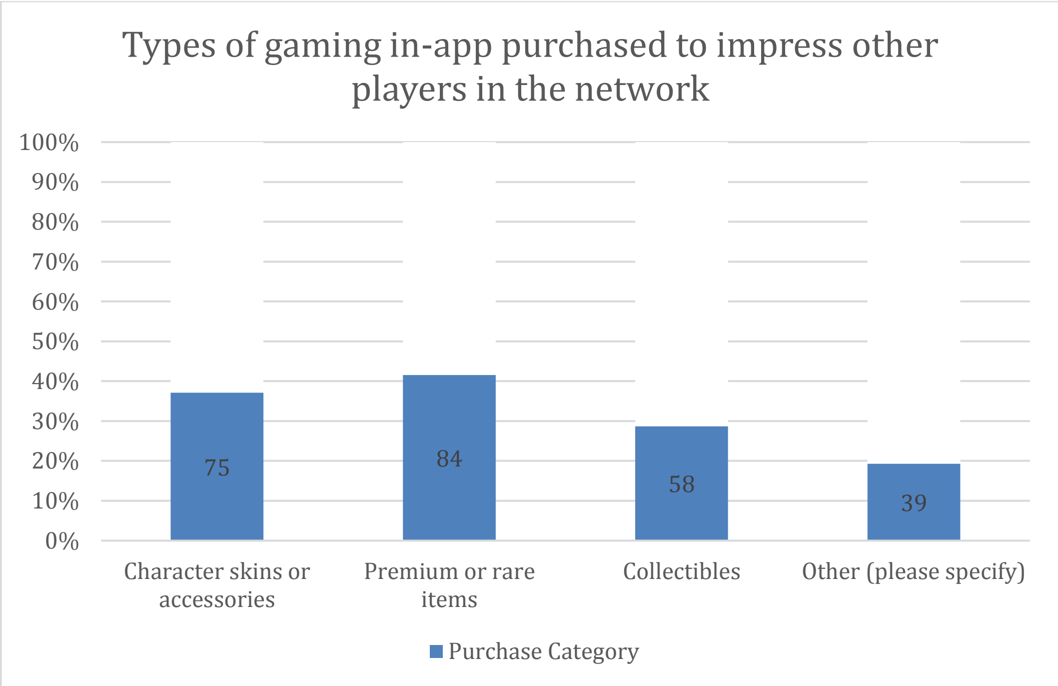


Figure 4.3 Number of players who make in-app purchases to impress other players in mobile game network

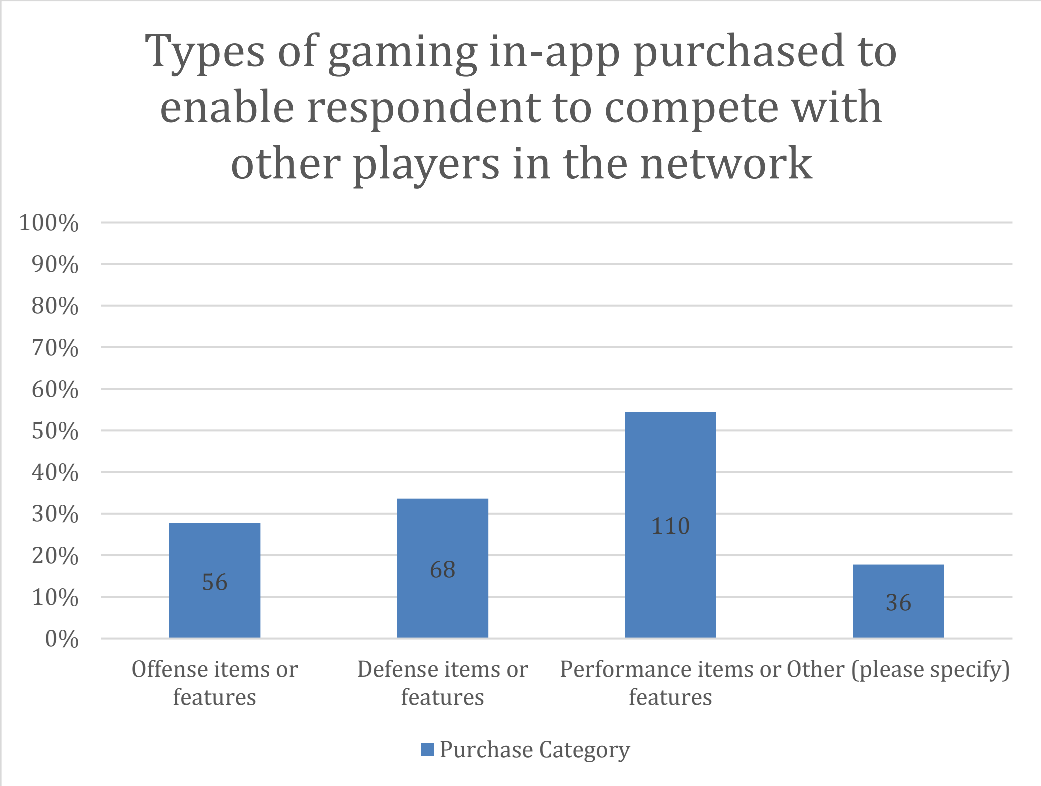


Figure 4.4 Number of players who make in-app purchases to compete with other players in mobile game network

Many mobile games have developed native currency that users can buy and later trade for in-app purchases; respondents were asked if they prefer trading for in-app purchases with real money or app-native money. Most respondents prefer native currency, with 64 respondents showing no preference (refer to Figure 4.5 for more information).

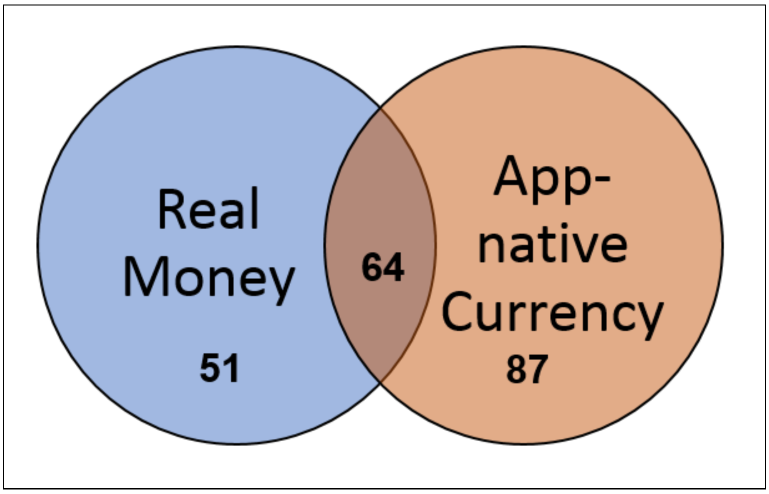


Figure 4.5 Number of respondents who prefer paying with real money versus paying with native currency

4.2 Spending Drivers Model

This section shows the correlation test results between 1) pleasure, 2) utility, 3) competition, 4) recognition, 5) native currency, and 6) pain of paying. Tests results determines which of the independent variables were associated with consumers' pain of paying (spending behaviour).

4.2.1 Pleasure

The primary reason of downloading mobile games is pleasure; consumers play games to experience pleasure and have a good time. While most mobile games can be obtained for free, users still need to pay if they wish to experience the full features of the game. This study proposed the following hypothesis:

H1a: *The more pleasure users experience while consuming a mobile app product, the less pain of paying they experience while deciding to purchase it.*

In Table 4.5, regression analysis was conducted to test the correlations between spending behaviour and the number of hours consumers spend playing mobile games a day. For additional insight, a second correlation was also tested between spending behaviour and the number of sessions consumers have playing mobile games a week.

Table 4.5 Correlation between hours of play and mobile game spending

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Spending behaviour and session per week	.407[a]	.165	.161	.938
Spending behaviour and hours per day	.653[a]	.427	.424	.827

($p < .0001$)

The association between the number of hours consumers play per day and their pain of paying felt when purchasing items or features within the game played has 0.653 correlation coefficient and 0.427 goodness of fit. This shows that the more pleasure players experience, the more their spending behaviour shifts to excessive (less pain of paying). Hence, **H1a** was accepted. The relationship between spending behaviour (Y) and number of play hours (X) is plotted in Figure 4.6.

Formula: Y = 0.4062*X + 0.9374

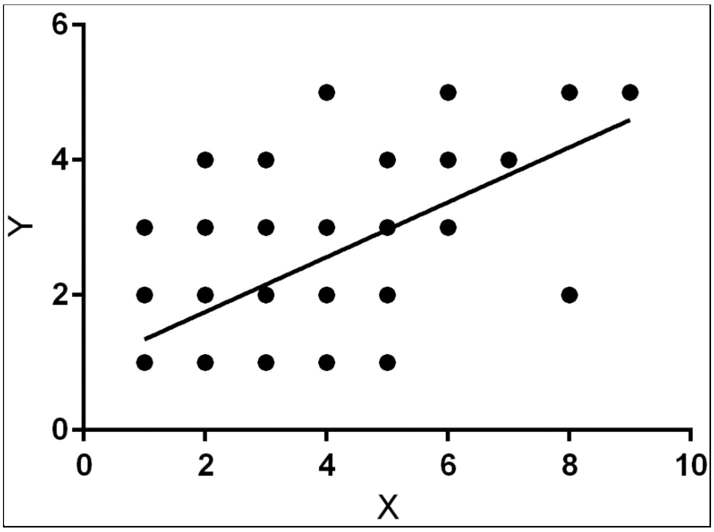


Figure 4.6 Spending behaviour vs play hours graph X: spending behaviour, Y: play hours

4.2.2 Utility

Consumers rely on mobile applications to manage their daily life. Like mobile games, most mobile applications can also be downloaded for free, but users still need to pay if they wish to experience more features. This study proposed the following hypothesis:

H1b: *The more utility users receive from a mobile app product, the less pain of paying they experience while deciding to purchase it.*

In Table 4.6, regression analysis was conducted to test the correlations between spending behaviour and the number of sessions consumers use utility apps per week. The analysis produced a 0.407 correlation coefficient and 0.165 goodness of fit. This shows that the variables have a moderate correlation, but low goodness of fit. Hence, **H1b** was rejected.

Table 4.6 Correlation between number of use sessions and mobile application spending

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.407[a]	.165	.161	.938

($p < .0001$)

4.2.3 Pleasure vs Utility

Paired t-test analysis was conducted to determine if a difference existed in spending behaviour between mobile games and mobile applications (refer to Table 4.7). This study proposed the following hypothesis:

H1c: *Mean of pain of paying for pleasure (gaming) apps (μP) is equal to mean pain of paying for utility:*

y apps (μU); μP = μU.

Table 4.7 Paired-Sample T-test mobile games and mobile applications

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Spending on items/features in utility apps versus spending on items/features on gaming apps	.094	.636	.045	.006	.182	2.103	201	.037

Paired t-test produced a P value of 0.037, which is considered statistically significant. This shows that consumers experience different pain of paying levels while consuming mobile applications and mobile games. Hence, the null hypothesis **H1c** was rejected, and the alternative hypothesis **H1c** was accepted to be true with 95% confidence.

H1c: *Mean of pain of paying for pleasure (gaming) apps (μP) is greater than the mean pain of paying for utility apps (μU); μP > μU.*

Empirical evidence clearly shows that mobile games generate more revenue than mobile applications (Google Play, 2018). Therefore, it was reasonable to assume that users experience more pain of paying consuming mobile applications than mobile games. But, counter to popular belief, analysis has shown that users feel less pain of paying consuming applications.

4.2.4 Native Currency

Most high grossing gaming apps have in-app stores that sell premium virtual items or features that players can buy and use inside the games. In most games, in-app store listings cannot be bought with real money, users should first buy native currency inside the game, and then buy store listings with the acquired currency.

This study suggested that consumers experience less pain of paying while shopping via virtual money than shopping via real money, and proposed the following hypothesis:

***H2a$_0$:** Mean of pain of paying for virtual credit (µV) is equal to mean pain of paying for in-app items (µR); µV = µR.*

Paired t-test analysis was conducted to determine if a difference existed in behaviour between real money spending and native currency spending (refer to Table 4.8).

Table 4.8 Paired-Sample T-Test native currency and real money

Paired Samples Test									
		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	Spending via native currency versus spending via real money.	.139	.670	.047	.046	.232	2.942	201	.004

The paired t-test produced a P value of 0.004, which is considered very statistically significant. This shows that consumers experience different pain of paying levels while paying with app-native currency and real currency. Hence, the null hypothesis **H2$_0$** was rejected, and the alternative hypothesis **H2$_a$** was accepted to be true with 95% confidence.

***H2$_a$:** Mean of pain of paying with native currency (µV) is less than the mean of pain of paying for in-app items (µR); µV < µR.*

This shows that consumers spend more money on in-app purchases when they first exchange money for apps' native money then buy in-app listings with the native money. This explains the wide use of native currency by top grossing mobile app sellers in Google Play Store.

4.2.5 Recognition

Gamers that play together in mobile game environments can buy appearance-related items like skills and collectables. These items offer no functional value, and gamers only buy them to make their game avatars more aesthetically pleasing. This suggests that impressing other players with pleasant looking avatars drives players to spend money on the game. To test this argument, the study proposed the following hypothesis:

$H3a_0$: *Mean of pain of paying for appearance items that grants users social recognition from their peers within the app network (μI), is equal to the mean of pain of paying on items or features in single-player mode (μP); μI = μP.*

The paired t-test produced a P value of 0.809, which is considered not statistically significant. This shows that there is no difference in spending on items in multi-player and single player games. Hence, this study failed to reject ***$H3a_0$*** with 95% confidence.

Table 4.9 Paired-Sample T-Test recognition between game AI and real players

Paired Samples Test										
		Paired Differences					t	Df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	spending on items or features that grants user recognition in multi-player mode games vs spending on items or features in single-player mode games	.010	.582	.041	-.071	.091	.242	201	.809

4.2.6 Competition

Gamers that play together in mobile game environments can also buy performance-related items that improve their chances of beating their rivals inside the games they play. This suggests that competing with other players with in-game performance related items drives players to spend money on the game. To test this argument, the study proposed the following hypothesis:

H3b₀: *Mean of pain of paying for purchases that grant users a competitive advantage against their peers (μC) is equal to the mean of pain of paying for purchases that grants users a competitive advantage against mobile app AI (μI); μC = μI.*

Paired t-test analysis was conducted to determine if a difference existed in behaviour between spending to beat real players and spending to beat game artificial intelligence engine in mobile games (refer to Table 4.10).

Table 4.10 Paired-Sample T-Test competition between game AI and real players

Paired Samples Test									
		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	Df	Sig. (2-tailed)
Pair 1	spending on items or features that would help beat other players in a mobile app game network versus spending on items or features that would help beat a mobile game engine	.005	.494	.035	-.064	.073	.143	201	.887

The paired t-test produced a P value of 0.887, which is considered not statistically significant. This shows that there is no difference in spending on competition items in multi-player and single player games. Hence, this study failed to reject ***H3b₀*** with 95% confidence.

4.3 Sociodemographic Analysis

This section segments the sample collected by 1) gender, 2) age, 3) discretionary income, and 4) gaming-mode to analyse differences in spending behaviour among distinct sociodemographic groups using two-sample t-test and one-way ANOVA tests.

4.3.1 Gender

Survey respondents were divided almost equally around gender, 102 women and 100 men (refer to Table 4.11 for details).

Table 4.11 Frequency analysis of respondents' gender

Gender		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	102	50.5	50.5	50.5
	Male	100	49.5	49.5	100.0
	Total	202	100.0	100.0	

A two-sample t-test was conducted to determine if the differences, listed in Table 4.12, existed between women and men respondents.

Table 4.12 Paired t-test output summary

Differences between women and men	Result
Pain of paying	No statistical difference between women and men
Overall Spending on apps	No statistical difference between women and men
Estimate percentage of income freely spent on discretionary goods	No statistical difference between women and men
Mobile application uses per week	No statistical difference between women and men
Spending on mobile applications	No statistical difference between women and men

Mobile games play hours per day	Women spend more hours a day playing mobile games than men
Spending on mobile games	No statistical difference between women and men

Counter to popular belief, this study found that on average, women spend more hours playing app mobile games than men, while noting no difference in their spending. This shows that women consume more gaming time than men to spend the same money as men despite their economic means and pain of paying being statistically equal (refer to Table 4.13 for group statistics and Table 4.14 for analysis output).

Table 4.13 Respondents' gender group statistics

Group Statistics	What is your gender? [Female 1 Male 0]	N	Mean	Std. Deviation
Pain of Paying Rating 1 is a Tightwad (difficulty spending money) and 11 is a Spendthrift (Difficulty controlling money)	0 (Males)	100	6.02	1.928
	1 (Females)	102	6.25	2.281
Estimate percentage of income freely spent on discretionary goods 1-5	0 (Males)	100	1.72	1.181
	1 (Females)	102	1.68	1.252
Overall Spending on apps 1-5	0 (Males)	100	2.05	1.058
	1 (Females)	102	1.88	1.018
Mobile application uses per week 1 to 7	0 (Males)	100	3.84	2.112
	1 (Females)	102	4.05	2.173
Spending on mobile applications 1-5	0 (Males)	100	2.04	1.082
	1 (Females)	102	1.99	.970
Mobile games play hours per day 1-8	0 (Males)	100	2.17	1.498
	1 (Females)	102	2.67	1.946

Spending on mobile games 1-5	0 (Males)	100	1.92	1.098
	1 (Females)	102	1.92	1.087

Table 4.14 Respondents' gender paired t-test output

Independent Sample T-Test		Levene's Test for Equality of Variances		t-test for Equality of Means	
		F	Sig.	t	df
Pain of Paying Rating 1-11	Equal variances assumed	2.312	.130	-.790	200
	Equal variances not assumed			-.791	195.777
Estimate percentage of income freely spent on discretionary goods 1-5	Equal variances assumed	.695	.405	.254	200
	Equal variances not assumed			.254	199.709
Overall Spending on apps 1-5	Equal variances assumed	.053	.818	1.148	200
	Equal variances not assumed			1.148	199.318
Mobile application uses per week 1 to 7	Equal variances assumed	.201	.655	-.693	200
	Equal variances not assumed			-.693	199.985
Spending on mobile applications 1-5	Equal variances assumed	1.396	.239	.345	200
	Equal variances not assumed			.344	196.748
	Equal variances assumed	11.543	.001	-2.030	200

Mobile games play hours per day 1-8	Equal variances not assumed			-2.035	189.372
Spending on mobile games 1-5	Equal variances assumed	.039	.844	-.010	200
	Equal variances not assumed			-.010	199.822

4.3.2 Age

Respondents' age groups ranged from 18 to 65 years and older, and most of them belonged to age groups between 25 and 44 years old (refer to Table 4.15 for details).

Table 4.15 Respondents' age frequency analysis

Age	Frequency	Percent	Valid Percent	Cumulative Percent
18 to 24	20	9.9	9.9	9.9
25 to 34	49	24.3	24.3	34.2
35 to 44	51	25.2	25.2	59.4
45 to 54	34	16.8	16.8	76.2
55 to 64	29	14.4	14.4	90.6
65 or older	19	9.4	9.4	100.0
Total	202	100.0	100.0	

Because the samples of different age groups varied in size, a one-way ANOVA test was conducted (see Table 4.16) to determine if statistical differences in income and mobile app spending and usage behaviour existed among the different age groups. The results showed no statistical difference in overall spending on apps, overall perceived pain of paying (measured on the ST-TW Scale) and no difference in percentage of discretionary income earned. The test reported no statistical differences in using and spending on mobile applications; however, it did show statistical differences in the number of hours spent playing mobile games and monetary spending.

Table 4.16 Respondents' age one-way ANOVA test output

One-way ANOVA				Sum of Squares	df
Pain of Paying Rating 1-11	Between Groups	(Combined)		60.453	4
		Linear Term	Unweighted	47.606	1
			Weighted	58.266	1
			Deviation	2.187	3
	Within Groups			835.665	197
	Total			896.119	201
Overall Spending on apps 1-5	Between Groups	(Combined)		29.413	4
		Linear Term	Unweighted	2.734	1
			Weighted	9.791	1
			Deviation	19.622	3
	Within Groups			187.344	197
	Total			216.757	201
Mobile application uses per week 1 to 7	Between Groups	(Combined)		25.987	4
		Linear Term	Unweighted	24.905	1
			Weighted	23.048	1
			Deviation	2.939	3
	Within Groups			894.414	197
	Total			920.401	201
Spending on mobile applications 1-5	Between Groups	(Combined)		26.816	4
		Linear Term	Unweighted	7.127	1
			Weighted	15.093	1
			Deviation	11.722	3
	Within Groups			184.140	197
	Total			210.955	201

Mobile games play hours per day 1-8	Between Groups	(Combined)		49.694	4
		Linear Term	Unweighted	20.769	1
			Weighted	32.826	1
			Deviation	16.868	3
	Within Groups			567.538	197
	Total			617.233	201
Spending on mobile games 1-5	Between Groups	(Combined)		29.688	4
		Linear Term	Unweighted	3.815	1
			Weighted	13.032	1
			Deviation	16.657	3
	Within Groups			209.044	197
	Total			238.733	201

The analysis showed no statistical differences among age groups except for playing and spending on mobile app games. Results show that average hours spent playing games dropped with age, as well as spending (refer to Figures 4.7 and 4.8). Results show that age groups 18-24, 25-34, and 35-44 years old exhibited similar spending behaviour on mobile games, despite that 25-34, and 35-44 years old groups spending less daily average of hours on playing mobile games.

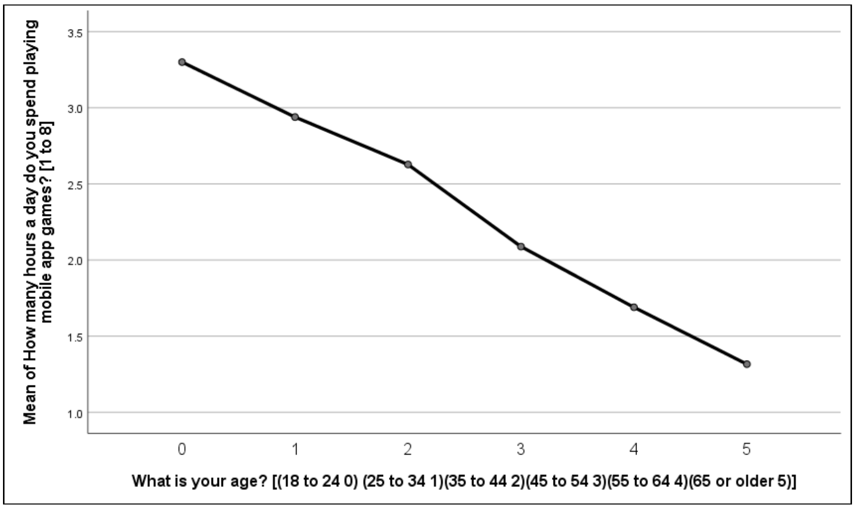


Figure 4.7 Age groups' average mobile games play time per day

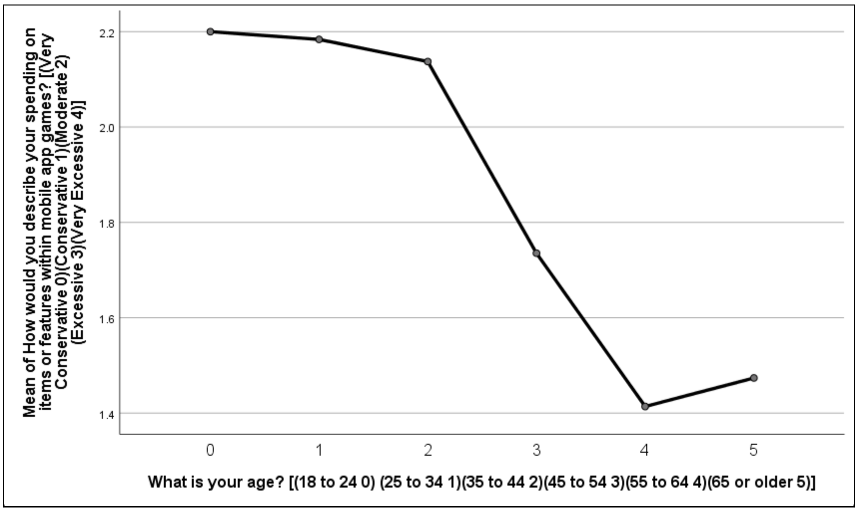


Figure 4.8 Age groups' spending on mobile games

The analysis test results shown in Table 4.16 are summarised below in Table 4.17.

