Applied Behavioral Economics in the Digital Context – Examining the Idea of "Free"

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This PhD dissertation could not have been completed without the kind support, guidance and patience of many individuals.

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Abstract

The birth of the digital revolution brought about by the ubiquitous penetration of smartphone usage across the globe has compelled businesses to rethink their business strategies. For resource-strapped digital entrepreneurs and practitioners, having a good understanding of the consumer decision-making process will help to shape relevant strategies for this new digital context. This dissertation provides a literature review on the evolution of consumer decision-making processes from the classical expected utility model to behavioral economics theories like prospect theory and the more contemporary nudge and zero-price theories. A two-stage conceptual framework involving an awareness stage and a subsequent conversion stage is also introduced for examining consumer behavior in the digital context. The main quantitative research focuses on examining the zero-price effect (ZPE) and the endowment effect within the digital context, with the methodology of situating participants in imagined scenarios, and then measuring their choice and corresponding Net Promoter Score (NPS), to identify how specific factors like application category and the type of free-related strategy moderate the level of affect. Results show that choice proportions and NPS vary according to category and strategy type (freemium or free-trial). One key useful managerial implication for digital practitioners who can potentially choose freemium strategy for leisure gaming or more trivial kind of applications and adopt the free-trial strategy for productivity type applications or those more “embedded” into the user’s daily workflow. Such understanding can also help practitioners to design more effective and non-intrusive digital “nudges” to encourage adoption, conversion and deeper engagement with the applications, which can be particularly useful in the fields of e-commerce, education, healthcare and finance.

A formal proposal to include the ZPE in the cognitive bias codex and a purpose-driven framework to link the codex to virality and conversion growth hacking strategies for digital practitioners are also included in this dissertation. This dissertation contributes both quantitatively to the study of applied behavioral economics as well as qualitatively to the nascent body of growth hacking literature particularly in the digital context. Future research using similar methodology can also be conducted to explore how independent variables like category or strategies moderate other behavioral effects such as framing or the IKEA effect. Furthermore, new studies on how the ZPE and endowment effect can complement other kind of interventions to constitute even more effective digital nudges can also be explored for influencing consumer or user behavior in the digital context.

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Abbreviations

App	Application
App store	Application store
BP	Bargain price
NPS	Net Promoter Score
ZP	Zero price
ZPE	Zero-price effect

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Chapter 1: An Overview of the Thesis

This chapter of the thesis illustrates the background of the current research project including an introduction, background of research, research problem and framework, research question, research objective, scope, a brief methodology and some key contributions of the study. The chapter's last section also highlights a brief outline of the entire thesis.

1.1. Introduction

The first two decades of the 21st century saw the birth of the digital revolution brought about by the ubiquitous penetration of smartphone usage across the globe. Businesses have been compelled to rethink their business strategies and supply chains, particularly their distribution channels. The COVID-19 pandemic, during which this dissertation was written and the corresponding research was conducted, is likely to have accelerated such a rethinking process, given that periodic city-wide lockdowns, the post-pandemic environment and social distancing practices have only made the digital channel more relevant, and potentially crucial, to ensuring continual business survival.

Notwithstanding this, when it comes to the digital economy, many presumptions that we hold about the physical tangible economy cannot be taken for granted. An example of a key difference is that in the digital retail context, relative to the physical retail context, the visual sensory cue plays a substantially more important role, replacing the tactile sensory cue used in the physical context. Li (2022) highlighted that the digital context of today provides unique opportunities for digital practitioners to consider their product positioning, content variety and uniqueness to execute a successful technology diffusion strategy using TikTok as the example. In fact, I would add on further to Li's (2022) analysis that the Chinese software developer ByteDance focused its innovation on auditory sensory cues and differentiated itself by introducing short-form rhythmic and beats music to complement user-generated lip-sync video content on its wildly popular mobile applications – Douyin in China and TikTok for markets outside of China – to challenge the dominance of other social networks such as Instagram and Snapchat. Moving beyond sensory cues, another difference is that in a physical retail context many products that we see in shopping malls or in a simple grocery store are already curated by the procurement or buying department or the manager. In the digital context, however, such as the internet or a mega-digital application store like Apple's App Store or Google Android's Play Store, digital offerings need to overcome a more substantial awareness hurdle to reach the end-customers or users. The odds seem stacked against the digital