Table 4.17 Respondents' age summary analysis results

Differences among age groups	Results
Pain of paying	No statistical difference among age groups
Overall Spending on apps	No statistical difference among age groups
Estimate percentage of income freely spent on discretionary goods	No statistical difference among age groups
Mobile application uses per week	No statistical difference among age groups
Spending on mobile applications	No statistical difference among age groups
Mobile games play hours per day	Younger age groups spend more hours playing than older age groups. **Average hours played drop with age, see Figure 4.7.**
Spending on mobile games	**Spending on mobile games also drops with age, see Figure 4.8.**

4.3.3 Discretionary Income

Respondents were asked to estimate the percentage of their income that they can freely spend on discretionary goods and services: 73.8% of respondents reported discretionary spending between 0% and 20% of earned income. Results are shown in Table 4.18.

Table 4.18 Respondents by estimate percentage of income freely spent on discretionary goods

Estimate percentage of income freely spent on discretionary goods	Frequency	Percent	Valid Percent	Cumulative Percent
5% or less	42	20.8	20.8	20.8
10%	46	22.8	22.8	43.6
20%	61	30.2	30.2	73.8
30%	37	18.3	18.3	92.1
40% or more	16	7.9	7.9	100.0
Total	202	100.0	100.0	

A one-way ANOVA test was conducted to determine if the differences in mobile app spending and usage existed among different discretionary income groups. The results are shown in Table 4.19 and explained in Table 4.20.

Table 4.19 Respondents' discretionary income one-way ANOVA test output

One-way ANOVA				Sum of Squares	df
Pain of Paying Rating 1-11	Between Groups	(Combined)		6.607	5
		Linear Term	Unweighted	.576	1
			Weighted	1.410	1
			Deviation	5.198	4
	Within Groups			889.511	196
	Total			896.119	201
Overall Spending on apps 1-5	Between Groups	(Combined)		14.349	5
		Linear Term	Unweighted	11.277	1
			Weighted	11.638	1

			Deviation	2.711	4
	Within Groups			202.409	196
	Total			216.757	201
Mobile application uses per week 1 to 7	Between Groups	(Combined)		67.690	5
		Linear Term	Unweighted	53.044	1
			Weighted	48.470	1
			Deviation	19.220	4
	Within Groups			852.711	196
	Total			920.401	201
Spending on mobile applications 1-5	Between Groups	(Combined)		12.010	5
		Linear Term	Unweighted	8.411	1
			Weighted	9.743	1
			Deviation	2.267	4
	Within Groups			198.946	196
	Total			210.955	201
Mobile games play hours per day 1-8	Between Groups	(Combined)		73.247	5
		Linear Term	Unweighted	64.930	1
			Weighted	72.694	1
			Deviation	.554	4
	Within Groups			543.985	196
	Total			617.233	201
Spending on mobile games 1-5	Between Groups	(Combined)		19.758	5
		Linear Term	Unweighted	12.942	1
			Weighted	16.815	1
			Deviation	2.942	4
	Within Groups			218.975	196
	Total			238.733	201

This table explains the results of the one-way ANOVA test conducted and shown in Table 4.19.

Table 4.20 Respondents' discretionary income summary analysis results

Difference among discretionary income groups	Results
Pain of paying	The data shows that as discretionary income grows, consumers become more spendthrift in life.
Overall spending on apps	Overall spending on apps grows with more discretionary income and peaks at 20% discretionary income group. But spending drops for the two highest discretionary income groups, see Figure 4.9.
Using utility apps per week	No statistical difference among discretionary income groups
Spending on mobile applications	Means plot shows similar pattern to overall app spending where spending peaks at the 20% discretionary income group, then drops for higher groups, see Figure 4.10.
Mobile games play hours per day	Means plot shows that the average hours spent playing games per day increase as discretionary income increases, peaking at groups with 20% discretionary income and above, see Figure 4.11.
Spending on mobile games	Plot also shows similar pattern to overall app spending where spending peaks at the group with 20% discretionary income then drops for higher groups, see Figure 4.12.

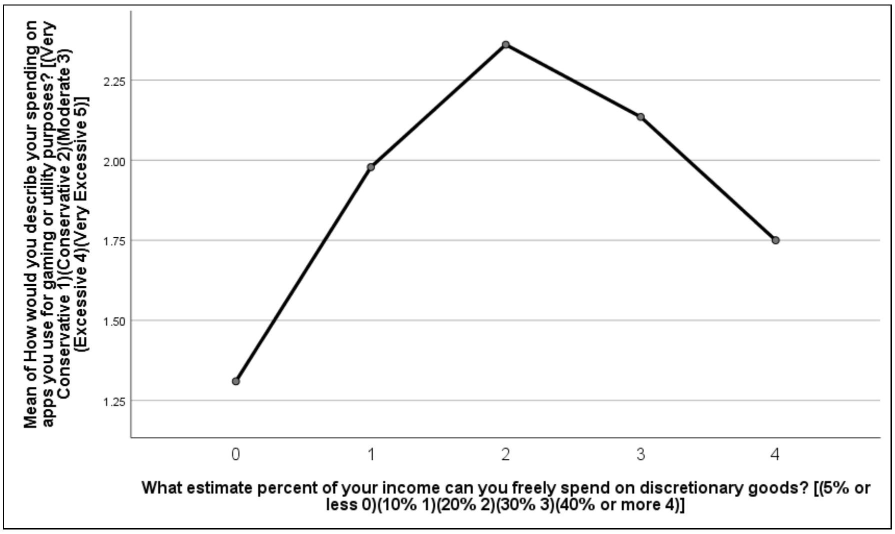


Figure 4.9 Discretionary income groups' spending on apps

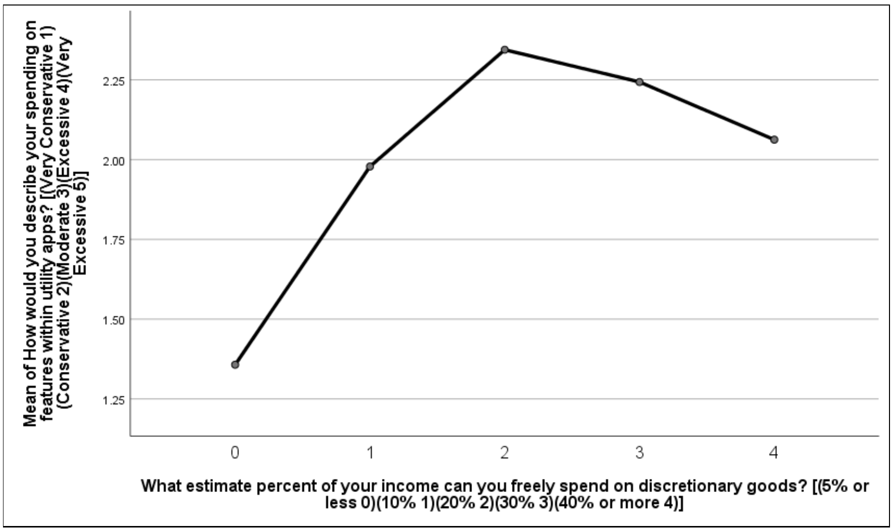


Figure 4.10 Discretionary income groups' spending on mobile applications

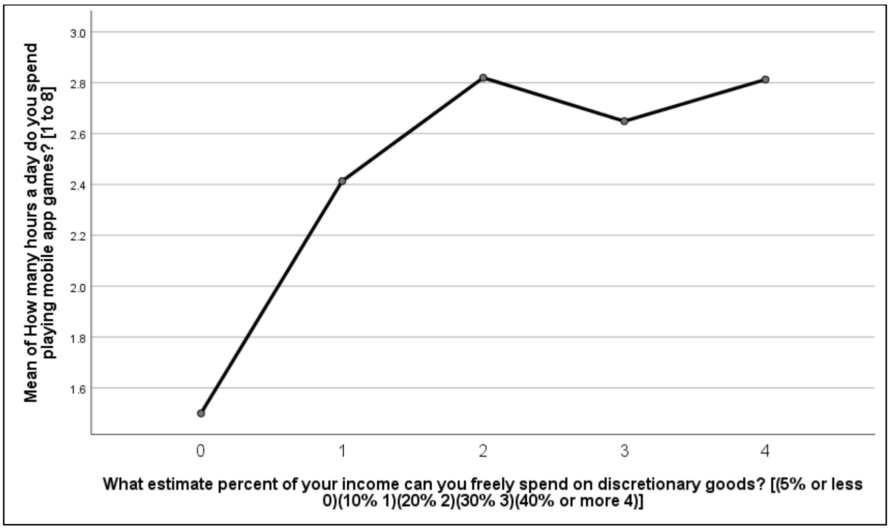


Figure 4.11 Discretionary income groups' average mobile games play time per day

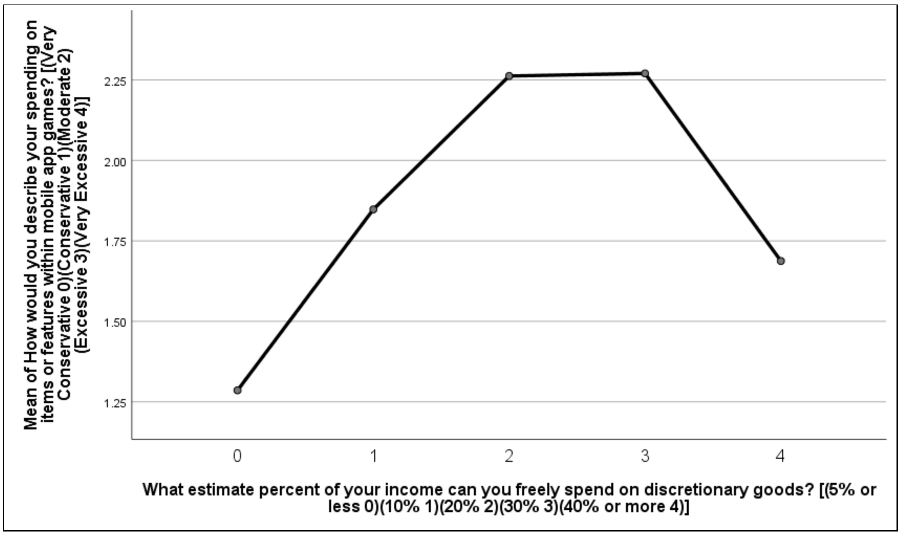


Figure 4.12 Discretionary income groups' spending on mobile games

4.3.4 Gaming Mode

Survey respondents were asked if they preferred to play multi-player mobile games, single-player mobile games, or both. Most of them preferred single-player games, with around 28% of them reporting no preference (refer to Figure 4.13 for details).

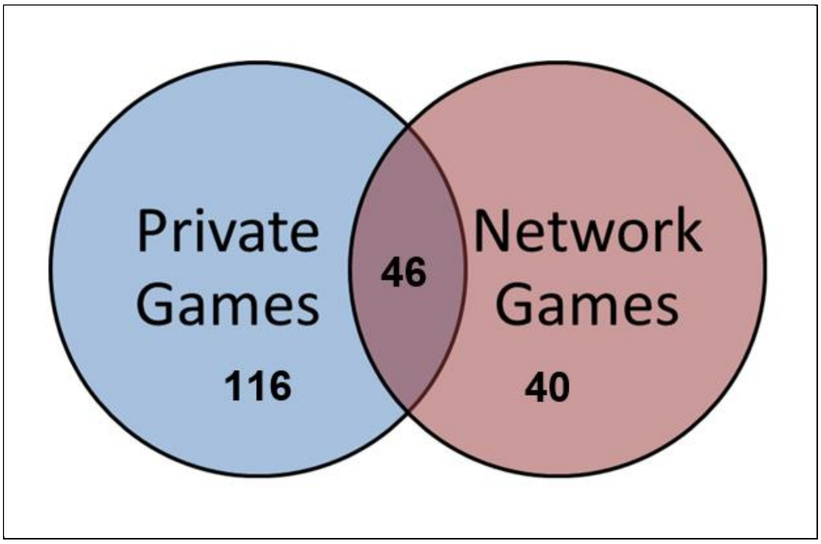


Figure 4.13 Number of private and network game players

A one-way ANOVA test was conducted to determine if the differences, listed in Table 4.21, existed among single-player mode gamers, multi-player mode gamers, and both modes gamers. The results are shown in Table 4.21 and explained in Table 4.22.

The analysis shows that statistical differences exist between single-player mode and multi-player mode groups in terms of amount of time spent playing and spending behaviour on games despite having no statistical difference in their overall pain of paying. This indicates that playing in a multi-level environment was associated with increased spending behaviour.

Table 4.21 Player-mode one-way ANOVA test output

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Overall Pain of Paying	Between Groups	7.469	2	3.735	.832	.437
	Within Groups	888.630	198	4.488		
	Total	896.100	200			
Mobile games play hours per day 1-8	Between Groups	140.129	2	70.064	29.490	.000
	Within Groups	470.418	198	2.376		
	Total	610.547	200			
Spending on mobile games 1-5	Between Groups	36.508	2	18.254	17.873	.000
	Within Groups	202.218	198	1.021		
	Total	238.726	200			

This table explains the one-way ANOVA analysis output of single and multi-player modes.

Table 4.22 Player-mode summary analysis results

Differences among players	Results
Pain of paying	No statistical difference among player-mode groups
Mobile games play hours per day	Means plot shows that multi-player mode gamers spend more hours a day playing than single-player mode gamers. Gamers who play both modes, spend more time playing than single-player mode gamers, see Figure 14.4
Spending on mobile games	Spending is also consistent with use, where multi-player mode gamers spend more money on mobile games than single-player mode gamers. Gamers who play both modes, spend more money than single-player mode gamers, see Figure 14.5

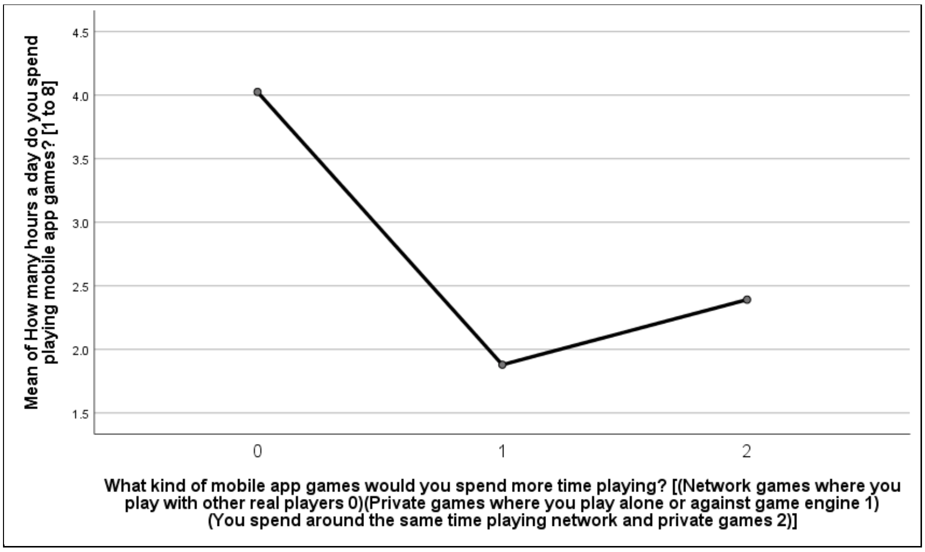


Figure 4.14 Player-modes' average mobile games play time per day

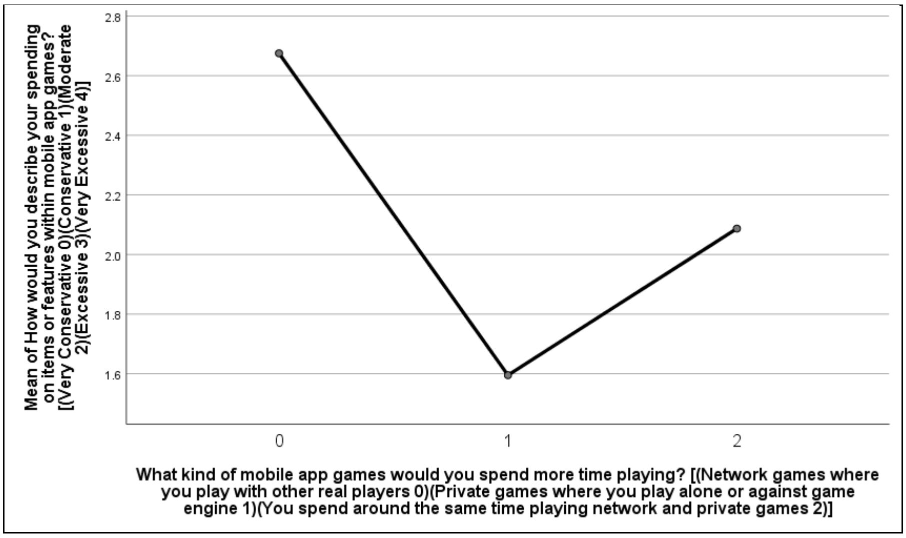


Figure 4.15 Player-modes' spending on mobile games

4.4 Research Results

Based on the analysis conducted, native currency and pleasure were accepted into the model, while competition and recognition were removed. The analysis showed that usefulness was a factor of pain of paying, when compared to pleasure; therefore, it was also retained in the final model, noting that on a continuous scale, utility has weak regression with pain of paying. This means that while basic application usefulness was associated with reduced consumers' pain of paying, more usefulness did not influence further reduction in pain of paying (refer to Figure 4.16 for model illustration).

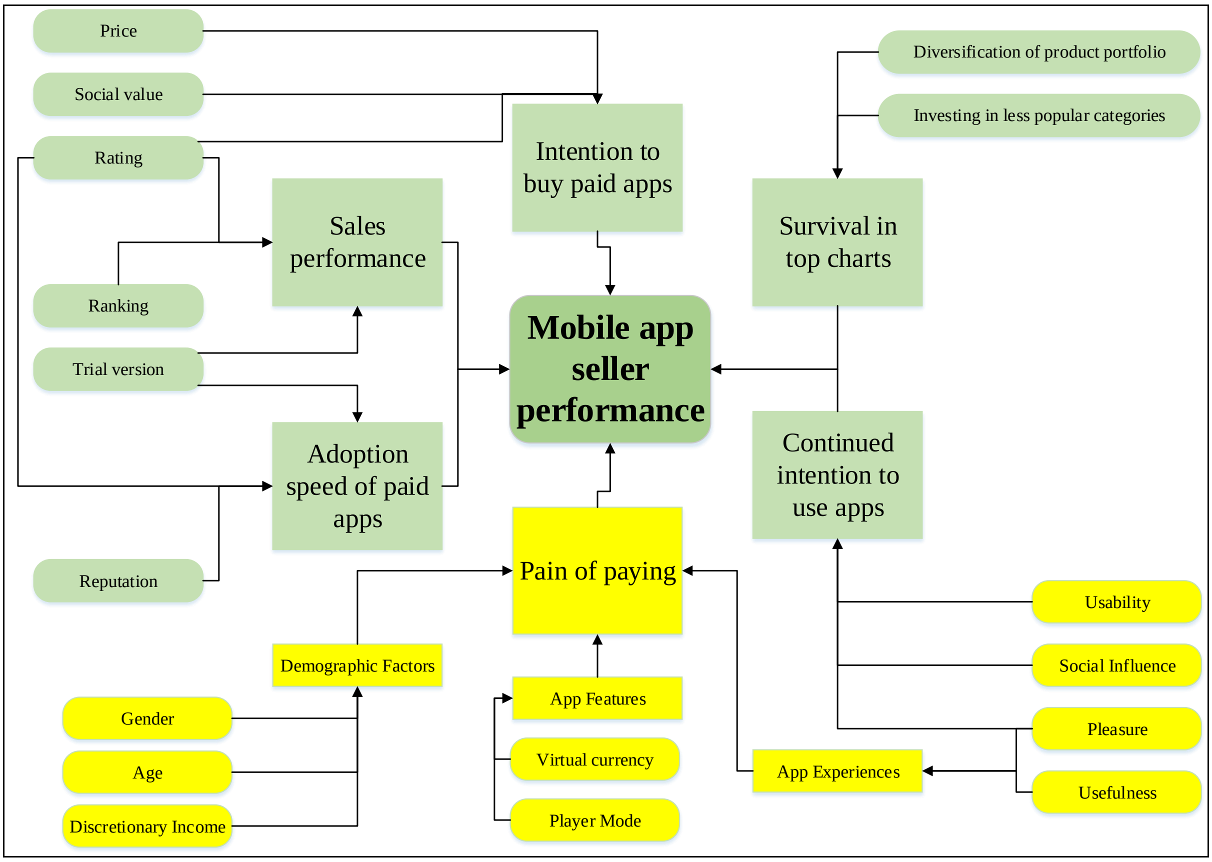


Figure 4.16 Model of factors that contribute to mobile app seller performance in the mobile app market based on primary (marked in yellow) and secondary sources

4.4.1 List of Tested Hypotheses

Table 4.23 lists the hypotheses tests results of the predictor variables' correlation with the pain of paying. The variables are pleasure, utility, virtual credit, peer recognition, and peer competition.

Table 4.23 Mobile app characteristics related hypotheses

Hypothesis	Related question number	Analysis	Result
H1a: *The more pleasure users experience while consuming a mobile app product, the less pain of paying they experience while deciding to purchase it*	RQ1	Regression Analysis	Accepted = there is a significant correlation between game pleasure and perceived pain of paying
H1b: *The more utility users receive from a mobile app product, the less pain of paying they experience while deciding to purchase it*	RQ2	Regression Analysis	Rejected = there is no significant correlation between application usefulness and perceived pain of paying
H1c0: *The mean of pain of paying for pleasure (gaming) apps (μP) is equal to mean pain of paying for utility apps (μU); μP = μU*	RQ3	Paired T-test	Rejected = there is a significant statistical difference between pain of paying for games and pain of paying for applications
H20: *The mean of pain of paying for virtual credit (μV) is equal to mean pain of paying for in-app items (μR); μV = μR*	RQ4	Paired T-test	Rejected = there is a significant statistical difference between pain of paying using native currency and pain of paying using real money

H3a0: *The mean of pain of paying for appearance items that grants users social recognition from their peers within the app network (μI), is equal to the mean of pain of paying on items or features in single-player mod (μP); μI = μP*	RQ5	Paired T-test	Failed to reject = there is no significant statistical difference between pain of paying for aesthetic items in multi-player games and pain of paying for aesthetic items in single-player games
H3b0: *The mean of pain of paying for purchases that grant users a competitive advantage against their peers (μC) is equal to the mean of pain of paying for purchases that grants users a competitive advantage against mobile app AI (μI); μC = μI*	RQ6	Paired T-test	Failed to reject = there is no significant statistical difference between pain of paying for competitive items in multi-player games and pain of paying for competitive items in single-player games

Table 4.24 lists the hypotheses that tested differences in pain of paying, spending and user behaviour between female and male gender groups. The results show that women and men are statistically equal on all measurements apart from time spent on playing mobile games where women spend more time playing than men.

Table 4.24 Gender related hypotheses

Hypothesis	Additional Related question number	Analysis	Result
H4a0: *The mean of pain of paying of women is equal to the mean of pain of paying of men*	ARQ1	Paired T-test	Failed to reject = no significant statistical difference between women and men
H4b0: *The mean of overall app spending of women is equal to the mean of overall app spending of men*	ARQ2	Paired T-test	Failed to reject = no significant statistical difference between women and men
H4c0: *The mean of estimate percentage of income spent on discretionary goods of women is equal to the mean of estimate percentage of income spent on discretionary goods of men*	ARQ3	Paired T-test	Failed to reject = no significant statistical difference between women and men
H4d0: *The mean of the number of mobile applications use a week of women is equal to the mean of the number of mobile applications use a week of men*	ARQ4	Paired T-test	Failed to reject = no significant statistical difference between women and men
H4e0: *The mean of spending on mobile applications of women is equal to the mean of spending on mobile applications of men*	ARQ5	Paired T-test	Failed to reject = no significant statistical difference between women and men
H4f0: *The mean of number of mobile games play hours a day of women is equal to the mean of number of mobile games play hours a day of men*	ARQ6	Paired T-test	Rejected = there is a significant statistical difference between women and men

H4g0: *The mean of spending on mobile games of women is equal to the mean of spending on mobile games of men*	ARQ7	Paired T-test	Failed to reject = no significant statistical difference between women and men

Table 4.25 lists the hypotheses that tested differences in pain of paying, spending and user behaviour among respondents' age groups. The results show that all age groups are statistically equal on all measurements apart from time and money spent on playing mobile games. The results show higher age groups spend less time and money on mobile games.

Table 4.25 Age related hypotheses

Hypothesis	Additional Related question number	Analysis	Result
H5a0: *The means of pain of paying of all age groups are equal*	ARQ8	One-way ANOVA	Failed to reject = no significant statistical difference among age groups
H5b0: *The means of overall app spending of all age groups are equal*	ARQ9	One-way ANOVA	Failed to reject = no significant statistical difference among age groups
H5c0: *The means of estimate percentage of income spent on discretionary goods of all age groups are equal*	ARQ10	One-way ANOVA	Failed to reject = no significant statistical difference among age groups
H5d0: *The means of the number of mobile applications use a week of all age groups are equal*	ARQ11	One-way ANOVA	Failed to reject = no significant statistical difference

			among age groups
H5e0: *The means of spending on mobile applications of all age groups are equal*	ARQ12	One-way ANOVA	Failed to reject = no significant statistical difference among age groups
H5g0: *The means of number of mobile games play hours a day of all age groups are equal*	ARQ13	One-way ANOVA	Rejected = there is a significant statistical difference among age groups
H5h0: *The means of spending on mobile games of all age groups are equal*	ARQ14	One-way ANOVA	Rejected = there is a significant statistical difference among age groups

Table 4.26 lists the hypotheses that tested differences in pain of paying, spending and user behaviour among respondents' discretionary income groups. The results show statistical differences for all variables apart from time spent using mobile applications. The results also indicate that higher discretionary income groups spend more time and money on mobile apps and report less overall pain of paying than lower discretionary income groups.

Table 4.26 Discretionary income related hypotheses

Hypothesis	Additional Related question number	Analysis	Result
H6a0: *The means of pain of paying of all discretionary income groups are equal*	ARQ15	One-way ANOVA	Rejected = there is a significant statistical difference among discretionary income groups
H6b0: *The means of overall app spending of all discretionary income groups are equal*	ARQ16	One-way ANOVA	Rejected = there is a significant statistical difference among discretionary income groups
H6c0: *The means of the number of mobile applications use a week of all discretionary income groups are equal*	ARQ17	One-way ANOVA	Failed to reject = no significant statistical difference among discretionary income groups
H6d0: *The means of spending on mobile applications of all discretionary income groups are equal*	ARQ18	One-way ANOVA	Rejected = there is a significant statistical difference among discretionary income groups
H6e0: *The means of number of mobile games play hours a day of all discretionary income groups are equal*	ARQ19	One-way ANOVA	Rejected = there is a significant statistical difference in mobile game play hours among discretionary income groups

H6f0: *The means of spending on mobile games of all discretionary income groups are equal*	ARQ20	One-way ANOVA	Rejected = there is a significant statistical difference among discretionary income groups

Table 4.27 lists the hypotheses that tested differences in pain of paying, spending and user behaviour among respondents' gaming player-mode preference. The results show that all groups are statistically equal on overall pain of paying, but statistically different on time and money spent on playing mobile games. The analysis indicates that multi-player mode gamers spend more time and money on mobile games than single-player mode gamers.

Table 4.27 Player-mode preference related hypotheses

Hypothesis	Additional Related question number	Analysis	Result
H7a0: *The means of pain of paying of all player-mode preference groups are equal*	ARQ22	One-way ANOVA	Failed to reject = no significant statistical difference among different player-mode preference groups
H7b0: *The means of number of mobile games play hours a day of all player-mode preference groups are equal*	ARQ23	One-way ANOVA	Rejected = there is a significant statistical difference among different player-mode preference groups
H7c0: *The means of spending on mobile games of all player-mode preference groups are equal*	ARQ24	One-way ANOVA	Rejected = there is a significant statistical difference among different player-mode preference groups

4.4.2 Summary of Research Findings

Consumers control their spending via a brain mechanism known in the psychology of money as the pain of paying. Pain of paying is felt whenever consumers pay for products or services; MRI scans have shown that a part of the brain that is associated with bad odours is activated whenever consumers contemplate exchanging money for value. The level of pain felt from paying varies across individuals and circumstances. Individuals that feel higher overall pain of paying are generally conservative in their spending, and individuals that feel lower overall pain of paying are generally excessive in their spending. Still, at an individual level, the pain felt varies with the circumstances that govern the transaction and the experience of the trade. In other words, experiences can temporally skew individuals' pain of paying levels. Temporal increase in pain of paying causes individuals to spend less money than they usually do, while temporal decrease in pain of paying causes individuals to spend more money than they usually do (Frederick et al. 2009; Knutson et al. 2007; Prelec & Loewenstein 1998; Zellermayer 1996). For example, an individual is likely to experience more pain when paying for taxes or fines, because coercion (being forced to pay money) and the belief that they are getting nothing in return shapes the circumstances of the trade, whereas buying a luxury car, for instance, is more likely to associate with less pain of paying because the consumer feels they are getting a good deal and are not forced into the transaction. The findings of the current research on pain of paying of mobile app users and the experiences that shape paying for mobile app software are briefly summarised below.

- Number of hours spent playing mobile games curtail individuals' pain of paying. The more hours spent playing the more the players skew towards more spending. This study found a correlation between spending behaviour and game time where users that play mobile games for longer hours a day tended to feel less pain when paying for extra premium content from the mobile games they play. In other words, the longer hours users played, the more they became willing to spend. A possible explanation for this is that gaming euphoria numbs the brain against pain of paying senses that are responsible for controlling spending. This phenomenon can be observed in casinos where long periods of gambling cause gamblers to lose control over their spending and often leads to gamblers going over their planned gambling budget.
- The study compared women and men gamers' spending behaviour and found them statistically equal in overall pain of paying. However, it found that women spent more time on average playing mobile games than men, but without spending more money.

This was not due to economic means, as both gender groups were surveyed on their discretionary income and were found to be statistically equal on that measure. The analysis indicated that women's pain of paying levels skewed less than men while experiencing mobile games. The conclusion drawn here is that women gamers exhibited more robust control over spending than men gamers while experiencing euphoria from playing mobile games.

- The study compared single-player and multi-player modes gamers' spending behaviour and found them statistically equal in overall pain of paying. However, the study found that multi-player gamers spent more money and time on mobile games than single-player gamers. This indicates that interaction with other gamers was associated with game time and monetisation as multi-player gamers exhibited more spendthrift spending behaviour than single-player gamers despite both groups measuring the same on the Spendthrift-Tightwad Scale.
- This study measured mobile game usage and spending across different age groups and found that mobile games play times uniformly dropped with age, and that spending remained constant for groups within 18-34 years old range. For age groups 35 years and older, monetary spending dropped significantly in comparison to the younger age groups.
- This study found that while consumers were generally conservative in spending on mobile apps, they were less resistant towards spending on useful apps than games. This indicates that consumers see useful apps as more worthy of their money than games. So, overall, mobile apps' usefulness correlated with less pain of paying than mobile games' pleasure. But unlike with games, spending behaviour for apps did not change with the amount of time spent on them. This indicates that the euphoria users experienced with games that ultimately reduce their pain of paying was experienced when interacting with functional applications. As a result, using mobile applications in more sessions did not translate to more money spent on them.
- This study found that the inclusion of native currency in mobile games reduced gamers' resistance to spend money. Many mobile games offer premium items and features that cannot be bought for real money; players must first buy in-app store credit like coins or jewels to later exchange with the desired premium purchases. The study found this strategy favourable among players as they tended to spend more real money to buy native currency. The study measured respondents' spending behaviour on both direct

and indirect purchasing strategies and found that mobile game players felt less pain of paying when trading with games' native currency than when trading with real money.

- The study surveyed a random selection of respondents with varying financial capacities. It found that individuals with higher discretionary income reported lesser levels of overall pain of paying, and more spending on mobile applications. This suggests that financial freedom was correlated with the general spending behaviour of people. Furthermore, the study found that higher discretionary income groups played mobile gamers for longer hours than individuals with lower discretionary income.

CHAPTER 5 - DISCUSSION OF RESEARCH FINDINGS

The sample size consisted of 202 participants, all of whom were Android mobile app consumers based in Australia. Focussing on a single country was seen as a positive for the study as it limited the external influences that could affect the responses. The data was collected via questionnaires administered to the respondents. In sociodemographic terms, it was suitable to use adult participants between the ages of 18-65 (or older), as minors are unable to purchase mobile apps without an adult's credit card and authorisation. The Australian based survey respondents were asked to estimate their discretionary spending budget and to rate their general spending, from very conservative to very excessive. The following sections discuss the research findings as regards the categories of pleasure, usefulness, native currency, interaction with strangers (competition and recognition), and socioeconomic and demographic factors.

5.1 Pleasure

Data analysis results indicate that spending rating changed with the experiences presented to them in the survey. This shows that spending behaviour varied with emotions or experience, even with a set spending budget. The pain of paying reflects a human psychological mechanism to conserve spending. The pleasure variable was measured by the time spent playing games, and the study found that playing long hours a day was shown to correlate with less pain of paying felt. This suggests that games that keep players "hooked" for longer hours can generate more revenue from their players than similar games that players enjoy for a limited amount of time in the day. The pleasure factor has also been confirmed by Kang's (2014) study, which tested the correlation between pleasure and intention to continue using mobile apps and found that pleasure drives continued intention of mobile users to use mobile apps. Furthermore, Lu, Liu and Wei (2016) also found that enjoyment was a driver of continuance intentions to use mobile apps, along with mobility. Figure 5.1 illustrates the relationship between enjoyment and continuance intention as found by Lu, Liu and Wei's (2016).

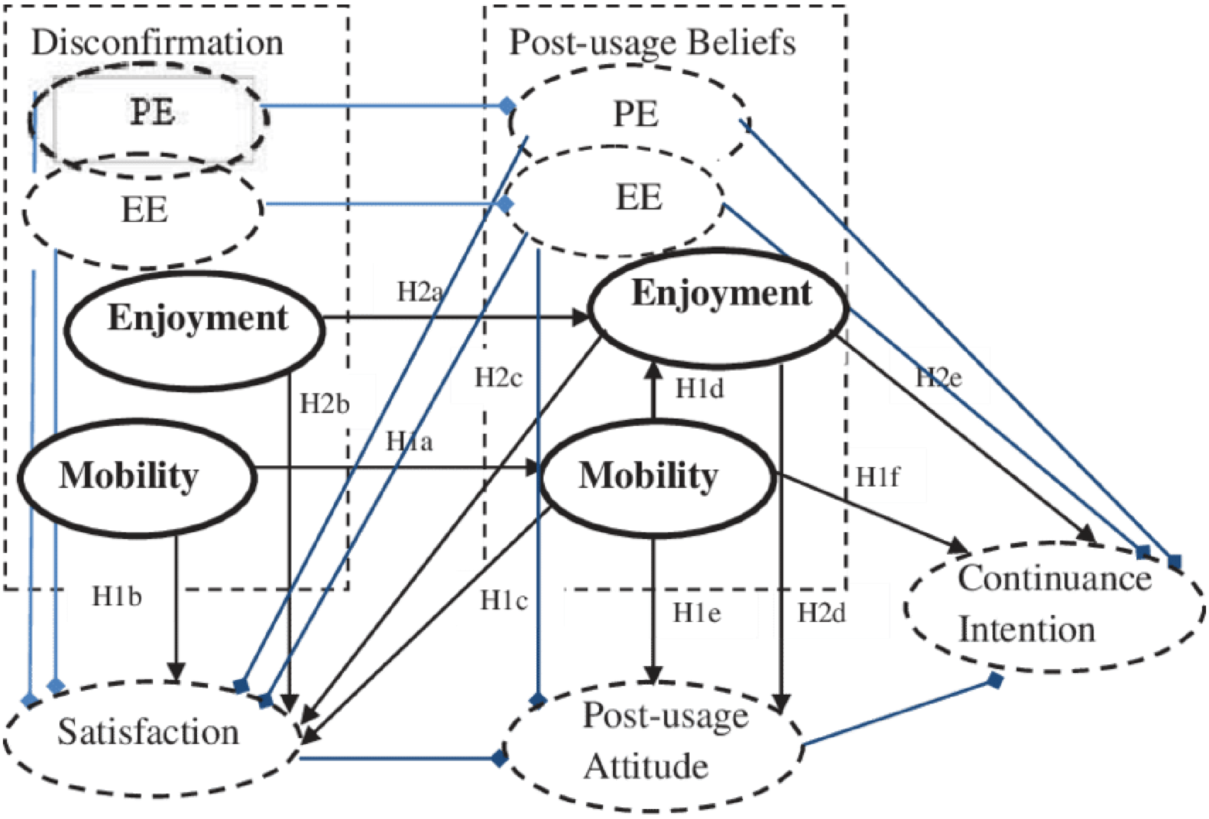


Figure 5.1 A revised mobile application continuance model

(Source: Lu, Liu and Wei 2016, p. 3)

The predicament of gaming and online gambling impedes the consumers' ability to exercise self-control during their purchases (Fisher, 1994; Siemens & Kopp, 2011). A survey of the experiences of online gamblers reiterated the issue of consumers' overspending to tend to their addictions.

When it comes to playing games in the app, gender was also a crucial issue as statistics delineated that females were more prone to playing games than males. Men are often depicted as being engrossed in game players, such as PlayStation and Xbox, while women are seen to prefer to consume other forms of entertainment on smartphones. However, surveys have shown that a higher percentage of women play games than men (Zenn 2018). Furthermore, this study found that while women also spent more time playing games than men, they spent the same amount of money as men. The current study suggests that women command a stronger control over spending compared to men, as they played longer hours than men, yet spent the same amount of money. Therefore, for women to reach the men's spending threshold, they required more mobile game playing time, noting no differences in the overall pain of paying or discretionary income between women and men sampled in this study.

Discretionary income was found to be an indication that consumers would spend more on app purchases. The study found that those with less discretionary income, were more resistant to making app purchases. Instead they would resort to seeking free alternatives on app stores for the premium apps they desired.

It can be understood that straining one's bank account would increase overall pain of paying, as the individual remains with little or no disposable income. Furthermore, the results show that individuals with higher incomes played games for longer hours compared to their counterparts from lower income brackets.

A look into the types of players offers a distinction between multi-player and single-player mode gamers. The former refers to players who are inclined toward community-network games, which leads to interactions with other human players. An example is Clash of Clans, found on the Google Play Store. Additionally, as the name suggests, single-player mode gamers indulge in games that do not lead to engagement with other players. Shikaku, found on Google Play Store, is an example that demonstrates the scope of single-player games (Google Play 2019).

This study utilised a one-way ANOVA to determine the existing differences in gamer spending behaviour in the three gaming modes: multi, single, and/or both. The results show that gamers who engaged in multi-player games spent more hours playing than users of single-player games. This thesis finding has been corroborated by Hardin (2016), who found that on average, multi-player gamers spent around 1 hour more on games than single-player gamers (refer to Figure 5.2 for details).

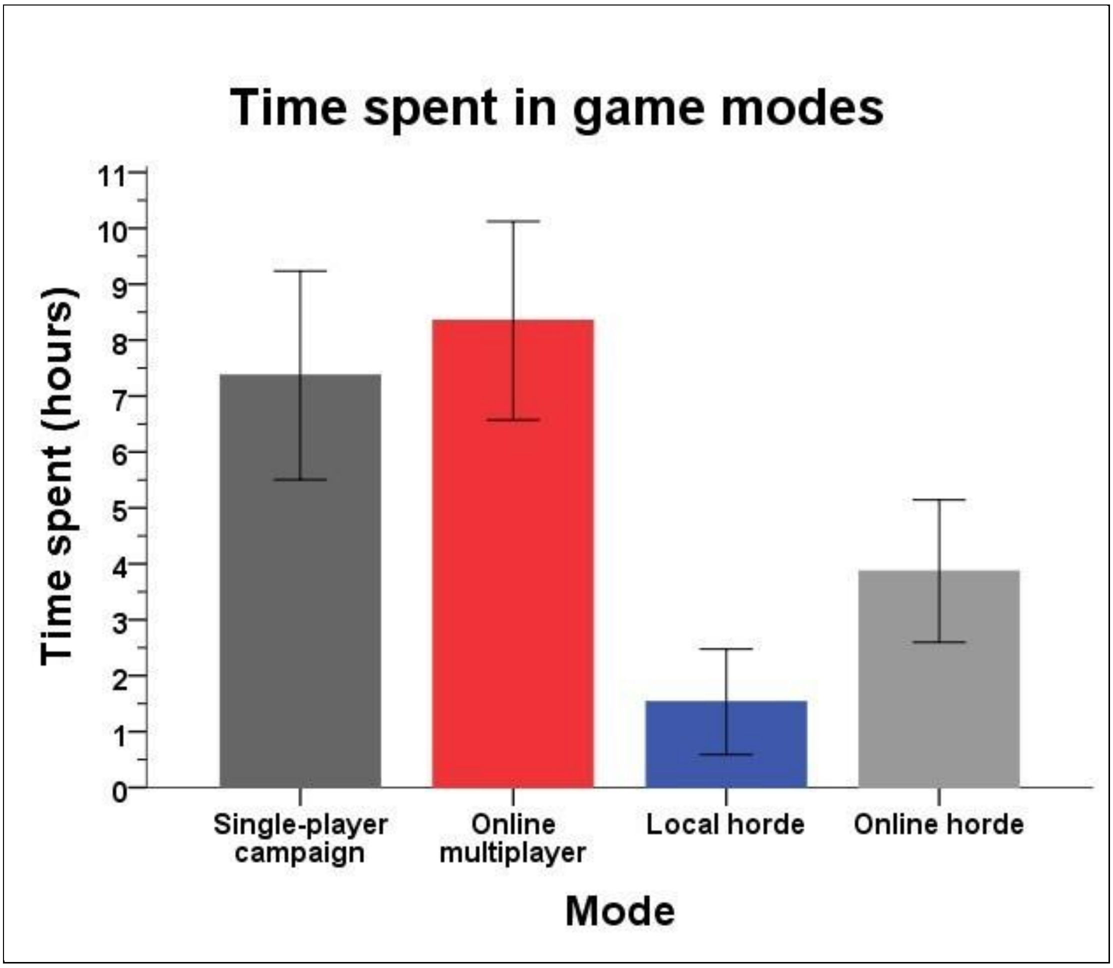


Figure 5.2 Average time spent in games modes

(Source: Hardin 2016, p. 1)

Notably, players that indulged in both modes appeared to spend more time than those playing in single-player mode. Another statistical difference was spending on games, as multi-player gamers spent more money than single-player gamers. However, players who fell under the categories of multi- and single-player mode appeared in-between the groups. Despite the difference in the pain of paying, players inclined toward multi-player gamers were more likely to spend time and money in comparison to single-players.

In summary, this result adds to Kang's (2014) findings that perceived enjoyment was positively associated with a continued intention to use mobile apps since the continued use led to enjoyment that was associated with more spending on the users' part.

5.2 Usefulness

The data analysis showed that mobile applications which Australians use for functional purposes cannot leverage their usefulness value; this is unlike games that can leverage their entertainment value to induce more spending from their users. According to the results of the analysis, utility value was correlated with the pain of paying, but the degree of usefulness had no linear relationship with pain of paying.

Also, the results showed that the mean of the pain of paying for gaming purposes differed from the mean of the pain of paying for utility purposes. The study found that the mean of utility spending was lower than the mean of game spending (refer to table 4.23, p.132). Furthermore, this suggests that people generally experience less pain of paying for utility apps than gaming apps when utility or entertainment value was not considered. Moreover, the study's findings imply that users were more inclined to spend on applications than games at the beginning. However, that inclination did not change with time, even if the application met users' expectations. Therefore, application sellers must leverage initial user excitement by making early sale offerings and should not wait until the user fully experiences that product, as their statistical inclination to buy does not improve after experiencing the product.

Davidson, Fredrikson and Livshits (2014) argued that app personalisation adds to the initial excitement, which may further persuade users to purchase the app. The idea of satisfaction is closely tied to utility, as consumers are less pained on experiencing effective apps. With such knowledge, it is evident that the number of downloads does not necessarily determine the effectiveness (or lack thereof) of a mobile app. The developer's experience in mobile applications and the user interface are plausible enough in maintaining the personalisation options. With these options, customers experience excitement due to enjoying the features in these mobile apps (Davidson, Fredrikson & Livshits 2014). For example, if a user is interested in wallpapers for their home screen, they will enjoy the installation of different apps that fulfil this feature. The flexibility of settings also makes it easier for developers to tweak their features for users to enjoy the app. These customer preferences are also well-linked with the issues of privacy, whereby users can store their details and avoid any form of data spread (Davidson, Fredrikson & Livshits 2014).

This study found a weak correlation between mobile app's usefulness and consumer spending; this adds to Hsu and Lin's (2014) findings that the application performance correlates with continued use but is not strongly correlated with consumer intention to buy paid apps.

5.3 Native Currency

Apps that develop their own native currency induced more spending from their Australian users. Utilizing different payment methods facilitates the situation and makes it easier for consumers to carry on with the disposition of funds. Inasmuch as the expectation would be that younger individuals indulge in gaming activities, research indicates that individuals between 25-34 and 34-44 are more likely to have higher income (Raghubir & Srivastava, 2008). Raghubir and Srivastava's (2008) results are also supported by this research which found that consumers in the 25-44 age group could afford more discretionary spending than consumers in the 18-24 age bracket. For this reason, the 25-44 age group had shorter gaming sessions yet spent the same as users in the 12-24 age group. Nazario's (2014) research findings support the positive role of native currency in app monetisation, explaining that native currency increased revenue of mobile apps because they kept consumers invested in the app by rewarding their loyalty.

The use of native currency is very prevalent among the highest grossing apps in the market (Google Play 2018). Overall, it is attributed to increasing revenue because this model allows app sellers to reward consumers with free native credit to keep them invested and incentivise loyalty (Nazario 2014). Refer to Figure 5.3 for a screenshot of rewards offered in the Harry Potter game that includes coins which are the native currency for this particular game.

Figure 5.3 Gold coins app-native currency of Harry Potter Game

(Source: Families Magazine 2018, p. 1)

The results also show that the difference between the mean of paying for listings with mobile app-native money and the mean of paying with real money was significantly different, with the mean of native money being lower than the mean of real money. This suggests that consumers are more willing to spend money on in-app purchases when the extra layer of native currency is added to the trade: consumers first exchange money for the apps' native money and then buy in-app listings with the native money. Overall, this explains the wide use of native currency by mobile app sellers and even theme parks like Disneyland. Introducing a native currency in trade correlates with less pain of paying felt by consumers. One suggestion for the popularity of native currency could be that for consumers buying native virtual money with real money feels more like currency exchange than a purchase, even though the exchange is non-reversible in apps. Australian consumers learn the trade value of their government's currency with experience and time. Similarly, they can easily judge the value-of-money in trades with other currencies because of their experience. So, when they trade their own currency for a non-familiar currency, they lose the advantage of experience and are no longer able to judge the trade effectively. Also, exchanging currency does not trigger the strict purchase decision mechanisms in consumers' brains, allowing them to make the purchase with less resistance.

The result augments Yamaguchi's (2004) review of native currency in online games, in which he argued that since virtual worlds have no inflation and that saving native currency incurs no interest; therefore, gamers are more incentivised to spend it than real money. The result also adds to Ariely's (2013) work on consumer behaviour regarding cash versus credit spending; his findings conclude that consumers feel less pain of paying when buying with more-abstract and less-familiar means, like a credit card, than when spending with more-familiar means, like paying with cash.

5.4 Interaction with Strangers (Competition and Recognition)

The study researched interactions with strangers in mobile games by analysing two factors: competing with strangers and receiving recognition (admiration) from strangers. Using the paired t-test analysis consumer spending on premiums in multi-player games were statistically compared to single player games. Whereas in multi-player games consumers can gain recognition and admiration from other gamers, this is not possible in single player games since players do not compete with anyone. The results found no statistical difference for Australian gamers in relation to these two factors. These results are in-line with other studies that found that interaction with strangers was not important for mobile app users and were not a reason to download mobile apps (Georgieva et al. 2015; Lim et al. 2015). However, this remains contrary to other observations that show that most top grossing apps' core value proposition is based on interaction with strangers (Google Play 2018).

5.5 Socio-Economic and Demographic Factors

5.5.1 Gender

This study analysed sample data by gender and found that gaming patterns in one aspect were different in females and males. This is a significant part of the research, as understanding of the patterns between the two groups augments any of the other ideas noted for understanding consumer behaviour in mobile apps. The results of gender disparities were put on display because of the two-sample t-test, which was conducted among the respondents as a way of realising the place of females and males in the study. There was no statistical difference in paying for apps, discretionary income, spending on utility apps, using utility apps on a weekly basis and spending on games. However, as reiterated in the discussion, there was a statistical difference while observing the number of hours that males and females spend on the gaming activities. Females' pain of paying mechanism or spending self-control is seen to be stronger in comparison to males, as they require more gaming time in order to spend as much as men do.

5.5.2 Age

This study analysed sample data by age and found no statistical differences among different age groups in terms of overall pain of paying and spending on mobile applications. However, the study did find differences in user behaviour and spending on mobile games. Overall, the study found that spending and average hours played during the day dropped with older age groups. Furthermore, the study found that the age group of 24-44 years old spent almost as much as the 18-24-year-old age bracket, despite playing less hours on average. This makes the

24-44 age group the most profitable for app sellers, as they spend more per time unit played compared to other age brackets.

5.5.3 Discretionary Income

Using the one-way ANOVA test, this study measured existing differences between discretionary incomes. Acquiring results from the respondents was more plausible as this offered unbiased information regarding the research topic. Amidst all the factors, discretionary income had a positive correlation income with spending on mobile apps, the study found that the higher the discretionary income was, the more players spend on mobile apps. The research touches on consumers' differential incomes in various ways, indicating that money was a factor in the definition of consumer behaviour in mobile apps.

5.7 Mobile App Seller Success

Throughout the research, the findings indicate that users experienced less pain when purchasing apps which give them pleasure. The fact that users have the alternative of accessing free apps, limits their desire to make any purchases from paid apps that have free alternatives. Despite the literature being inconclusive regarding the value of offering free trials for the developers, the prevalence of free app trials in the market suggests that offering free trials leads to consumer conversion to paid apps (Arora, Ter Hofstede & Mahajan 2017; Hsu & Lin 2015; Liu, Au & Choi 2014). For users, the availability of both free and paid mobile applications in the Google and Apple Stores, means they are often more likely to settle on the former. They mostly pick the paid apps only when the apps offer markedly superior experiences, which are not offered via the free apps.

5.7.1 Reputation

To sustain developer reputation and customer loyalty, it is necessary for developers to ensure that their products are distinct from other apps. For example, in the taxi industry, there are numerous mobile taxi apps that have been developed to facilitate the service. Inasmuch as Uber was the first company to initiate the idea of ordering taxis online, the entry to the market from other app companies such as Hailo or Lyft are threatening their service delivery. Fortunately, for Uber they have continued to maintain their quality standards, making it possible for consumers to retain their loyalty, despite the proliferation of other taxi applications. That Uber developers have striven to gain extraordinary customer ratings in both Google Play and Apple's

App stores also works in their favour. Uber has a rating of 4.0 in Google Play Store (Google Play 2019), which is categorised as relatively high in comparison with other applications. It is evident that the developers have created a rapport with consumers, who leave positive reviews on app stores. Apps within the same domain with lower ratings cannot be classified as veteran in either Google Play or Apple's App Store and are put at a disadvantage since veteran apps like Uber are given priority due to their higher ranking. 2.4.2 Monetisation

5.7.2 Personalisation

App personalisation strongly depends on customers' preferences since the application is developed for their particular purposes. Personalisation of apps responds to different aspects of the users, such as socio-demographics, context, and behaviour. Focusing on the socio-demographic features means that the developers are sensitive to the existing diversities among users. This study suggests that apps can be created depending on a user's age, sex, sexual orientation, and any other unique aspects (refer to Figure 5.4) (App Samurai 2019).

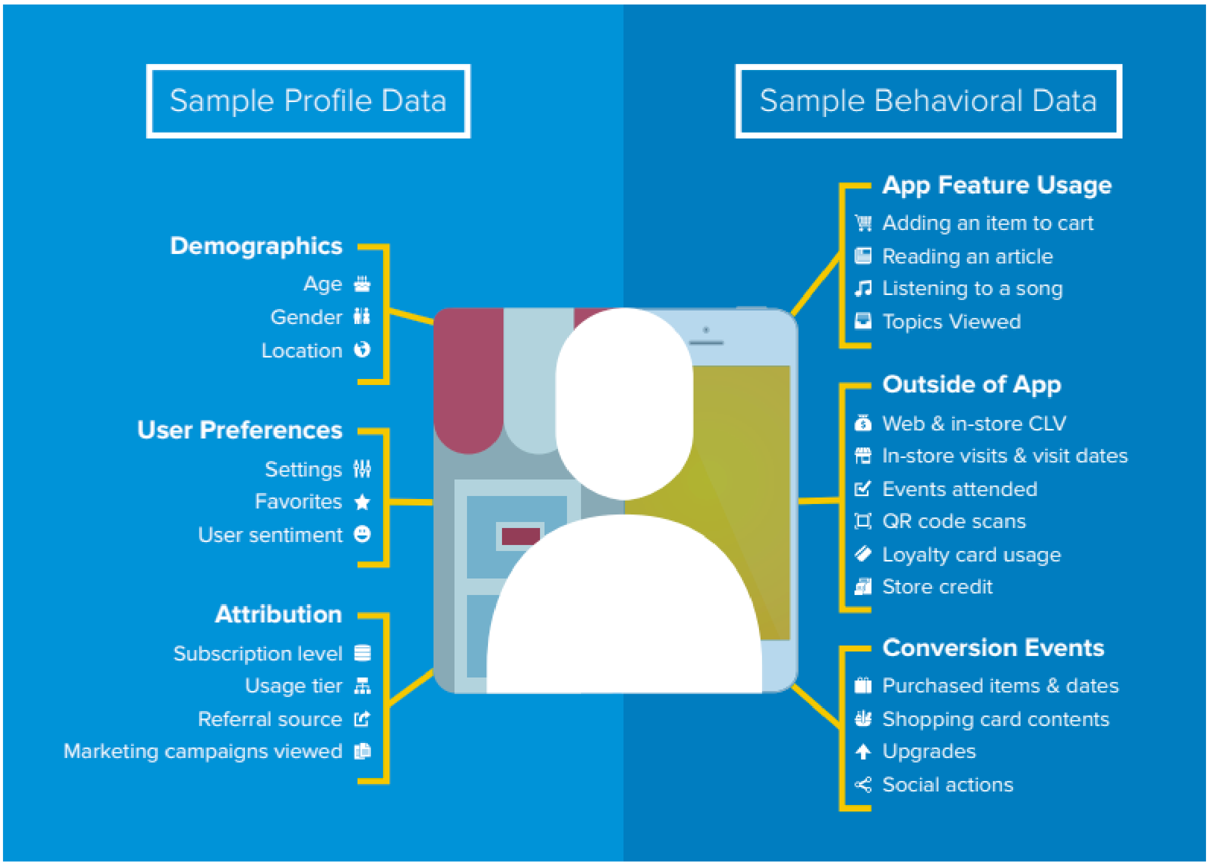


Figure 5.4 Mobile app personalisation based on sample profile data and behavioural data

(Adapted from App Samurai 2019, p. 1)

Another relevant factor to be taken into consideration in developing apps for physically dependent businesses, for example, food apps, they should investigate the geographical proximities of their customers, to increase the app's effectiveness. When it comes to the behavioural context, developers need some understanding of the lifestyles of their consumers. If, for example, they are dealing exclusively with vegetarians, then it is a given that all the food options in the apps should only be vegetarian. Such personalisation means that the users are more satisfied with the app since developers are seen to be responding to their specifications and preferences (Levenson 2017).

5.7.3 Ratings

When developers are invested in constantly improving their products, they can capture the consumers' attention by creating better experiences for them. The developers' ability to improve their customers' experiences will impact upon their ratings and ranking in app stores. Building their ratings and reviews in these stores is highly influential as other consumers subscribe to services based on the same ratings and reviews.

5.7.4 Competition

Dealing with the competition means that developers continually update their apps. The continuous evolution of smartphone hardware and operating systems requires the developers to continuously update and improve their products in order not to restrict their users to outdated "stagnated" features; however, developers also have to bear in mind that highly frequent updates may drive customers away as the apps can be perceived as buggy and unstable (Nayebi, Adams & Ruhe 2016). Therefore, it is important for developers to continuously improve and test their products so as to keep updates sufficient, but at a minimum frequency. In the case of substitution threats, it would be plausible enough for developers to investigate their app's weakness or user complaints (Khalid et al. 2014), while fixing the app for an improved experience.

5.7.5 Consumer Preferences

Customer ratings that discuss the efficiency of apps appear more believable, which has a significant effect on the extent to which customers download mobile apps from either Google Play or Apple's App store (Arora, Ter Hofstede & Mahajan 2017; Hsu & Lin 2014; Liu, Au & Choi 2014). Each consumer desires different experiences from apps, such as entertainment, networking, productivity, and information. Among all of these different categories of mobile app uses, one element, word of mouth, has been found to be the most reliable influence toward the acquisition of the apps (Kim, Lee & Son 2011). Other drivers, such as usefulness, trial performance, monetary value, app ranking, ease of use, and pleasure, despite being delineated as part of the determinants toward mobile app purchases, did not override the effectiveness of customer reviews and recommendations. More precisely, about 59% of consumers check ratings before purchasing or acquiring a mobile app. This majority percentage emphasises the effectiveness of ratings in influencing consumer behaviour.

Power, nature of urgency, and legitimacy are the three categories used to understand the influence of the different stakeholders on the developer's projects (Santana 2012). The difficulties that developers face while building their apps are often reduced when there is exposure to effective stakeholders, and the diversity of these individuals makes it easier for developers to acquire more information and ideas for successful app development.

5.7.6 Free Trials

The findings of the research as regards the use of free trials were conflicting as to the benefit of this strategy for mobile app success. On the one hand, app developers that do not expose the consumers to these trial versions risk losing customers, as they will not be motivated to investigate and potentially purchase the app. On the other hand, a free trial can be seen as a gamble for both consumers and app developers since it has been shown that free trials slow down the adoption of paid apps (Arora, Ter Hofstede & Mahajan 2017; Liu, Au & Choi 2014).

5.7.7 Care for Consumers

Finally, Siemens and Kopp (2011) researched the subject of self-control while attempting to understand the place of gambling in the lives of consumers. They found that if individuals were capable of regulating and controlling their day-to-day livelihoods, it became much easier for them to exercise discipline when dealing with the dilemma of spending their money on the addictive behaviour (Siemens & Kopp, 2011). It can be understood that it is necessary for consumers to understand the role of self-regulation, which works toward ensuring that they do not deplete or waste their resources. Furthermore, the research by Ariely (2013) supported this subject by looking into spending behaviour from a different perspective. They found it was much easier to spend via credit card, as parting with cash psychologically impacted consumers, incurring pain during the process.

CHAPTER 6 - CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The mobile application market is among the largest e-commerce platforms in the world, where millions of products are offered by a large community of developers and sellers to over a billion customers. Despite being one of the largest markets in the world, the mobile applications market remains homogeneous because of it being dominated by two major distribution platforms: Apple and Google. App sellers operating on these platforms are bound by distributer’s ecosystem’s rules. These ecosystems shape how sellers develop, monetise and market their apps and shape how users behave in the market. This has prompted several researchers to study how users behave and how app sellers can succeed in these markets (Khalid et al. 2015; Kim, Lee & Son 2011; Lee & Raghu 2014; Lim et al. 2015; Liu, Au & Choi 2014). Because this study was conducted in Google’s Google Play Market, its findings and recommendations are applicable to Android app sellers operating on that distribution platform.

The Pavlovian and Marshallian models are useful in delving into the scope of consumer behaviour; they each hold different opinions in their attempt to offer an exposition of customers’ behaviour in their handling of mobile apps. The theories have undergone criticism from behavioural psychologists, who do not concur with the Marshallian model; they argue that consumers make certain decisions before indulging in the purchases. It appears more logical, according to behavioural scientists, to understand that customers often think irrationally before making the decision to purchase any given commodities (Langholtz et al. 2002; Psychology Today 2018).

There are certain reasons for the preference of either Android or iOS platform, as the consumers are aware of their desires as regards mobile apps. Some applications harbour complicated settings that may be strenuous for the users, thereby impeding their experience. It is quite necessary to ensure that the consumers are well-satisfied with these services offered by the mobile apps, as that satisfaction works towards lessening their pain during the purchasing experience, and allows them to feel fulfilled after purchasing a product that caters to their desires and needs. This study not only focuses on consumer spending on mobile apps but also their place in addictive activities, such as gambling. The ideas are identical as the activities can involve spendthrift and irresponsible behaviour, which can lead to bankruptcy, debt or depletion of resources.

The incorporation of regression analysis in the research attempted to delineate the link between pain of paying and spending on mobile app and games. This knowledge allowed an in-depth look into consumers' personalities, indicating that those who spent more would purchase the apps in a similar manner. If an individual is not inclined to spend irresponsibly, they will not end up making unnecessary purchases to service their addictive behaviours.

The thesis's hypotheses results indicate that consumers' satisfaction was directly proportional to their pain of paying. The two concepts are interrelated as they do not work independently from one another. Additionally, the research focused in depth on the issues surrounding productivity, which was dependent on the consumers' reasons for having an interest in any of the given mobile apps. Some consumers considered productivity from an entertainment perspective, while others looked at it from a scope of utility perspective.

It is apparent that apps utility is more useful for some consumers, as some would prefer them over entertainment apps. When the consumers are accustomed to apps that are useful, they experience less pain during the purchase process. For example, as indicated in the discussion, the fact that Apple Music requires a fee appears worthwhile as it makes it easier for iOS users to access the music. The idea surrounding Apple Music is that the consumers are happy to pay for the app due to its usefulness. In addition to the $4.99 individual plan mentioned in the discussion, Apple offers different plans that delineate utility linked with this app. There is a family plan catering to six people, and it is priced at $7.99 per month, and there is a university student plan, which is $2.49 per month (Apple Music 2019). With all these options, it becomes much easier to lure the consumer into spending money on the mobile app.

Customer ratings and reviews are used to assist the consumers in making decisions on whether the apps are effective and worthy of the purchase. Individuals are often attracted to products that have been reviewed positively by their fellow users. It only makes sense to hold such beliefs as lack of testimonials or customer reviews may not lead to purchase, which leads to pain during the process. The discussion indicates that consumers are affected when they have to pay with money; hence, their preference was to use other modes of payment, such as credit cards. Therefore, paying using cash for apps that are ineffective interferes with the consumers' psychological well-being (Raghubir & Srivastava, 2008).

Coming back to the issue of customer reviews, the study indicates that influence from social interaction with family and strangers influenced consumers into downloading certain apps. For example, social media apps such as Twitter and Facebook have extremely high downloads in both the Google Play and Apple's App stores, as individuals are fixated on online socialisation. The extent of social influence in this manner, therefore, is a factor that contributes to consumer behaviour in their acquisition of mobile apps. Unlike Twitter and Facebook, which are free apps, the idea of social influence plays an indisputable role in facilitating the place of paid apps in the financial lives of consumers.

The discussion indicates clearly that the ratings of these apps in the stores had an impact on the customers. It is important for mobile app sellers to pay attention to their products' ratings. Also, the literature findings agreed that consumer ratings were indeed important for app monetisation (Arora, Ter Hofstede & Mahajan, 2017; Hsu and Lin 2014; Liu, Au & Choi 2014).

One of the hypotheses in this study was that consumers are more pained when they pay for games than when paying for functional or useful applications. However, it became evident through later analysis that consumers end up paying more for games because unlike applications they ease consumers' pain of paying. This finding is supported by previously published research by Kang (2014) and Lu, Liu and Wei (2016), who both found that enjoyment had a positive effect on the continued use of mobile applications, which ultimately translates to more monetisation.

The hypotheses of this research maintain the assertion that consumers are pained when they purchase mobile apps in general. However, the pain felt varies according to the experiences these apps deliver. The data collected, analysed, and presented extrapolate on the idea that consumer behaviours in mobile apps is indeed irrational. The following are a summary of the findings from the current study of consumers using mobile games:

- The mean of pain of paying for applications is statistically less than the mean of pain of paying for games.
- The mean of the pain of paying with app virtual credit is statistically less than the mean of pain of paying with real money.
- The mean of pain of paying for items that award social recognition in multi-player games is equal to the mean of pain of paying for items in single player games.
- The mean of pain of paying for items awarding a competitive advantage against other players is equal to the mean of pain of paying for items awarding a competitive advantage against mobile app AI.

6.2 Research Outcome/Answers as per Research Questions

The study has proposed six main questions regarding factors that affect pain of paying. This section highlights the research questions, hypotheses, research answers, and outcomes (refer to Figure 6.1 below).

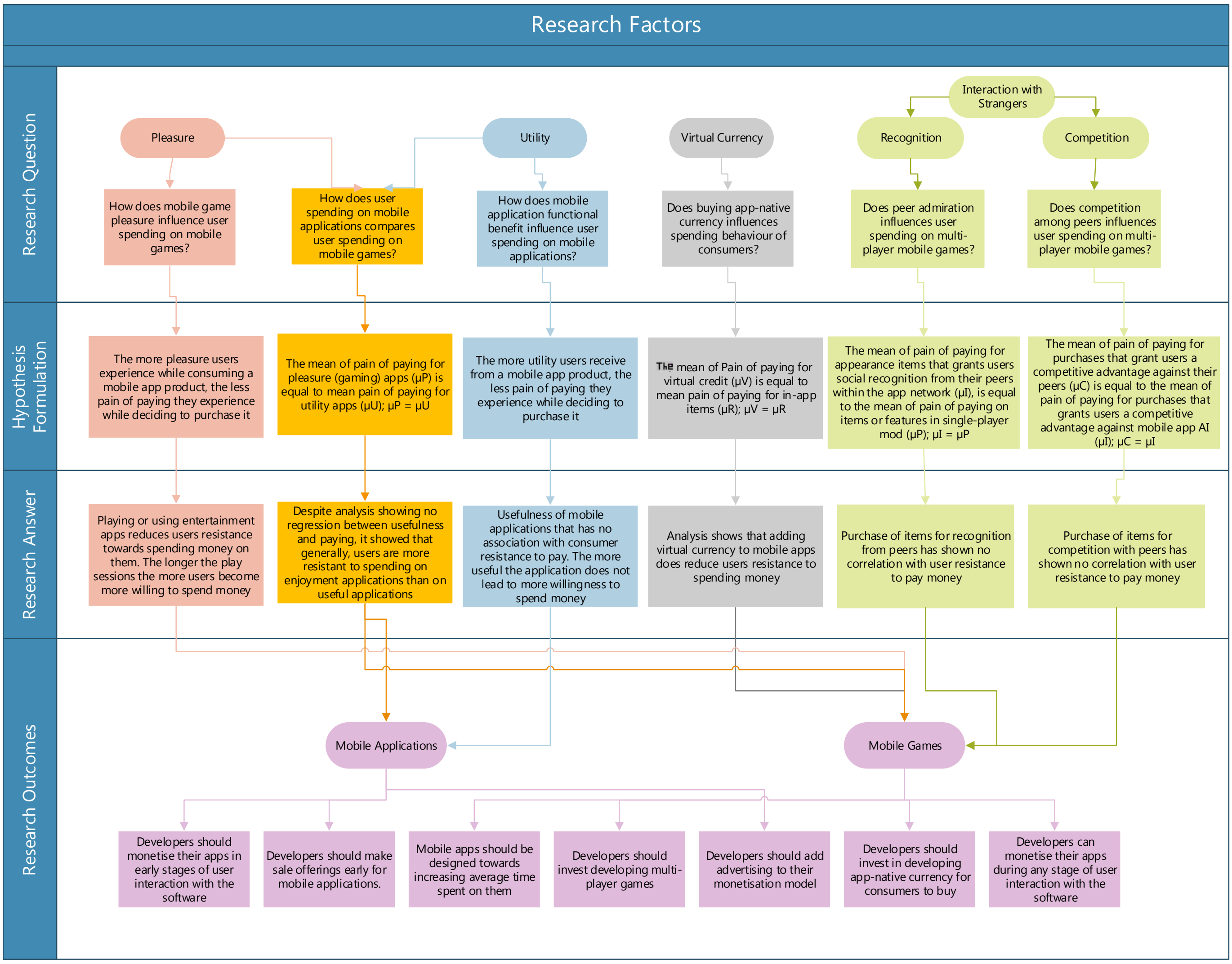


Figure 6.1 Research questions, hypothesis, research answers, and outcomes

The main objective of this study was to test correlations between factors that influenced consumer purchasing and consumer spending on mobile apps. Table 6.1 summarises the new knowledge contributed by this study and contrasts it with existing knowledge from previous literature.

Table 6.1 Summary of existing knowledge, and new knowledge produced by this research study

Item	Existing Secondary/Literature Knowledge	Newly Discovered Knowledge (Primary Research)	Compare/Contrast Between Existing and Newly Discovered Knowledge
Pain of paying	Pain of paying changes with means of payment and nature of the trade.	Pain of paying is affected by different product experiences and the	The pain of paying not only varies according to the

		discretionary income available to the consumers.	method of payment and the circumstances of the trade, but also varies with the product/service experience. This discovery is only measurable in products where consumers continue to experience and pay for simultaneously like in mobile apps that offer in-app purchases while being consumed by users.
Enjoyment and spending	Game enjoyment positively affects the continued play of the games.	Longer play sessions of games reduces payment resistance and results in more spending. Higher discretionary income groups spend longer gaming sessions and depict more excessive spending behaviour than lower discretionary income groups. Players who prefer multi-player mobile games also spend longer sessions playing and depict more excessive spending behaviour than single-player mode players.	Previous literature has already established that enjoyment increases the amount of time spent on games, this research found that the extra time spent reduces paying resistance of users and leads to increased spending.

Usefulness and spending	Application performance does not result in more spending.	Application usefulness also does not reduce payment resistance or result in more spending. Spending on mobile applications increases with higher discretionary income.	Existing knowledge asserts that the performance of mobile applications does not increase user spending, this study measured usefulness and found that it does not increase user spending.
Usefulness vs Enjoyment	Mobile games gross more than mobile application.	Pain of spending on games is higher than pain of spending on applications.	Existing knowledge asserts that mobile games monetise better than mobile applications. However, this study discovered that initially, people consumers are more resistant to spending on mobile games than applications. But the reason games monetise better is that games are successful in reducing the spending resistance of users. While in applications, user resistance to pay remains fixed.
Native currency	Consumers experience less pain paying with less familiar currency or less familiar form of a currency.	Consumers experience less pain paying with native currency inside mobile game than with plastic card credit.	Existing knowledge established that less people experience less pain of paying when spending with credit than with cash.

	Consumers experience less pain of paying with plastic card credit than with cash. Most mobile games employ their own native currency at an extra development cost.		This study took it further and compared credit to native currency and found that consumers spend more with native currency than with credit. The suggested explanation is that the less familiar consumers are with the currency the less spending control they can exert with it.
Women vs men gamers	Women spend more hours on average playing games than men.	Women have longer gaming sessions than men but remain similar in spending behaviour on games.	Existing knowledge asserts that women gamers spend more time on average playing mobile games, new knowledge discovered by this research assert that while women spend more time playing, they remain statistically equal to men in spending money on games despite being having equal in economic means.
Age groups spending and playing mobile games	Higher working age groups enjoy higher income than younger working age groups.	Higher working age groups have more discretionary income than younger working age groups. Higher working age groups have shorter gaming sessions than younger working age groups.	Existing knowledge established that higher working age groups generate higher income than younger age groups, new knowledge discovered that not only older age groups enjoy higher income, but also enjoy a higher discretionary percentage of income

		Higher working age groups have similar spending behaviour to younger working age groups.	than younger age groups. In the area of mobile games, this study discovered that due to higher discretionary income, older age groups spend less average time playing mobile games yet spend more money on them compared to younger age groups.

6.3 Recommendations for App Business Model Selection

Another objective of this study was to develop a decision diagram for monetisation model selection to help mobile app sellers select the best fit model for their apps. The criteria are based on research findings and reviewed market statistics.

Google Play Store classifies apps into applications for functional utility and games for entertainment purposes. The first selection node in the diagram determines the type of the app, whether it is an application or a game. The next node determines the average session time of the app, if the seller reports a session time over 5 minutes then adding advertisements would be cost-beneficial to them. This time duration key performance indicator is based on market statistics that show 5 minutes to be the average session time of gamers overall (refer to Table 6.2).

Table 6.2 Average session time for gamers

Average Number of Game Sessions Played:

GAMER TYPE	PER DAY	PER MONTH	AVERAGE SESSION TIME
All Gamers:	4.31	133.6	5 min, 35 sec
Heavy Gamers:	10.6 (2.5x)	328.4 (2.5x)	5 min, 53 sec
Core Gamers:	16.6 (3.9x)	514.4 (3.9x)	6 min, 3 sec
Light Gamers:	0.6	17.1	3 min, 32 sec

Source: Verto Analytics, April 2016

Source: Verto Analytics, cited by Hwong (2016, p. 1)

The next selection node for application is the availability of free alternatives for applications and daily gaming hours for games. The literature review was inconclusive regarding the effect of free alternatives on paid downloads; Hsu and Lin (2015) found that free alternatives did not negatively affect intention to buy paid app downloads; however, Arora, Ter Hofstede and Mahajan (2017) found that it slowed adoption speed of paid apps. Based on the disagreement in the literature and the thesis finding that mobile app users tended to be generally conservative, the current study recommends avoiding paid downloads for applications when free alternatives are available and instead using the freemium model. The average of total daily gaming hours, however, are 24 minutes for average gamers and 1 hour for heavy gamers (see Table 6.3).

This study has also shown that investing in native currency reduces pain of paying and increases spending; hence, games that implement their own currency should opt for higher earning models like in-app purchases rather than a simple freemium model. Therefore, based on the cited statistics in Table 6.3 and this study's findings on native currency, games that report over 1-hour daily average use or implement native currency are recommended to invest in an in-game store so as to offer in-app purchases to players who are likely to be heavy gamers. Games that report less than 1-hour daily average use and do not implement native currency are advised to select the lower earning, freemium model.

Table 6.3 Average daily time spent by gamers

Average Time Spent Playing Games per Day (hours/minutes):

GAMER TYPE	TIME SPENT PER DAY	TIME SPENT COMPARED TO AVERAGE USER (%)
All Gamers:	24min	
Heavy Gamers:	1h, 2min	+258%
Core Gamers:	1h, 40min	+416%
Light Gamers:	2min	-92%

Source: Verto Analytics, April 2016

Source: Verto Analytics, cited by Hwong (2016, p. 1)

For applications, the study surveyed the sample on the popularity of categories and found that personalisation was by far the most popular category, followed by fitness, diet, and productivity. The study recommends that popular categories that scored over 80 in the survey (refer to Figure 4.1) use the higher earning subscription model, and applications in less popular categories to use the lower earning freemium model. Refer to Figure 6.2 for monetisation model selection decision model.

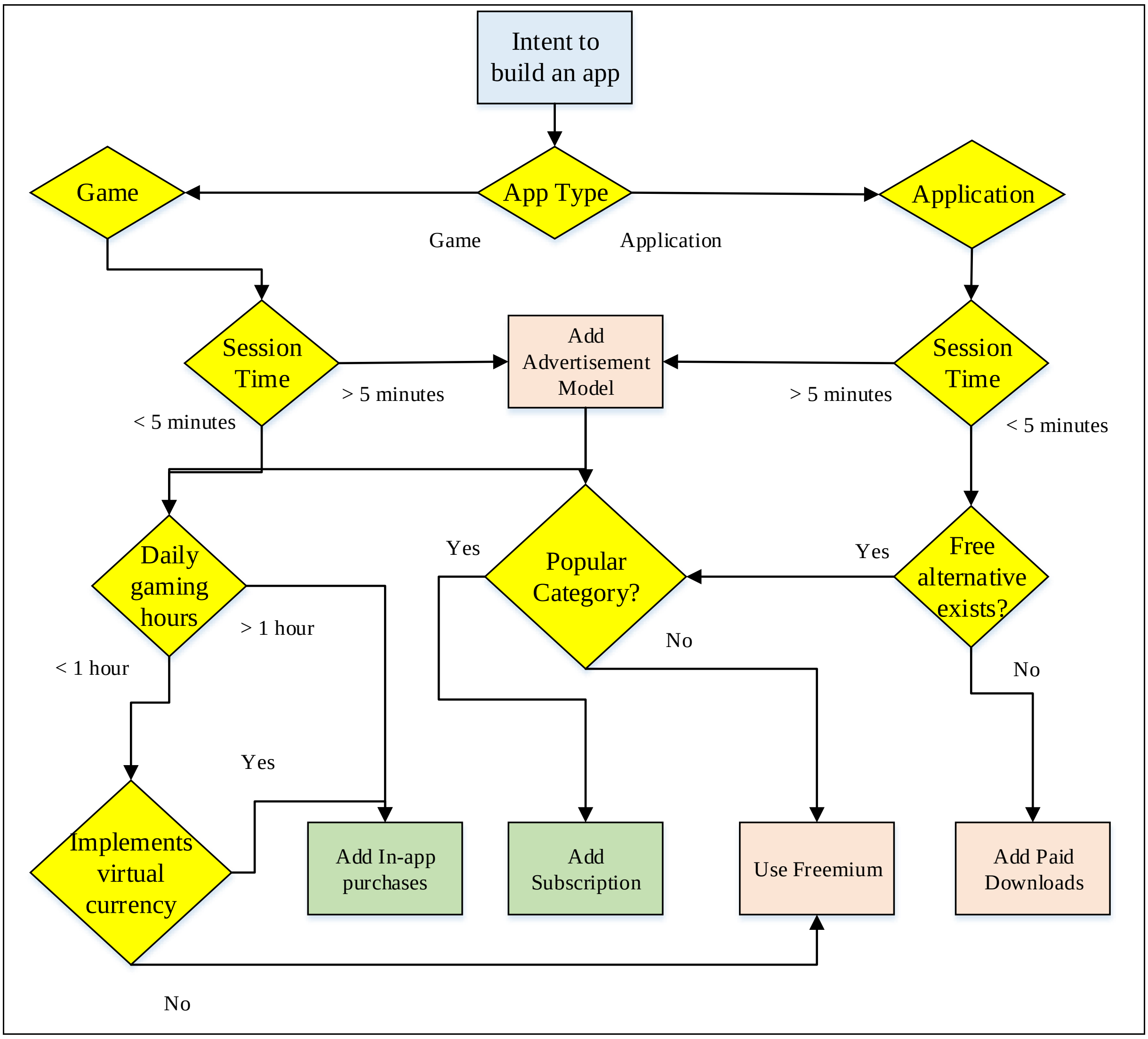


Figure 6.2 Android monetisation model selection decision flow chart

6.4 Recommendations for Mobile App Seller Success

Finally, for app sellers to succeed in the market and boost their app sales they should work on improving their ratings, reputation, and monetisation by following the recommendations in Table 6.4.

Table 6.4 Summary of Recommendations

Recommendation	Actions Required to Apply the Suggested Recommendation
Maintain higher ratings because it is the first impression consumers get.	Responding to customer complaints.
	Fix bug in timely manner.
	Provide customer service when needed.
	Actively ask users to provide high star rating and provide a shortcut link to direct users to the rating dialog box.
Build a reputation in mobile app stores.	Responding to positive and negative comments.
	Aim for building superior apps in terms of quality and experience.
	Provide refunds when warranted, to reflect honest trading.

Boost game monetisation.	Design games that players can spend long session playing, however games should be designed to provide a fulfilling experience as opposed to repetitive action games that trigger addictive tendencies like slot machine gambling games.
	Focus development resources on multi-player mode games because as study shows network-gamers depict less conservative spending behaviour than single-mode players.
	Make sale offerings early for mobile applications.
	Adopt uncapped monetisation models for mobile applications like subscription because spending behaviour of application consumers remains statistically constant.

Mobile apps product life cycle consists of four stages (Knitowski 2017). These are outlined as follows:

1. Strategy and planning.
2. Development and testing.
3. Product launch.
4. User engagement and monetisation.

As a suggestion for mobile app sellers to produce successful products, Figure 6.3 provides a set of summary recommendations for each stage of the mobile apps' life cycle.

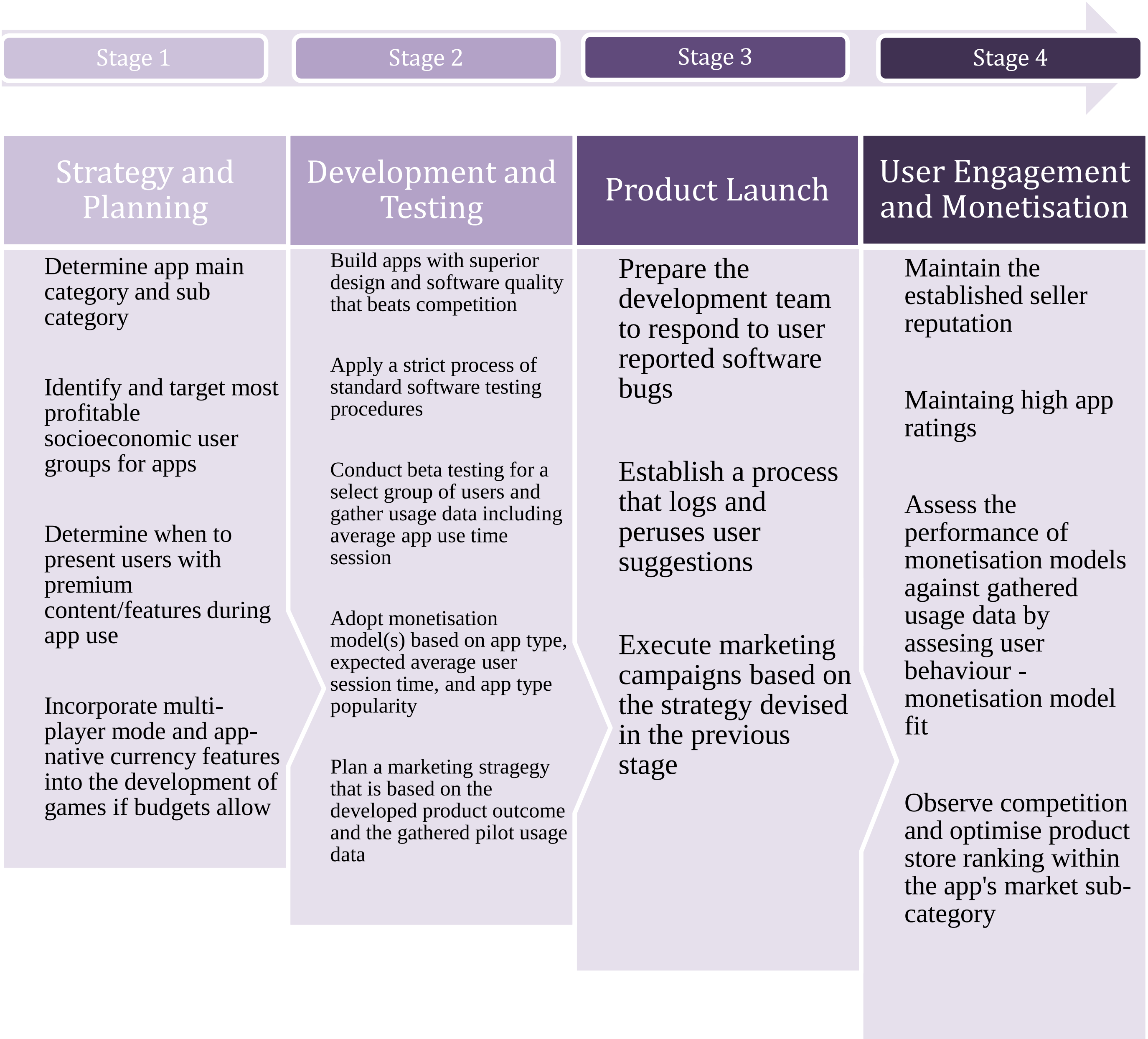


Figure 6.3 Recommendations for each product life stage of mobile apps from inception to market

6.4.1 Stage One: Strategy and Planning

The first step in product planning is determining the category in which the planned app belongs; this research found that user behaviour varies according to type of app used, and therefore all design and later planning depends on first determining app type. Mobile apps' main categories are games and applications. Games are apps that offer enjoyment to customers and applications are apps that provide usefulness and problem solving to customers. The monetisation model selection diagram for these main categories is illustrated in Figure 6.2, section 6.3.

The second step in product planning is determining the target user groups for the planned app; this study found no statistical differences among different socioeconomic user groups in spending on applications. However, for games, this study found that sellers should target user age groups between 18 and 44 years.

Based on this research findings, freemium applications should attempt to monetise very early compared to games, meaning that applications should offer their premium features during their first interaction with users. This is recommended because this study found the following:

- Users initially displayed less pain of paying towards applications compared to games.
- The users' continued reliance on an application did not sway their spending behaviour or their willingness to buy premium features.

On the other hand, freemium games should allow players to first experience and enjoy them, and as players become invested in playing them, games then should attempt to monetise by offering players premium content. This is recommended because this study found the following:

- Users initially displayed more pain of paying towards games compared to applications.
- Continued play of mobile games for longer sessions relaxed players' pain of paying and increased their willingness to buy premium content or features.

To apply these strategies, applications should be designed to communicate their value to users on the very first interaction, and games should be designed for longer play time and be able to entertain users for longer time every play session.

For games, sellers should invest in developing native currency for the games to reward users and enable them to purchase premium content with it. Moreover, sellers should design games that support multi-player modes so that players can cooperate or compete inside the games. It is worth mentioning, however, that native currency and multi-player support require higher development budgets and time. But if sellers could fund these features, they could potentially boost their earnings. These features are recommended because this study found as follows:

- Multi-player mode players play longer hours and exhibit higher spending behaviour compared to single-player mode players.
- Players exhibit higher spending behaviour when spending on games with native currency than with real money spent via online debit.

6.4.2 Stage Two: Development and Testing

Proper software development methodologies and tests are well established in the software industry. One such methodology is the agile methodology, which is an iterative software development approach that aims to build software incrementally (Linchpin SEO 2019). Figure 6.4 illustrates the agile method's steps.

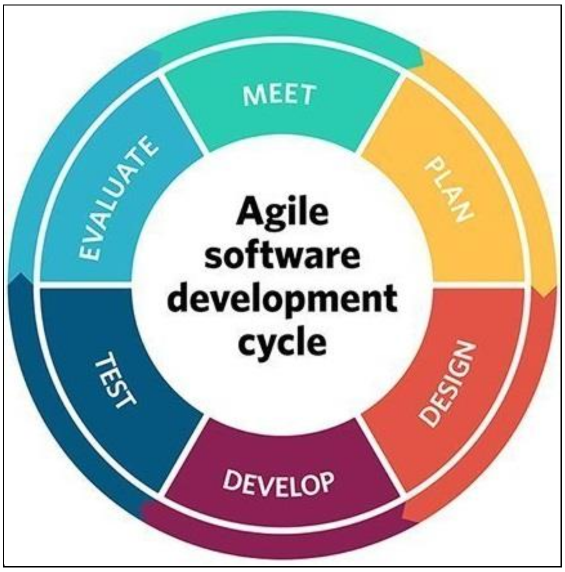


Figure 6.4 Agile software development cycle stages

Source: Rouse and Silverthorne (2017, p. 1)

Alternatively, the developers may use a form of agile named rapid application development (RAD) for faster app development. RAD leverages quick software development tools and user feedback over strict software requirements and is credited with shortening the production-to-market time for software products (Anderson 2019). Figure 6.5 illustrates the RAD method's steps.

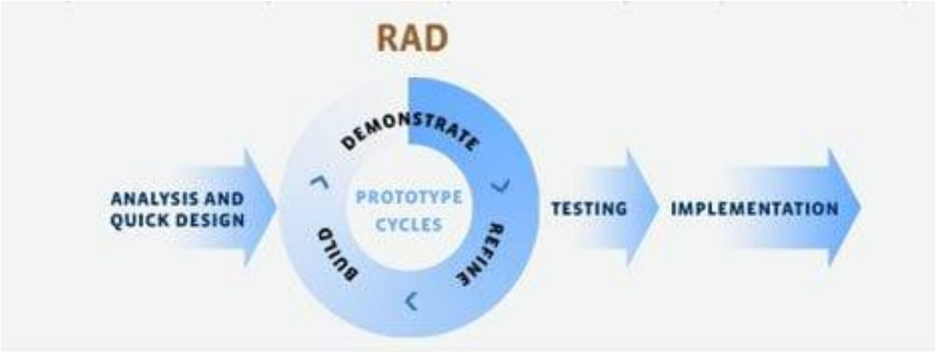


Figure 6.5 RAD software development cycle stages

Source: Anderson (2019, p. 1)

Reccomendations for the development process based on the findings of the current study are as follows. During the development process, app sellers should survey the market for established and for newly emerging competition; they should analyse competing app features and store feedback in order to either incorporate successful features in their product or to build an overall superior product.

Thorough software testing is also necessary prior to publishing to ensure a solid product launch and minimise initial negative reviews/ratings on the app store page due to software bugs. App sellers should determine and implement the selection of tests that are relevant and necessary for their product, ranging from alpha to acceptance to beta testing (Software Testing Help 2019).

App sellers should distribute the app package (APK for Android) to a select group of customers for pilot testing where statistical usage data can be gathered to inform the sellers of the expected user behaviour and average sessions times they can expect from customers in the market.

Upon gathering usage data, sellers then should devise a business model comprised of the monetisation models available on Google Play platform and incorporate these models into the app's software. As part of this research outcomes, Figure 6.2 in section 6.3 suggests a monetisation model selection method based on app type, user average session time, app category popularity, the presence of free alternatives in the market, and the use of native currency.

Finally, the app sellers should devise a marketing strategy that is based on the adopted business model and the gathered pilot usage data. App sellers can either leverage one or a combination of marketing strategies in their overall strategy to reach customers (refer to Figure 6.6, which illustrates the types of marketing strategies used for mobile app marketing).

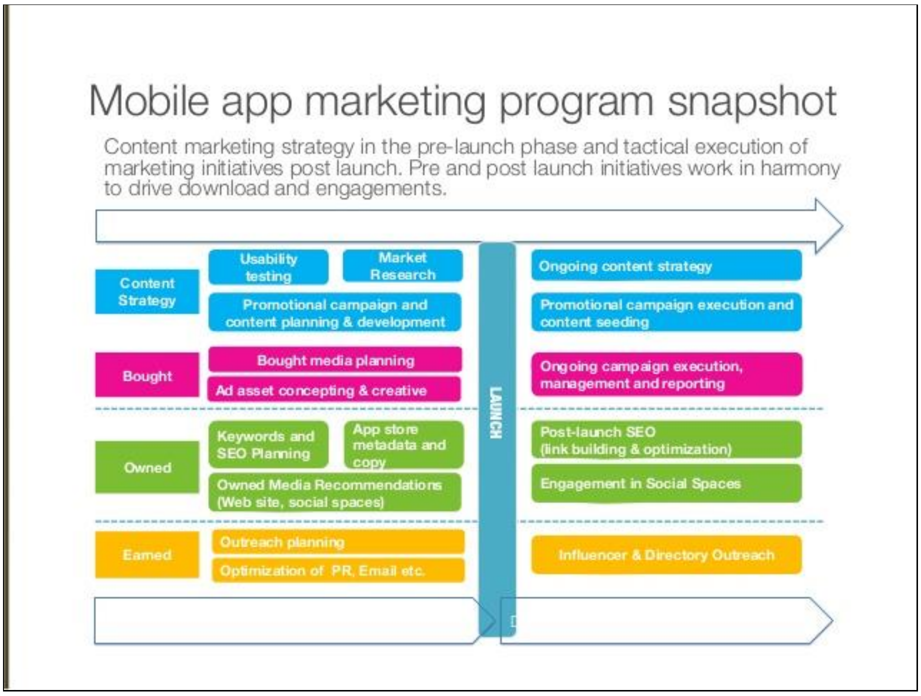


Figure 6.6 Marketing strategies for mobile apps

Source: Pasqua (2013, p. 76)

Marketing strategies are categorised as follows.

Paid marketing: App sellers pay to advertise their product on websites, social media platforms and other mobile apps to generate traffic to their apps using pay per impression or pay per click (Pasqua 2013). This strategy is suitable for apps with high earning monetisation models (refer to Figure 2.7) because with pay per click, the sellers must pay for each download, and not all downloaders will convert to premium buyers.

Owned marketing: App sellers employ free marketing methods, such as leveraging their own websites and blogs, to advertise their apps, and more importantly boost their store ranking (visibility) by conducting constant app store optimisation (Pasqua 2013). This marketing strategy is suitable for all monetisation models, but sellers must be aware that it is often labour intensive and the increased costs manifests in labour wages.

Earned marketing: App sellers create viral media content or hire social media influencers to generate interest and positive sentiment towards the mobile app product (Pasqua 2013). The costs of this strategy varies according to the production costs of viral media or the service rates of a selected influencer. However, the strategy remains only suitable for apps with high earning monetisation models because the costs of media production or influence are often substantial.

6.4.3 Stage Three: Product Launch

Sellers often expect problems when releasing new software. Optimal software testing methodologies are recommended to minimise release problems and bugs (Dohi, Nishio & Osaki 1999). However, new releases will still contain bugs and other problems that are then later discovered and reported by the public. In the mobile app market, app users who are confronted with these problems and defects will often resort to app listing reviews and ratings to report and complain about the bugs (Khalid et al. 2015). Negative reviews and ratings can mean that newly released apps have an unsuccessful start and would most likely dissuade undecided customers from installing them. To minimise the impact of this, the app sellers should be prepared to respond to reported problems and to fix them in a timely manner.

Newly created apps are always subject to optimisation, feature changes, and updates before reaching maturity. Sellers can adopt software maturity methodologies like the capability maturity model (refer to Figure 6.7) to refine and optimise their software products (Rouse & Jayaram 2007).

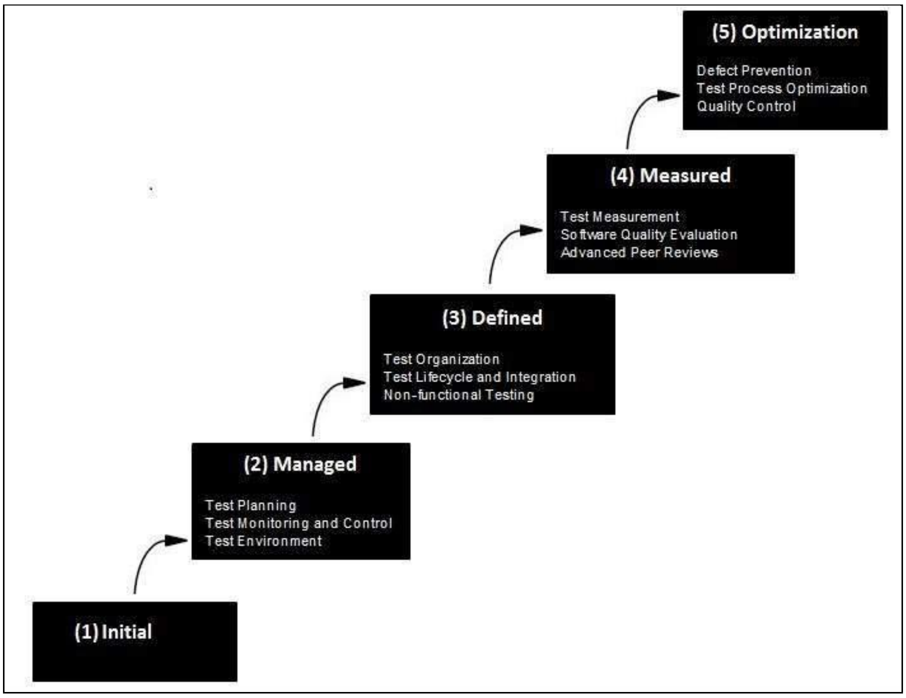


Figure 6.7 Levels of Capability Maturity Model

Source: Tutorials Point (n.d, p. 1)

Upon an apps release it reaches optimisation stage. At this stage, sellers are recommended to systematically gather user suggestions and feature requests that are often sent by emails and expressed in reviews. Sellers should use dedicated models for feedback collection, review, preauthorisation, and eventually application to the mobile app (Fabijan, Olsson & Bosch 2015). This achieves more user satisfaction, builds their reputation as responsive sellers, and improves app value.

Finally, the sellers should embark on executing one or more of the marketing campaigns planned in stage two above and continuously assess their performance using measurable metrics (detailed in Table 6.5).

Table 6.5 App usage, engagement and profitability metrics

Engagement and app usage	Profitability
Installs	Cost Per Install (CPI)
App Acquisition	Cost Per Acquisition (CPA)
Stickiness	Conversion Rate (CR)
Retention Rate	Lifetime Value (LTV)
Active Users	Return On Investment (ROI)
Monthly Active Users (MAU)	Average Revenue Per User (ARPU)
Daily Active Users (DAU)	Average Revenue Per Paying User (ARPPU)
Churn Rate	Return On Advertising Spend (ROAS)

Source: Coniglio (2019, p. 1)

6.4.4 Stage Four: User Engagement and Monetisation

Seller reputation is necessary for maintaining success and sales in the mobile app market (Arora, Ter Hofstede & Mahajan 2017). Reputation is grown over time and is established by building quality apps and providing good customer service; the latter is reflected in reviews and ratings and should be maintained by doing the following:

- Respond to user complaints.

- Acknowledge feature requests.
- Providing refunds when possible.

Apps' reputations are often reflected by their ratings. Mobile app ratings are the first indication of product quality that the users see upon finding a new app to install. Arora, Ter Hofstede and Mahajan (2017), Hsu and Lin (2015), and Liu, Au and Choi (2014) have all emphasised the importance of ratings in maintaining high rankings in stores and generating sales from their apps. Therefore, this study recommends that mobile app sellers should maintain high ratings by doing the following:

- Address user negative reviews and attempt to fix reported issues.
- Ask users via an in-app dialogue box to award them a 5-star rating if the users are satisfied with the apps.

As apps gather more users from the market, sellers should gather statistical usage data, such as daily active users, retention rates, and average session times, to track user behaviour on the apps and evaluate overall user behaviour fit to the business model. If the measured market user behaviour differs from what was predicted or measured during pilot testing, the app sellers should revise their business model composition to fit the market behaviour. (Figure 6.4, section 6.3 illustrates the monetisation model supported in Google Play platform.)

Finally, app sellers must observe competition within apps' subcategories and keep looking for clone apps. Clone apps are a problem in the market, especially for successful apps, where 97% of top paid apps in Google Play were cloned (Arxan 2014). App sellers should also track similar apps that compete for the same store search keywords and continuously conduct app store optimisation to improve and maintain their store ranking, which Liu, Au and Choi (2014) found to be very important for organic traffic and visibility, especially for hedonic apps. App store ranking can be improved by optimising the following:

- App title.
- Short description.
- Long description.
- App screenshots.

Furthermore, app sellers should also focus on:

- Attracting more downloads.

- Improve conversion rates.
- Attending ratings and reviews.
- Fix app issues and improve performance.

6.5 Developed Strategic Model as per Research Outcome

Figure 6.8 is a diagrammatic overview of the research recommendations mobile app sellers should apply during the four stages of a mobile app lifecycle to maximise the prospects of success in the market. The diagram is derived from factors and recommendations gathered from primary and secondary sources. The mobile app success factors found in this research and in the discussed literature are included in this framework.

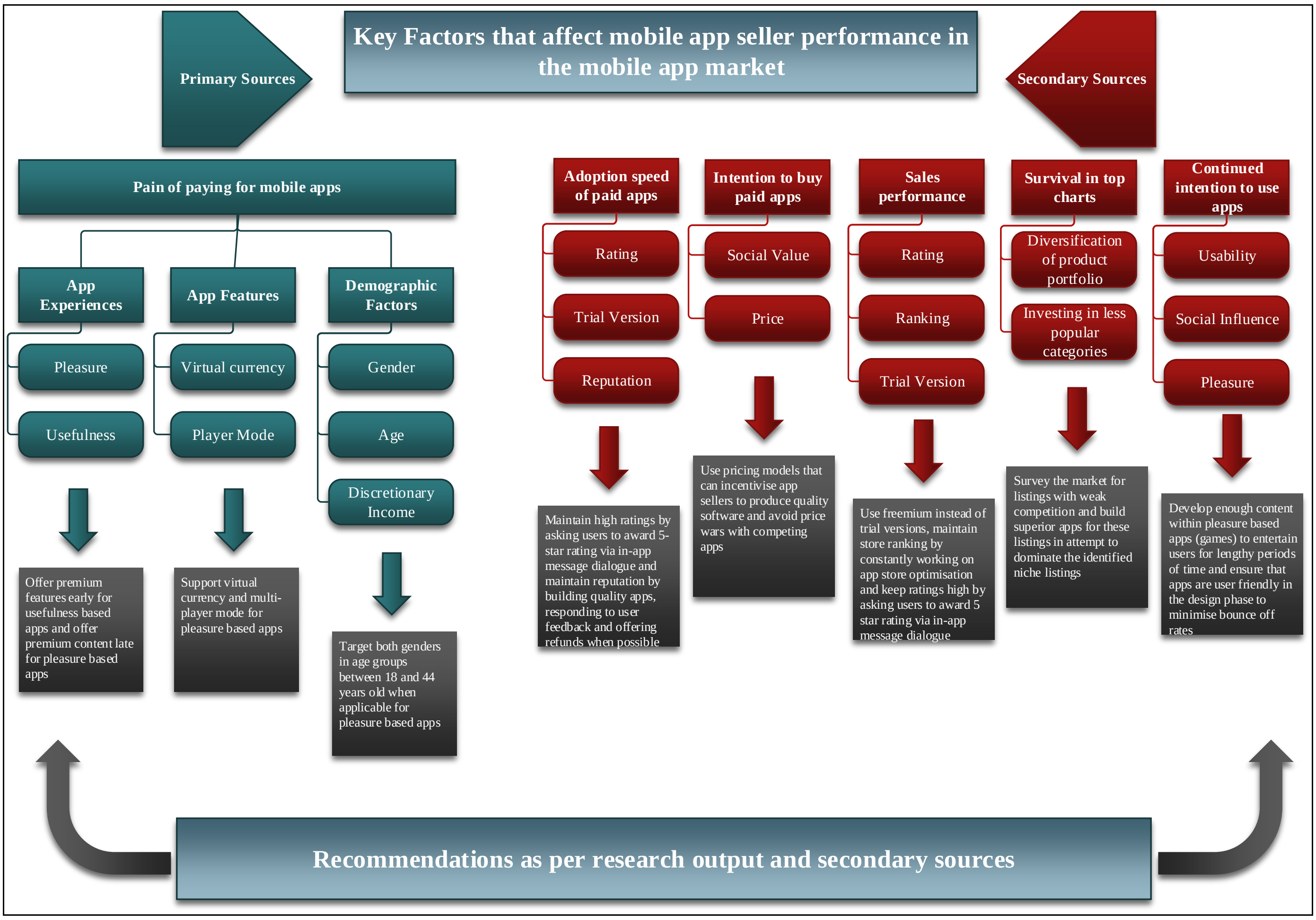


Figure 6.8 Strategic model of factors that contribute to mobile app seller performance in the mobile app market

Based on the analysis conducted, native currency and pleasure were accepted into the model, while competition and recognition were removed. The analysis showed that utility is a factor of pain of paying, when compared to pleasure; therefore, it is also retained in the final model, noting that on a continuous scale, utility has weak regression with pain of paying. This means that while basic application usefulness is associated with reduced consumers' pain of paying, more usefulness does not influence further reduction in pain of paying (refer to Figure 4.16 for model illustration).

For app sellers to succeed in the market and boost their app sales, they should maintain higher ratings because it is the first impression noted by the consumers. First, the developers should respond to customer complaints, as this indicates their faith in them. Responding to complaints means that the app developers utilise the negative feedback or criticism to create a better experience for the customers.

Additionally, fixing bugs in a timely manner shows that the developers care about the consumers as well as their experiences. If the apps remain unfixed, the developers risk losing the traffic due to a poor reception by the consumers. Since the customer is often placed first, it is necessary to provide customer service when needed. Developers that can offer excellent customer service retain and attract more customers. For higher ratings, as well, it would be feasible enough to actively request users to provide them, while the developers provide a shortcut link to direct users to the rating dialog box. Furthermore, it would be plausible enough to build a reputation in the store by 1) responding to positive and negative comments, 2) aiming to build superior apps in terms of quality and experience, and 3) providing refunds when warranted, to reflect honest trading. First, when developers focus on all comments from customers, they maintain the positives while rectifying the negatives. Again, when they are inclined toward more superior apps, the customers observe their efforts, and they are inevitably captured by the quality and experience. Most importantly, the developers should earn the customers' trust by ensuring that the latter receive any refunds when required.

Finally, boosting game monetisation is significant as it works toward generation of profits and revenue. It takes place when developers create and design games that players can spend long sessions playing, thereby, offering fulfilling experiences. The games should not be repetitive action games that end up causing addictive tendencies like slot machine gambling games. Additionally, for game monetisation, designers should focus development resources on multi-player games as the study indicated that network players spend more money compared to single-mode players. Lastly, the success of app sellers is dependent on the development of fun native currency (like gold coins or jewels) for consumers to use during in-app purchases.

For consumers, the main recommendation is that they should resort to employing rational and logical thoughts while making any purchases to lessen the feelings of pain. These individuals should oversee their behaviours and maintain self-control to ensure they do not spend more money than they earn. Unless one’s discretionary income is high enough, maintaining self-regulation impedes any cases of resource depletion. Living beyond one’s means should not be part of the experiences affiliated with consumer behaviour in mobile apps. Consumer behaviour, as indicated, is dependent on different factors, which delineate the proper or improper disposition of funds. It is best for consumers to understand their wants, desires, and needs before resorting to the purchase of certain products, and in this case, paid mobile apps.

6.6 Recommendations for Future Research Study

The mobile app market is one of the largest online markets in the world, boasting millions of products and over a billion users. In the year 2017, the industry had surpassed expectation and reached an 86 billion dollar valuation (App Annie 2018). Yet, the market is relatively new, which provides ample opportunities for researchers to explore and study.

Future researchers are recommended to investigate user spending behaviour of Apple mobile app consumers, and to contrast their findings with this study. Market indicators have shown that Apple consumers are higher spenders on mobile apps compared to Android users, who were the subject of this study (Statista 2018).

Consumer behaviour of people varies across countries due to the cultural and economic differences among them (Lim et al. 2015). This study was confined to the Australian market but could be be extended to address other countries. Future researchers are advised to apply this research on data gathered from other countries such as the US, India and China, who are the top countries in terms of number of smartphone users (Newzoo 2019).

Future researchers can also research other aspects of the app market, such as software security and user data privacy, which both are of great significance and implications to today’s societies, as shown in the case of the Facebook data leak that reportedly affected the privacy of 50 million users (Wong 2018).

Finally, many niche industries exist within the mobile app market, like medicine and education. Industry professionals from these sectors develop mobile apps dedicated to improving the services they offer to people in their respective societies. Further research is recommended to understand their needs and potentially invent new technologies that could further realise their online potential.

REFERENCES

Abran, A, Khelifi, A, Suryn, W & Seffah, A 2003, 'Usability meanings and interpretations in ISO standards', *Software Quality Journal*, vol. 11, no. 4, pp. 325-338.

Ajzen, I 1985, 'From intentions to actions: A theory of planned behavior', in J Kuhl & J Beckmann (eds), *Action control*, pp. 11-39, Springer Publishing, Berlin.

Ajzen, I 1991, 'The theory of planned behavior', *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 179-211.

Akinci, S, Atilgan-Inan, E & Aksoy, S 2010, 'Re-assessment of ES-Qual and E-RecS-Qual in a pure service setting', *Journal of Business Research*, vol. 63, no. 3, pp. 232-240.

Alvarez, B & Vázquez Casielles, R 2005, 'Consumer evaluations of sales promotion: the effect on brand choice', *European Journal of Marketing*, vol. 39, no. 1/2, pp. 54-70.

AMAC Training n.d., *Models and theories of health behaviour (4): The theory of reasoned action*, viewed 16 January 2019, http://amactraining.co.uk/resources/handy-information/free-learning-material/models-and-theories-of-health-behaviour-change-index/models-and-theories-of-health-behaviour-4/

Amalfitano, D, Amatucci, N & Memon, AM 2017, 'A general framework for comparing automatic testing techniques of Android mobile apps', *The Journal of Systems & Software*, vol. 125, pp. 322-343.

Amine, LS & Tamer Cavusgil, S 1986, 'Export marketing strategies in the British clothing industry', *European Journal of Marketing*, vol. 20, no. 7, pp. 21-33.

Analytics Vidhya 2015, *7 Types of regression techniques you should know*, viewed 15 December 2018, https://www.analyticsvidhya.com/blog/2015/08/comprehensive-guide-regression/

Anderson, C 2009, *Free: the future of a radical price*, Random House, New York.

Anderson, K 2019, *What is rapid application development (RAD)?*, viewed 29 September 2019, https://blog.capterra.com/what-is-rapid-application-development/

Android Developers 2018, *Google play billing overview*, viewed 17 December 2018, https://developer.android.com/google/play/billing/billing_overview

App Annie 2018, *Consumer spend in app stores exceeded $86 billion in 2017,* viewed 20 November 2018, https://www.appannie.com/en/insights/market-data/consumer-spend-app-stores-86-billion-2017/

App Samurai 2019, *How to do mobile app personalization that retains users,* viewed 15 August 2019, https://appsamurai.com/how-to-do-mobile-app-personalization-that-retains-users/

App Store 2018, *Ratings, reviews, and responses*: *App Store*, viewed 20 September 2018, https://developer.apple.com/app-store/ratings-and-reviews/

Apple Music 2019, *Apple Music*, viewed 27 March 2019, https://www.apple.com/au/apple-music/

Apple Store, A 2015, *Mobile app categories in the app store*, viewed 10 January 2016, https://itunes.apple.com/au/genre/ios/id36?mt=8

Ariely, D 2013, *Cash versus credit*, viewed 29 October 2018, http://danariely.com/2013/03/21/cash-versus-credit/

Arkes, HR & Blumer, C 1985, 'The psychology of sunk cost', *Organizational Behavior and Human Decision Processes,* vol. 35, pp. 124-140.

Arora, S, Ter Hofstede, F & Mahajan, V 2017, 'The implications of offering free versions for the performance of paid mobile apps', *Journal of Marketing,* vol. 81, no. 6, pp. 62-78.

Arxan 2014, *Arxan's annual report: 'state of mobile app security' reveals an increase in app hacks for top 100 mobile apps*, viewed 30 September 2019, https://www.arxan.com/press-releases/arxans-annual-report-state-of-mobile-app-security-reveals-an-increase-in-app-hacks-for-top-100-mobile-apps

Atkinson, JS, Mitchell, JE, Rio, M & Matich, G 2018, 'Your WiFi is leaking: what do your mobile apps gossip about you?', *Future Generation Computer Systems,* vol. 80, pp. 546-557.

Azarian, I 2013*, Why is documentation extremely important for developers?,* viewed 10 December 2018, https://www.seguetech.com/why-is-documentation-extremely-important-for-developers/

Babakus, E & Mangold, WG 1992, 'Adapting the SERVQUAL scale to hospital services: an empirical investigation', *Health Services Research,* vol. 26, no. 6, p. 767.

Baghbaniyazdi, S & Ferdosara, H 2017, 'The most successful business model of mobile applications: A comparative analysis of six Iranian mobile games', *Journal of Software,* vol. 12, no. 3, pp. 201-211.

Baker, J, Levy, M & Grewal, D 1992, 'An experimental approach to making retail store environmental decisions', *Journal of Retailing,* vol. 68, no. 4, p. 445.

Bar-Isaac, H & Tadelis, S 2008, 'Seller reputation', *Foundations and Trends® in Microeconomics,* vol. 4, no. 4, pp. 273-351.

Bawa, K & Shoemaker, R 2004, 'The effects of free sample promotions on incremental brand sales', *Marketing Science,* vol. 23, no. 3, pp. 345-363.

BC Campus 2018, *Reliability and validity of measurement, research methods in psychology*, viewed 1 December 2018, https://opentextbc.ca/researchmethods/chapter/reliability-and-validity-of-measurement/

Becker, SW, Ronen, J & Sorter, GH 1974, ‘Opportunity costs-an experimental approach’, *Journal of Accounting Research*, vol. 12, no. 2, pp. 317-329.

Belk, R & Tumbat, G 2005, ‘The cult of Macintosh’, *Consumption Markets & Culture,* vol. 8, no. 3, pp. 205-217.

Benzion, U, Rapoport, A & Yagil, J 1989, ‘Discount rates inferred from decisions: an experimental study’, *Management Science*, vol. 35, no. 3, pp. 270-284.

Bhakat, R & Muruganantham, G 2013, ‘A review of impulse buying behavior’, *International Journal of Marketing Studies*, vol 5, no. 3, p. 156.

Bick, A, Fuchs-Schündeln, N & Lagakos, D 2018, ‘How do hours worked vary with income? Cross-country evidence and implications’, *American Economic Review,* vol. 108, no. 1, pp. 170-99.

Bloomberg 2005, *Google buys Android for its mobile arsenal*, viewed 1 March 2016, http://www.bloomberg.com/bw/stories/2005-08-16/google-buys-android-for-its-mobile-arsenal

Boag, P 2015, *Why you should want to be a user experience developer*, viewed 16 March 2019, https://boagworld.com/dev/why-you-should-want-to-be-a-user-experience-developer/

Bond, R. & Smith, PB 1996, ‘Culture and conformity: A meta-analysis of studies using Asch's (1952b, 1956) line judgment task’, *Psychological Bulletin,* vol. 119, no.1, p. 111.

Burns, KE, Duffett, M, Kho, ME, Meade, MO, Adhikari, NK, Sinuff, T & Cook, DJ 2008, ‘A guide for the design and conduct of self-administered surveys of clinicians’, *Canadian Medical Association Journal,* vol. 179, no. 3, pp. 245-252.

Business Insider 2015, *Google Play has more apps than Apple now but it's still behind in one key area*, viewed 1 March 2016, http://www.businessinsider.com.au/google-play-vs-apple-app-store-2015-2?r=US&IR=T

Calder, BJ, Phillips, LW & Tybout, AM 1981, ‘Designing research for application’, *Journal of Consumer Research,* vol. 8, no. 2, pp. 197-207.

Canalys 2012, *Top 25 US developers account for half of app revenue*, viewed 1 March 2016, http://www.canalys.com/newsroom/top-25-us-developers-account-half-app-revenue

Colman, AM, Norris, CE & Preston, CC 1997, ‘Comparing rating scales of different lengths: Equivalence of scores from 5-point and 7-point scales’, *Psychological Reports,* vol. 80, no. 2, pp. 355-362.

Coniglio, G 2019, *Mobile app marketing – A guide to the main KPIs (Part 1)*, viewed 30 September 2019, http://blog.instal.com/mobile-app-marketing-a-guide-to-the-main-kpis-part-1/

Cooper, RG 1979, ‘The dimensions of industrial new product success and failure’, *The Journal of Marketing*, vol 43, no. 3, pp. 93-103.

Cox III, EP 1980, ‘The optimal number of response alternatives for a scale: A review’, *Journal of Marketing Research*, vol. 17, no. 4, pp. 407-422.

Cronbach, LJ 1946, ‘Response sets and test validity’, *Educational and Psychological Measurement*, vol. 6, no. 4, pp. 475-494.

Cruz, AMR, & Paiva, S 2016, *Modern software engineering methodologies for mobile and cloud environments*, IGI Global, Hershey, PA, USA.

Cyr, K 2015, *Key stakeholders in mobile strategy development [Part 2]*, viewed 10 December 2018, https://www.mobify.com/insights/key-stakeholders-in-mobile-strategy-development-part-2/

Davidson, D, Fredrikson, M, & Livshits, B 2014, ‘MoRePriv: Mobile OS support for application personalization and privacy’, *ACSAC 14: Proceedings of the 30th Annual Computer Security Applications Conference,* ACM, New York, NY, USA, pp. 236-245.

DeCoster, J 2000, *Scale construction notes*, viewed 19 May 2017, http://www.stat-help.com/scale.pdf

DeFranzo, S E 2012, *4 main benefits of survey research*, viewed 20 November 2018, https://www.snapsurveys.com/blog/4-main-benefits-survey-research/

Dent, S 2014, *What you need to know about Uber, Lyft and other app-based car services,* viewed 14 March 2019, https://www.engadget.com/2014/06/27/uber-lyft-explainer/

DeVellis, RF 2016, *Scale development: theory and applications*, Sage publications, California.

Dey, D & Lahiri, A 2013, ‘The zero-day DLC strategy: a case for versioning to facilitate product sampling’, *Working Paper, Rochester*, http://www.teis-workshop.org/papers/2013/02_The_Zero-Day_DLC_Stra1egy.pdf

Diamantopoulos, A & Siguaw, JA 2000, *Introducing LISREL*, Sage Publications, London, UK.

Digi Capital 2014, *Mobile apps to hit >$70B revenue driven by explosion of diversity*, viewed 07 October 2014, http://www.digi-capital.com/news/2014/04/mobile-apps-to-hit-70b-revenue-driven-by-explosion-of-diversity/

Distimo 2011, *In-depth view on download volumes in the Google Android market*, viewed 1 March 2016, www.distimo.com/publications

Dohi, T, Nishio, Y & Osaki, S 1999, ‘Optimal software release scheduling based on artificial neural networks’, *Annals of Software Engineering*, vol. 8, no. 1-4, pp. 167-185.

Donovan, RJ, Rossiter, JR, Marcoolyn, G & Nesdale, A 1994, 'Store atmosphere and purchasing behavior', *Journal of Retailing*, vol. 70, no. 3, pp. 283-294.

Eskandari, M, Kessler, B, Ahmad, M, de Oliveira, AS & Crispo, B 2017, 'Analyzing remote server locations for personal data transfers in mobile apps', *Proceedings on Privacy Enhancing Technologies*, vol. 2017, no. 1, pp. 118-131.

Fabijan, A, Olsson, HH and Bosch, J 2015, 'Customer feedback and data collection techniques in software R&D: A literature review', *International Conference of Software Business,* Springer, Cham, pp. 139-153.

Families Magazine 2018, *REVIEW: Is the Harry Potter Hogwarts mystery app suitable for kids?*, viewed 15 September 2019, https://www.familiesmagazine.com.au/harry-potter-hogwarts-mystery-app/

Faugère, C & Tayi, GK 2007, 'Designing free software samples: a game theoretic approach', *Information Technology and Management*, vol. 8, no. 4, pp. 263-278.

Fisher, I 1930, *The theory of interest*, Augustus M. Kelley Publishers 1965, New York.

Fisher, S 1994, 'Identifying video game addiction in children and adolescents', *Addictive Behaviors*, vol. 19, no. 5, pp. 545-553.

Floyd, FJ & Widaman, KF 1995, 'Factor analysis in the development and refinement of clinical assessment instruments', *Psychological Assessment*, vol. 7, no.3, p. 286.

Frederick, S, Novemsky, N, Wang, J, Dhar, R & Nowlis, S 2009, 'Opportunity cost neglect', *Journal of Consumer research*, vol 36, no. 4, pp. 553-561.

French, JR, Raven, B & Cartwright, D 1959, 'The bases of social power', *Classics of Organization Theory*, vol. 7, pp. 311-320.

Friedman, LA & Neumann, BR 1980, ‘The effects of opportunity costs on project investment decisions: A replication and extension’, *Journal of Accounting Research*, vol. 18, no. 2, pp. 407-419.

Garson, D 2007, *Survey research*, viewed 20 September 2018 http://www.chass.ncsu.edu/garson/pa765/survey.htm

Gartner 2014, *Gartner says less than 0.01 percent of consumer mobile apps will be considered a financial success by their developers through 2018*, viewed 20 September 2018, https://www.gartner.com/en/newsroom/press-releases/2014-01-13-gartner-says-less-than-one-tenth-percent-of-consumer-mobile-apps-will-be-considered-a-financial-success-by-their-developers-through-2018

Gartner 2017, *Gartner survey finds that most smartphone users spend nothing on apps*, viewed 5 May 2018, https://www.gartner.com/en/newsroom/press-releases/2017-01-26-gartner-survey-finds-that-most-smartphone-users-spend-nothing-on-apps

Georgieva, G, Arnab, S, Romero, M & Freitas, SD 2015, ‘Transposing freemium business model from casual games to serious games’, *Entertainment Computing*, vol. 9-10**,** pp. 29-41.

Gęsiarz, F & Crockett, MJ 2015, ‘Goal-directed, habitual and Pavlovian prosocial behavior’, *Frontiers in Behavioral Neuroscience*, vol. 9, p. 135.

Gliem, JA & Gliem, RR 2003, ‘Calculating, interpreting, and reporting Cronbach’s alpha reliability coefficient for Likert-type scales’, Retrieved from https://scholarworks.iupui.edu/bitstream/handle/1805/344/Gliem%20%26%20Gliem.pdf?sequence=1&isAllowed=y

Google Play 2015, *Mobile app categories in Google Play Store*, viewed 10 January 2016, https://play.google.com/store?hl=en

Google Play 2018, *Top grossing apps*, viewed 29 October 2018, https://play.google.com/store/apps/collection/topgrossing

Google Play 2019, *Shikaku*, viewed 15 February 2019, https://play.google.com/store/apps/details?id=com.novellectual.shikaku&hl=en_AU

Google Play 2019, *Uber*, viewed 15 February 2019 https://play.google.com/store/apps/details?id=com.ubercab

Google Play Console Help 2018, *Select a category for your app or game*, viewed 15 September 2018, https://support.google.com/googleplay/android-developer/answer/113475?hl=en

Gordon, ME 2013, *The history of app pricing and why most apps are*, viewed 19 September 2018, http://flurrymobile.tumblr.com/post/115189750715/the-history-of-app-pricing-and-why-most-apps-are

Graf-Vlachy, L, Buhtz, K & König, A 2018, 'Social influence in technology adoption: taking stock and moving forward', *Management Review Quarterly*, vol. 68, no. 1, pp. 37-76.

Hardin, B 2016, *Time spent playing different game modes*, viewed 21 September 2019, https://www.gamersexperience.com/mock-time-spent-analysis/

Harman, M, Jia, Y & Zhang, Y 2012, 'App store mining and analysis: MSR for app stores', *IEEE Press*, pp. 108-111.

Hassan, S, Shang, W & Hassan, A 2017, 'An empirical study of emergency updates for top Android mobile apps', *Empirical Software Engineering*, vol. 22, no. 1, pp. 505–546.

Help Scout 2018, *Pricing psychology: 10 timeless strategies to increase sales*, viewed 15 September 2018, https://www.helpscout.net/blog/pricing-strategies/

Heyman, J. & Ariely, D 2004, 'Effort for payment: a tale of two markets', *Psychological Science*, vol. 15, no. 11, pp. 787-793.

Hinterhuber, A 2008, ‘Customer value-based pricing strategies: why companies resist’, *Journal of Business Strategy*, vol. 29, no. 4, pp. 41-50.

Hopper, E 2019, *Maslow's hierarchy of needs explained*, viewed 15 January 2019, https://www.thoughtco.com/maslows-hierarchy-of-needs-4582571

Horst, P 1968, *Personality: measurement of dimensions*, Jossey-Bass, Cornell University, New York.

Hřebíček, J, Schimak, G, Kubásek, M, & Rizzoli, AE 2013, ‘Environmental software systems: fostering information sharing’, *Proceedings of the 10th IFIP WG 5.11 International Symposium,* Heidelberg: Springer, Austria.

Hsu, CL & Lin, JCC 2015, ‘What drives purchase intention for paid mobile apps?–An expectation confirmation model with perceived value’, *Electronic Commerce Research and Applications*, vol. 14, no. 1, pp. 46-57.

Husson University 2018, *Top consumer behavior theories*, viewed 11 December 2018, https://online.husson.edu/consumer-behavior-theories

Hwong, C 2016, *The average mobile game day*, viewed 15 April 2019, https://www.vertoanalytics.com/average-mobile-game-day/

iMore 2018, *History of the app store*, viewed 11 September 2018, https://www.imore.com/history-app-store

Jiang, Z & Sarkar, S 2009, ‘Speed matters: the role of free software offer in software diffusion’, *Journal of Management Information Systems,* vol. 26, no. 3, pp. 207-240.

Johnstone, E & Dodd, CA 2000, ‘Placements as mediators of brand salience within a UK cinema audience’, *Journal of Marketing Communications,* vol. 6, no.3, pp. 141-158.

Joppe, M, 2005, *Survey techniques*, viewed 3 March 2016, http://www.ryerson.ca/~mjoppe/ResearchProcess/SurveyTechniques

Jurevicius, O 2013, *Porter's five forces,* viewed 27 March 2019, https://www.strategicmanagementinsight.com/tools/porters-five-forces.html

Kang, S 2014, 'Factors influencing intention of mobile application use', *Int. J. of Mobile Communications,* vol. 12, no. 4, pp. 360-379.

Kannan, PK & Kopalle, PK 2001, 'Dynamic pricing on the internet: importance and implications for consumer behavior', *International Journal of Electronic Commerce,* vol. 5, no. 3, pp. 63-83.

Katona, G & Mueller, E 1955, 'A study of purchase decisions', *Consumer Behavior: The Dynamics of Consumer Reaction*, vol. 1, pp. 30-87.

Kaur, A 2013, 'Maslow's need hierarchy theory: applications and criticisms', *Global Journal of Management and Business Studies,* vol. 3, no. 1, pp. 1061-1064.

Kelman, HC 1958, 'Compliance, identification, and internalization three processes of attitude change', *Journal of Conflict Resolution,* vol. 2, no. 1, pp. 51-60.

Kemp, C & Gyger, B 2013, *Professional Heroku programming,* J, Wiley & Sons, Chichester, U.K.

Kempf, DS 1999, 'Attitude formation from product trial: Distinct roles of cognition and affect for hedonic and functional products', *Psychology & Marketing,* vol. 16, no.1, pp. 35-50.

Khalid, H, Shihab, E, Nagappan, M & Hassan, AE 2015, 'What do mobile app users complain about?', *IEEE Software,* vol. 32**,** no. 3, pp. 70-77.

Kim, HW, Lee, HL & Son, JE 2011, 'An exploratory study on the determinants of smartphone app purchase', *Proceedings of the 11th International DSI and the 16th*

APDSI Joint Meeting, Taipei, Taiwan.

Kim, J & Morris, JD 2007, ‘The power of affective response and cognitive structure in product-trial attitude formation’, *Journal of Advertising*, vol. 36, no. 1, pp. 95-106.

Kim, SC, Yoon, D & Han, EK 2016, ‘Antecedents of mobile app usage among smartphone users’, *Journal of Marketing Communications*, vol. 22, no. 6, pp. 653-670.

Kim, SJ, Wang, RJH, Maslowska, E & Malthouse, EC 2016, ‘Understanding a fury in your words: the effects of posting and viewing electronic negative word-of-mouth on purchase behaviors’, *Computers in Human Behavior*, vol. 54, pp. 511-521.

Kitchenham, BA & Pfleeger, SL 2002, ‘Principles of survey research: part 3: constructing a survey instrument’, *ACM SIGSOFT Software Engineering Notes*, vol. 27, no.2, pp. 20-24.

Knitowski, A 2017, *Why you should be paying attention to mobile application lifecycle management*, viewed 29 September 2019, https://www.phunware.com/blog/paying-attention-to-mobile-application-lifecycle-management/

Knutson, B, Rick, S, Wimmer, GE, Prelec, D & Loewenstein, G 2007, ‘Neural predictors of purchases’, *Neuron*, vol. 53, no. 1, pp. 147-156.

Kooti, F, Grbovic, M, Aiello, LM, Bax, E & Lerman, K 2017, ‘February. iPhone's digital marketplace: characterizing the big spenders’, *Proceedings of the tenth ACM international conference on web search and data mining*, pp. 13-21.

Kotler, P 1965, ‘Behavioral models for analyzing buyers’, *Journal of Marketing*, vol. 29, no. 4, pp. 37-45.

Kunz, W, Schmitt, B & Meyer, A 2011, ‘How does perceived firm innovativeness affect the consumer?’, *Journal of Business Research*, vol. 64, no. 8, pp. 816-822.

Laerd Statistics 2018a, *Mean, mode and median - measures of central tendency - when to use* *with different types of variable and skewed distributions*, viewed 26 November 2018, https://statistics.laerd.com/statistical-guides/measures-central-tendency-mean-mode-median.php

Laerd Statistics 2018b, *Cronbach's alpha in SPSS statistics - procedure, output and interpretation of the output using a relevant example*, viewed 26 November 2018, https://statistics.laerd.com/spss-tutorials/cronbachs-alpha-using-spss-statistics.php

Laerd Statistics 2018c, *One-way ANOVA in SPSS statistics*, viewed 27 November 2018, https://statistics.laerd.com/spss-tutorials/one-way-anova-using-spss-statistics.php

Laibson, D 1995, ‘Hyperbolic discount functions, undersaving, and savings policy’, *No 5635, NBER Working Papers*, National Bureau of Economic Research, Inc, Harvard University.

Langholtz, HJ, Marty, AT, Ball, CT & Nolan, EC 2002, *Resource-allocation behavior*, Springer Science & Business Media, Berlin.

Lee, G & Raghu, TS 2014, ‘Determinants of mobile apps' success: evidence from the app store market’, *Journal of Management Information Systems*, vol. 31, no. 2, pp. 133-170.

Lenhart, A & Madden, M 2007, *Teens, privacy & online social networks: how teens manage their online identities and personal information in the age of MySpace*, viewed 16 March 2019, https://www.pewtrusts.org/en/research-and-analysis/reports/2007/04/18/teens-privacy-and-online-social-networks-how-teens-manage-their-online-identities-and-personal-information-in-the-age-of-myspace

Levenson, H 2017, *Mobile app personalization: how to do it right*, viewed 15 March 2019, https://usabilitygeek.com/mobile-app-personalization-how-to/

Levy, SJ 1959, ‘Symbols for sale’, *Harvard Business Review*, vol. 37, no. 4, pp. 117-119.

Li, G, Zhang, R & Wang, C 2015, ‘The role of product originality, usefulness and motivated consumer innovativeness in new product adoption intentions’, *Journal of Product Innovation Management*, vol. 32, no. 2, pp. 214-223.

Liao, SL, Shen, YC & Chu, CH 2009, ‘The effects of sales promotion strategy, product appeal and consumer traits on reminder impulse buying behaviour’, *International Journal of Consumer Studies*, vol. 33, no. 3, pp. 274-284.

Lim, SL, Bentley, PJ, Kanakam, N, Ishikawa, F & Honiden, S 2015, ‘Investigating country differences in mobile app user behaviour and challenges for software engineering’, *IEEE Transactions on Software Engineering*, vol. 41, no. 1, pp. 40-64.

Linchpin SEO 2019, *A beginner’s guide to the agile method & scrums*, viewed 29 September 2019, https://linchpinseo.com/the-agile-method/

Liu, CZ, Au, YA & Choi, HS 2014, ‘Effects of freemium strategy in the mobile app market: An empirical study of Google Play’, *Journal of Management Information Systems*, vol. 31, no. 3, pp. 326-354.

Lu, J, Liu, C & Wei, J 2016, ‘How important are enjoyment and mobility for mobile applications?’, *Journal of Computer Information Systems*, vol. 57, no. 1, pp. 1-12.

Liu, X, Ai, W, Li, H, Tang, J, Huang, G, Feng, F & Mei, Q 2017, ‘Deriving user preferences of mobile apps from their management activities’, *ACM Transactions on Information Systems (TOIS)*, vol. 35, no. 4, p. 39.

Macrumors 2014, *Flappy Bird creator reveals why he pulled the app, 'considering' returning Flappy Bird to app store*, viewed 1 March 2016, http://www.macrumors.com/2014/03/11/flappy-bird-dong-nguyen-interview/.

Malhotra, NK, Hall, J, Shaw, M & Oppenheim, P 2006, *Marketing research: an applied application*, Pearson Education, Australia.

McDaniel, C & Gates, R 2002, *Marketing research: the impact of the Internet*, Thomson

USA.

McLeod, S 2018, *What is a hypothesis?*, viewed 08 December 2018, https://www.simplypsychology.org/what-is-a-hypotheses.html

Medium 2017, *Why ratings and reviews matter in app store optimization,* viewed 20 September 2018, https://medium.com/app-radar-highlights/why-ratings-and-reviews-matter-in-app-store-optimization-5c93d285f029

Michaeli, A 2015, *App stores growth accelerates in 2014*, viewed 20 November 2018, https://blog.appfigures.com/app-stores-growth-accelerates-in-2014/

Miller, B 2020, *ARPU: how to calculate average revenue per user*, viewed 15 July 2020, https://clevertap.com/blog/arpu-everything-you-need-to-know-about-average-revenue-per-user/

Miller, M 2018, *Top predictions for the app economy in 2018*, viewed 20 November 2018, https://www.appannie.com/en/insights/market-data/predictions-app-economy-2018/

Minelli, R & Lanza, M 2013, 'Software analytics for mobile applications--Insights & lessons learned', *IEEE 17th European Conference on Software Maintenance and Reengineering*, pp. 144-153.

Minitab Blog Editor 2018a, *Understanding t-tests: 1-sample, 2-sample, and paired t-tests*, viewed 08 December 2018, http://blog.minitab.com/blog/adventures-in-statistics-2/understanding-t-tests-1-sample-2-sample-and-paired-t-tests

Minitab Blog Editor 2018b, *Understanding t-Tests: t-values and t-distributions*, viewed 08 December 2018, http://blog.minitab.com/blog/adventures-in-statistics-2/understanding-t-tests-t-values-and-t-distributions

MintLife 2018, *What is price anchoring - price anchoring explained*, viewed 08 October 2018, https://blog.mint.com/how-to/price-anchoring/

Mistrík, I, Tang, A, Bahsoon, R & Stafford, JA 2013, *Aligning enterprise system and software architectures*, Business Science Reference, Hershey PA.

Mobi Thinking 2011, *Global mobile statistics*, viewed 29 October 2018, http://mobithinking.com/mobile-marketing- tools/latest-mobile-stats

Moldovan, S, Goldenberg, J & Chattopadhyay, A 2011, 'The different roles of product originality and usefulness in generating word-of-mouth', *International Journal of Research in Marketing*, vol. 28, no. 2, pp. 109-119.

Myers, MD 1997, 'Qualitative research in information systems', *Management Information Systems Quarterly*, vol. 21, no. 2, pp. 241-242.

National Health and Medical Research Council 2018, *National statement on ethical conduct in human research (2007)*, viewed 17 December 2018, https://nhmrc.gov.au/about-us/publications/national-statement-ethical-conduct-human-research-2007-updated-2018#introduction___section_1

National Research Council 2013, *Nonresponse in social science surveys: a research agenda*, National Academies Press, Washington D.C.

Nayebi, F, Desharnais, JM & Abran, A 2012, 'The state of the art of mobile application usability evaluation', *IEEE Canadian Conference on Electrical & Computer Engineering (CCECE)*, pp. 1-4.

Nayebi, M, Adams, B & Ruhe, G 2016, 'Release practices for mobile apps -- What do users and developers think?', *IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering (SANER)*, pp. 552-562.

Nazario, K 2014, *Virtual money in apps can mean real life cash for developers*, viewed 10 January 2015, https://www.appmakr.com/blog/virtual-currencies-the-key-to-real-currency-from-your-app/

Neowin 2018, *If your kids made in-app purchases without your consent, Google may refund you*, viewed 19 November 2018, https://www.neowin.net/news/if-your-kids-made-in-app-purchases-without-your-consent-google-may-refund-you/

Neuman, WL 2014, *Social research methods: qualitative and quantitative approaches*, 7th ed., Pearson Education Limited, Harlow, UK.

Newsted, PR, Huff, S, Munro, M & Schwarz, A 1998, *Introduction to survey instruments*, MISQ Discovery, pp. 553-554.

Newzoo 2019, *Top 20 countries/markets by smartphone users*, viewed 30 September 2019, https://newzoo.com/insights/rankings/top-countries-by-smartphone-penetration-and-users/

Ngwe, D 2017, Fake discounts drive real revenues in retail, *HBS Working Paper Series*, Harvard Business School.

Nisbett, RE & Ross, L 1980, *Human inference: strategies and shortcomings of social judgment*, Prentice-Hall, Englewood Cliff, NJ.

Noort, A 2015, *Show me the money: business models for app developers*, viewed 10 January 2016, http://blog.personagraph.com/show-me-the-money-business-models-for-app-developers

Oppenheim, AN 1992, *Questionnaire design, interviewing and attitude measurement*, New ed., Pinter Publishers, New York, US.

Osei, BA & Abenyin, AN 2016, 'Applying the Engell–Kollat–Blackwell model in understanding international tourists' use of social media for travel decision to Ghana', *Information Technology & Tourism*, vol. 16, no. 3, pp. 265-284.

Osman, N & Sahraoui, AK 2018, 'A software requirement engineering framework to enhance critical success factors for ERP implementation', *International Journal of Computer*

Applications, Foundation of Computer Science, vol. 180, no. 10, pp. 32-37.

Osterwalder, A, Pigneur, Y, Tofts, S, Pash, A & Trapani, G 2011, ‘Business model generation’, *ITNOW*, vol. 53, pp. 60-61.

Pasqua, R 2013, *Mobile app marketing* [PowerPoint presentation], viewed 29 September 2019, https://www.slideshare.net/rachelpasqua/mobile-app-marketing-nyu-school-of-continuing-education-18751905

Patel, N 2018, *A crucial piece of the mobile app marketing puzzle*, viewed 20 September 2018, https://neilpatel.com/blog/app-store-optimization/

Pearson Assessments 2006, *Survey Tracker Plus*, viewed 3 May 2018, http://www.pearsonncs.com/surveytracker/index.htm

Pettersen, P 2014, *Mobile apps poised to hit $70B in revenues by 2017*, viewed 20 November 2018, https://impact.com/thought-leadership/mobile-apps-poised-hit-70b-revenues-2017/

Philstar 2018, *The pain of paying (psychology of money)*, viewed 11 September 2018, https://www.philstar.com/lifestyle/health-and-family/2016/09/28/1628122/pain-paying-psychology-money

Play Console Help 2018, *Get discovered on Google Play search*, viewed 20 September 2018, https://support.google.com/googleplay/android-developer/answer/4448378?hl=en

Podsakoff, PM, MacKenzie, SB, Lee, JY & Podsakoff, NP 2003, ‘Common method biases in behavioral research: a critical review of the literature and recommended remedies’, *Journal of Applied Psychology*, vol. 88, no. 5, p. 879.

Prelec, D. & Loewenstein, G 1998, ‘The red and the black: mental accounting of savings and debt’, *Marketing science*, vol. 17, no.1, pp. 4-28.

Preston, CC & Colman, AM 2000, ‘Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences’, *Acta Psychologica,* vol. 104, no. 1, pp. 1-15.

Psychology Today 2018, *Psychology of money, psychology today Australia*, viewed 15 September 2018, https://www.psychologytoday.com/au/blog/one-among-many/201505/psychology-money

Raghubir, P, & Srivastava, J 2008, ‘Monopoly money: the effect of payment coupling and form on spending behavior’, *Journal of Experimental Psychology: Applied,* vol. 14, no. 3, pp. 213-225.

Rakestraw, TL, Eunni, RV & Kasuganti, RR 2013, ‘The mobile apps industry: a case study’, *Journal of Business Cases and Applications,* vol. 9, p.1.

Rao, AR, Bergen, ME & Davis, S 2000, ‘How to fight a price war’, *Harvard Business Review*, vol. 78, no. 2, pp. 107-120.

Research Optimus 2018, *What is frequency analysis?*, viewed 26 November 2018, https://www.researchoptimus.com/article/frequency-analysis.php

Rick, SI, Cryder, CE & Loewenstein, G 2008, ‘Tightwads and spendthrifts’, *Journal of Consumer Research*, vol. 34, no. 6, pp. 767-782.

Rouse, M & Jayaram, MN 2007, *Capability maturity model (CMM)*, viewed 30 September 2019, https://searchsoftwarequality.techtarget.com/definition/Capability-Maturity-Model

Rouse, M & Silverthorne, V 2017, *Agile software development*, viewed 29 September 2019, https://searchsoftwarequality.techtarget.com/definition/agile-software-development

Roy, A & Berger, P 2005, ‘E-mail and mixed mode database surveys revisited: exploratory analyses of factors affecting response rates’, *Journal of Database Marketing & Customer Strategy Management,* vol. 12, no. 2, pp. 153-171.

Ruiz, IJM, Nagappan, M, Adams, B & Hassan, AE 2012, ‘Understanding reuse in the

Android market', *2012 20th IEEE International Conference on Program Comprehension (ICPC),* pp. 113-122.

Saccomani, P 2017, *What factors really impact your app store ranking?,* viewed 11 February 2019, https://www.mobiloud.com/blog/factors-really-impact-app-store-ranking/

Santana, A 2012, 'Three elements of stakeholder legitimacy', *Journal of Business Ethics*, vol. 105, no. 2, pp. 257-265.

Schindler, R 1989, 'The excitement of getting a bargain: some hypotheses concerning the origins and effects of smart-shopper feelings', *Advances in Consumer Research,* vol.16, pp. 447-453.

Schmall, T 2018, *iPhone and Android users are completely different people*, viewed 15 July 2020, https://nypost.com/2018/10/25/iphone-and-android-users-are-completely-different-people/

Sefferman, A 2016, *The 2016 guide to mobile app ratings and reviews*, viewed 14 February 2019, https://www.apptentive.com/blog/2016/07/26/2016-guide-mobile-app-ratings-reviews/

Sekaran, U 2003, *Research method for business: a skill building approach*, John Wiley & Sons, Hoboken, NJ.

Seneviratne, S, Seneviratne, A, Kaafar, MA, Mahanti, A & Mohapatra, P 2017, 'Spam mobile apps: characteristics, detection, and in the wild analysis', *ACM Transactions on the Web (TWEB),* vol. 11, no. 1, p. 4.

Sheth, J N, Newman, BI & Gross, BL 1991, 'Why we buy what we buy: a theory of consumption values', *Journal of Business Research*, vol. 22, no. 2, pp. 150-170.

Siemens, JC & Kopp, SW 2011, ‚The influence of online gambling environments on self-control', *Journal of Public Policy & Marketing,* vol. 30, no. 2, pp. 279-293.

Sills, SJ & Song, C 2002, ‘Innovations in survey research: an application of web-based surveys’, *Social Science Computer Review*, vol. 20, no. 1, pp. 22-30.

Simon, HA 1955, ‘A behavioural model of rational choice’, *Quarterly Journal of Economics*, vol.69, pp. 99-118.

Social Research Methods 2018, *Social research methods knowledge base*: *the T-Test*, viewed 03 December 2018, http://www.socialresearchmethods.net/kb/stat_t.htm

Software Testing Help 2019, *Types of software testing: different testing types with details*, viewed 29 September 2019, https://www.softwaretestinghelp.com/types-of-software-testing/

Soodan, V 2016, ‘Influence of emotions on consumer buying behavior’, *Journal of Entrepreneurship, Business and Economics*, vol. 4, no. 2, pp. 163-181.

Stack Exchange 2018, *Power for two sample t test, cross validated*, viewed 17 December 2018, https://stats.stackexchange.com/questions/17042/power-for-two-sample-t-test

Statista 2018a, *Chart: Apple users more willing to pay for apps*, viewed 15 September 2018, https://www.statista.com/chart/14590/app-downloads-and-consumer-spend-by-platform/

Statista 2018b, *Average price of paid apps in the Apple App Store and Google Play as of 1st quarter 2018 (in U.S. dollars)*, viewed 16 September 2019, https://www.statista.com/statistics/262387/average-price-of-android-ipad-and-iphone-apps/

Statistics How To 2018a, *Concurrent validity definition and examples*, viewed 03 December 2018, https://www.statisticshowto.datasciencecentral.com/concurrent-validity/

Statistics How To 2018b, *Predictive validity definition and examples*, viewed 03 December 2018, https://www.statisticshowto.datasciencecentral.com/predictive-validity/

Statistics Solutions 2018a, *Assumptions of linear regression*, viewed 15 December 2018, https://www.statisticssolutions.com/assumptions-of-linear-regression/

Statistics Solutions 2018b, *One sample t-test*, viewed 08 December 2018, https://www.statisticssolutions.com/manova-analysis-one-sample-t-test/

Statistics Solutions 2018c, *Paired sample t-test,* viewed 08 December 2018, https://www.statisticssolutions.com/manova-analysis-paired-sample-t-test/

Steele, TJ, Schwendig, WL & Kilpatrick, JA 1992, 'Duplicate responses to multiple survey mailings: a problem?', *Journal of Advertising Research*, vol. 32, no. 2, pp. 26-33.

Stern, H 1962, 'The significance of impulse buying today', *Journal of Marketing,* vol. 26, no. 2, pp. 59-62.

Surbhi, S 2016, *Difference between null and alternative hypothesis (with comparison chart)*, viewed 08 December 2018, https://keydifferences.com/difference-between-null-and-alternative-hypothesis.html

Sydow, L 2018a, *Global app downloads grew 15% and consumer spend 20% in Q2 2018 versus a year ago,* viewed 20 November 2018, https://www.appannie.com/en/insights/market-data/global-app-downloads-grew-15-and-consumer-spend-20-in-q2-2018-versus-a-year-ago/

Sydow, L 2018b, *Global app store records shattered yet again in Q1 2018*, viewed 20 November 2018, https://www.appannie.com/en/insights/market-data/q1-2018-apps-record-downloads-spend/

Syer, MD, Adams, B, Zou, Y & Hassan, AE 2011, 'Exploring the development of micro-apps: A case study on the BlackBerry and Android platforms', *2011 IEEE 11th International Working Conference on Source Code Analysis and Manipulation*, pp. 55-64).

Syer, MD, Nagappan, M, Hassan, AE & Adams, B 2013, ‘Revisiting prior empirical findings for mobile apps: an empirical case study on the 15 most popular open-source Android apps’, *Proceedings of the 2013 Conference of the Center for Advanced Studies on Collaborative Research,* pp. 283-297.

Szymanski, DM, Kroff, MW & Troy, LC 2007, ‘Innovativeness and new product success: Insights from the cumulative evidence’, *Journal of the Academy of Marketing Science,* vol. 35, no. 1, pp. 35-52.

Tabanchnick, BG & Fidell, LS 2013, *Using multivariate statistics,* 6th (ed.), Pearson, Boston.

Tao, K & Edmunds, P 2018, ‘Mobile APPs and global markets’, *Theoretical Economics Letters,* vol. 8, no. 8, p. 1510.

Tatham, RL, Hair, JF, Anderson, RE & Black, WC 1998, *Multivariate data analysis*, Prentice Hall, New Jersey.

Thaler, R 1980, ‘Toward a positive theory of consumer choice’, *Journal of Economic Behavior and Organization*, vol. 1, no. 1, pp. 39-60.

Thaler, R 1985, ‘Mental accounting and consumer choice', *Marketing Science,* vol. 3, no. 4, pp. 199-214.

Thaler, RH 1999, ‘Mental accounting matters’, *Journal of Behavioral Decision Making,* vol. 12, no. 3, pp. 183-206.

Tiwana, A 2014, *Platform ecosystems: aligning architecture, governance, and strategy,* Morgan Kaufmann, Amsterdam.

Towards Data Science 2018, *How are logistic regression & ordinary least squares regression (linear regression) related?,* viewed 15 December 2018, https://towardsdatascience.com/how-are-logistic-regression-ordinary-least-squares-regression-related-1deab32d79f5

Tutorials Point n.d., *Capability maturity model*, viewed 20 July 2019, https://www.tutorialspoint.com/software_testing_dictionary/capability_maturity_model.htm

Tversky, A & Kahneman, D 1974, 'Judgment under uncertainty: heuristics and biases', *Science*, vol. 185, no. 4157, pp. 1124-1131.

Tversky, A & Kahneman, D 1981, 'The framing of decisions and the psychology of choice', *Science*, vol. 211, no. 4481, pp. 453-458.

Tygoramar, A 2008, *Engel Kollat Blackwell model of consumer behaviour,* viewed 17 January 2019, http://atvsnowblower.info/engel-kollat-blackwell-model-of-consumer-behaviour-15/

Ugoni, A & Walker, BF 1995, 'The T Test: An introduction', *COMSIG Review*, vol. 4, no. 2, p. 37.

University of Virginia 2018, *Using and interpreting Cronbach's alpha*, viewed 29 November 2018, https://data.library.virginia.edu/using-and-interpreting-cronbachs-alpha/

Vallerand, RJ, Deshaies, P, Cuerrier, JP, Pelletier, LG & Mongeau, C 1992, 'Ajzen and Fishbein's theory of reasoned action as applied to moral behavior: a confirmatory analysis', *Journal of Personality and Social Psychology,* vol. 62, no. 1, pp. 98-109.

Van der Horst, F & Matthijsen, E 2013, 'The irrationality of payment behaviour', *Occasional Studies,* vol. 11, no. 4.

Vasa, R, Hoon, L, Mouzakis, K & Noguchi, A 2012, 'A preliminary analysis of mobile app user reviews', *Proceedings of the 24th Australian Computer-Human Interaction Conference,* pp. 241-244.

Villota, EJ & Yoo, SG 2012, 'An experiment of influences of Facebook posts in other users', *2018 International Conference on eDemocracy & eGovernment (ICEDEG),* pp. 83-

88.

Vision Mobile 2013, *Developer economics 2013: the tools report,* viewed 1 March 2016, http://www.visionmobile.com/product/developer-economics-2013-the-tools-report/

Voss, KE, Spangenberg, ER & Grohmann, B 2003, 'Measuring the hedonic and utilitarian dimensions of consumer attitude', *Journal of Marketing Research,* vol. 40, no. 3, pp. 310-320.

Wang, HY & Wang, SH 2010, 'User acceptance of mobile internet based on the unified theory of acceptance and use of technology: investigating the determinants and gender differences', *Social Behavior and Personality: An International Journal,* vol. 38, no. 3, pp. 415-426.

Wicker, B, Keysers, C, Plailly, J, Royet, JP, Gallese, V & Rizzolatti, G 2003, 'Both of us disgusted in my insula: the common neural basis of seeing and feeling disgust', *Neuron,* vol. 40, no. 3, pp. 655-664.

Wilson, M 2019, *How to improve app ratings and reviews*, viewed 13 March 2019, https://www.apptentive.com/blog/2019/08/22/improve-mobile-app-ratings-and-reviews/

Wong, JC 2018, Facebook says nearly 50m users compromised in huge security breach, *The Guardian*, viewed 30 September 2019, https://www.theguardian.com/technology/2018/sep/28/facebook-50-million-user-accounts-security-berach

Yamaguchi, H 2004, 'An analysis of virtual currencies in online games', *The Japan Center for International Finance Social Science Research Institute*.

Yammarino, FJ, Skinner, SJ & Childers, TL 1991, 'Understanding mail survey response behavior a meta-analysis', *Public Opinion Quarterly,* vol. 55, no. 4, pp. 613-639.

Yen, M, Drinka, D & Kanamori, Y 2013, 'Exploring and evaluating e-business models: a preliminary study of a community-based website', *Communications of the IIMA*, vol. 13, no. 3, p. 6.

Zellermayer, O 1996, *The pain of paying*, PhD Thesis, Carnegie Mellon University, Pittsburgh, PA, viewed 15 March 2019, https://www.researchgate.net/publication/280711796_The_Pain_of_Paying

Zenn, J 2018, *The biggest mobile gaming consumers in 2018 (and beyond) are women*, viewed 10 December 2018, https://gameanalytics.com/blog/mobile-consumers-women-2018.html

Zhao, X, Wang, L, Guo, X & Law, R 2015, 'The influence of online reviews to online hotel booking intentions', *International Journal of Contemporary Hospitality Management*, vol. 27, no. 6, pp. 1343-1364.

Zhu, H, Xiong, H, Ge, Y & Chen, E 2014, 'Mobile app recommendations with security and privacy awareness', *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '14)*, pp. 951-960.

Zikmund, WG & Babin, BJ 2007, *Exploring marketing research 9th ed*, Thomson Higher Education.

Zubaydi, M, Gide, E & Guo, W 2018, 'A study of consumer spending behaviour in the Australian mobile application market', *2018 5th Asia-Pacific World Congress on Computer Science and Engineering (APWC on CSE)*, pp. 259-264.

APPENDICES

Appendix-A Ethics Approval Letter

CELEBRATING
25 YEARS

Secretary, Human Research Ethics Committee
Ph: 07 4923 2603
Fax: 07 4923 2600
Email: ethics@cqu.edu.au

A/Prof Ergun Gide and
Mr Maen Zubaydi
School of Engineering and Technology
CQUniversity

13 July 2017

Dear A/Prof Gide and Mr Zubaydi

HUMAN RESEARCH ETHICS COMMITTEE ETHICAL APPROVAL PROJECT: H17/02-018 A STUDY OF CONSUMER SPENDING BEHAVIOUR TO IMPROVE BUSINESS MODELLING STRATEGY IN THE MOBILE APP MARKET.

The Human Research Ethics Committee is an approved institutional ethics committee constituted in accord with guidelines formulated by the National Health and Medical Research Council (NHMRC) and governed by policies and procedures consistent with principles as contained in publications such as the joint Universities Australia and NHMRC *Australian Code for the Responsible Conduct of Research.* This is available at http://www.nhmrc.gov.au/publications/synopses/_files/r39.pdf.

On 13 June 2017, the Chair of the Human Research Ethics Committee considered your application under the Low Risk Review Process and your project was granted Conditional approval. On 12 July 2017, the Chair considered and approved your modification to recruitment (submitted on 4 July 2017). This letter confirms that your project has now been granted full approval under this process pending ratification by the full committee at its July 2017 meeting.

The period of ethics approval will be from 12 July 2017 to 20 November 2017. The approval number is H17/02-018; please quote this number in all dealings with the Committee. HREC wishes you well with the undertaking of the project and looks forward to receiving the final report.

The standard conditions of approval for this research project are that:

(a) you conduct the research project strictly in accordance with the proposal submitted and granted ethics approval, including any amendments required to be made to the proposal by the Human Research Ethics Committee;

(b) you advise the Human Research Ethics Committee (email ethics@cqu.edu.au) immediately if any complaints are made, or expressions of concern are raised, or any other issue in relation to the project which may warrant review of ethics approval of the project. *(A written report detailing the adverse occurrence or unforeseen event must be submitted to the Committee Chair within one working day after the event.)*

(c) you make submission to the Human Research Ethics Committee for approval of any proposed variations or modifications to the approved project before making any such changes;

(d) you provide the Human Research Ethics Committee with a written “Annual Report” on each anniversary date of approval (for projects of greater than 12 months) and “Final Report” by no later than one (1) month after the approval expiry date; *(Forms may be downloaded from the Office of Research Moodle site - http://moodle.cqu.edu.au/mod/book/view.php?id=334905&chapterid=17791.)*

(e) you accept that the Human Research Ethics Committee reserves the right to conduct scheduled or random inspections to confirm that the project is being conducted in accordance to its approval. Inspections may include asking questions of the research team, inspecting all consent documents and records and being guided through any physical experiments associated with the project

(f) if the research project is discontinued, you advise the Committee in writing within five (5) working days of the discontinuation;

(g) A copy of the Statement of Findings is provided to the Human Research Ethics Committee when it is forwarded to participants.

Please note that failure to comply with the conditions of approval and the *National Statement on Ethical Conduct in Human Research* may result in withdrawal of approval for the project.

You are required to advise the Secretary in writing within five (5) working days if this project does not proceed for any reason. In the event that you require an extension of ethics approval for this project, please make written application in advance of the end-date of this approval. The research cannot continue beyond the end date of approval unless the Committee has granted an extension of ethics approval. Extensions of approval cannot be granted retrospectively. Should you need an extension but not apply for this before the end-date of the approval then a full new application for approval must be submitted to the Secretary for the Committee to consider.

The Human Research Ethics Committee wishes to support researchers in achieving positive research outcomes. If you have issues where the Human Research Ethics Committee may be of assistance or have any queries in relation to this approval please do not hesitate to contact the Secretary, Sue Evans or myself.

Yours sincerely,

Redacted

A/Prof Tania Signal
Chair, Human Research Ethics Committee

Cc: Project file

Conditionally Approved

Appendix-B Research Questionnaire

CQUniversity AUSTRALIA

A study of consumer spending behaviour to improve business modelling strategy in the mobile app market

1. Information Sheet

Project Overview

This project will investigate how consumer spending behaviour of mobile app changes with different experiences users have while consuming app products. The researcher aims to help mobile app sellers properly model their apps according to correlating consumer behaviour, and earn sustainable income that enables them to continue improving their products for their consumer base and remain in competition with bigger developer studios.

Participation Procedure

Participants will be asked to answer questions regarding their experiences and spending while using mobile apps, and it is envisaged that the survey will take no more than 10 minutes to complete.

Benefits and Risks

Participants face no risks responding to the survey beyond inconvenience and possible discomfort when disclosing their spending preferences in mobile app stores, their contact details are not collected in the recruitment process This project cannot promise to directly benefit participants.

Confidentiality / Anonymity

Identity or contact details of respondents will not be collected.

Outcome / Publication of Results

This project will produce a strategic business modelling guideline that helps mobile app developers adopt business models that are more optimal for consumer spending behaviour associated with their products. The results will be disseminated in the form of a summary article provided to participants upon request. Participants may contact the research student or supervisor via email addresses provided for a copy of the article.

Right to Withdraw

Participants retain the right to withdraw at any moment while participating in the survey, if they choose to withdraw, they can close the online questionnaire. The survey will be set to not record incomplete survey responses.

Feedback

Participants will not receive specific feedback on their responses, but are informed at the end of the survey where they can check project findings if they are interested.

Questions/ Further Information

Principal Supervisor: A/Prof Ergun Gide, email e.gide1@cqu.edu.au
Student: Maen Zubaydi, email maen.zubaydi@cqumail.com

Concerns / Complaints

Please contact CQUniversity's Office of Research (Tel: 07 4923 2603; E-mail: ethics@cqu.edu.au; Mailing address: Building 32, CQUniversity, Rockhampton QLD 4702) should there be any concerns about the nature and/or conduct of this research project.

ELECTRONIC CONSENT:

Clicking on the "NEXT" button below indicates that:

· You are 18 years or over
. You reside in Australia
. You have read the above information
· You voluntarily agree to participate; and
· you give your consent for the data you provide in the following survey to be used for the research purpose described above.

2

CQUniversity AUSTRALIA

A study of consumer spending behaviour to improve business modelling strategy in the mobile app market

2. Buying and shopping

* 1. Which of the following descriptions fits you better? Please move the slider button to a position between 1 and 11, where 1 is a Tightwad (difficulty spending money) and 11 is a Spendthrift (Difficulty controlling money)

1 Tightwad Neither Spendthrift 11

2. What is your gender?

- Female
- Male

3. What is your age?

- 18 to 24
- 25 to 34
- 35 to 44
- 45 to 54
- 55 to 64
- 65 or older

* 4. What estimate percent of your income can you freely spend on discretionary goods?

- ◯ 5% or less
- ◯ 10%
- ◯ 20%
- ◯ 30%
- ◯ 40% or more

* 5. What mobile app store do you shop at?

- ◯ Apple's App Store
- ◯ Google Play
- ◯ Windows Store
- ◯ Other

* 6. How would you describe your spending on apps you use for gaming or utility purposes?

◯ Very Conservative ◯ Conservative ◯ Moderate ◯ Excessive ◯ Very Excessive

A study of consumer spending behaviour to improve business modelling strategy in the mobile app market

3. Utility mobile apps

* 7. What kind of utility apps do you use on your phone?

- [ ] Book readers
- [ ] Food & Drink
- [ ] Health & Fitness
- [ ] Medical
- [ ] Personalization
- [ ] Productivity
- [ ] Other

* 8. How often do you use your utility apps?

once a week or less | Four times a week | Everyday

* 9. How would you describe your spending on features within utility apps?

○ Very Conservative ○ Conservative ○ Moderate ○ Excessive ○ Very Excessive

A study of consumer spending behaviour to improve business modelling strategy in the mobile app market

4. Gaming mobile apps

10. What kind of gaming apps do you play on your phone?

- [ ] Action or Adventure
- [ ] Board or card games
- [ ] Puzzles
- [ ] Simulation
- [ ] Sports or racing
- [ ] Strategy
- [ ] Trivia or word

* 11. How often do you play mobile app games?

once a week or less | Four times a week | Everyday

* 12. How many hours a day do you spend playing mobile app games?

One hour or less | Five hours | Nine hours or more

* 13. How would you describe your spending on items or features within mobile app games?

○ Very Conservative ○ Conservative ○ Moderate ○ Excessive ○ Very Excessive

CQUniversity AUSTRALIA

A study of consumer spending behaviour to improve business modelling strategy in the mobile app market

5. Engaging with other players in the game

* 14. What kind of mobile app games would you spend more time playing?

- ◯ Network games where you play with other real players
- ◯ Private games where you play alone or against game engine
- ◯ You spend around the same time playing network and private games

15. When you play network mobile app games, what kind of purchases would impress other players in the game?

- ☐ Character skins or accessories
- ☐ Premium or rare items
- ☐ Collectibles
- ☐ Other (please specify)

* 16. How would you describe your spending on items that would impress other players in a mobile app game network?

◯ Very Conservative ◯ Conservative ◯ Moderate ◯ Excessive ◯ Very Excessive

17. When you play network mobile app games, what kind of purchases would help you beat other players in the game?

- [ ] Offense items or features
- [ ] Defense items or features
- [ ] Performance items or features
- [ ] Other (please specify)

* 18. How would you describe your spending on items or features that would help you beat other players in a mobile app game network?

○ Very Conservative ○ Conservative ○ Moderate ○ Excessive ○ Very Excessive

* 19. While playing alone, how would you describe your spending on items or features that would help you beat an app game engine?

○ Very Conservative ○ Conservative ○ Moderate ○ Excessive ○ Very Excessive

CQUniversity AUSTRALIA

A study of consumer spending behaviour to improve business modelling strategy in the mobile app market

6. Buying virtual currency

* 20. Some app games offer their own currency units (like gold coins or jewels) that you can buy or earn for free. These units can be exchanged for premium items or features within the game.

Do you prefer buying premium goods directly with your money or by exchanging them with your game units?

- ◯ I prefer buying directly with my own money
- ◯ I prefer exchanging with game units
- ◯ It doesn't make any difference to me

* 21. How would you describe your spending on games that offer credit units (like gold coins or jewels) that you later exchange for premium goods?

◯ Very Conservative ◯ Conservative ◯ Moderate ◯ Excessive ◯ Very Excessive

* 22. How would you describe your spending on gaming apps that offer premium goods in exchange for real money only?

◯ Very Conservative ◯ Conservative ◯ Moderate ◯ Excessive ◯ Very Excessive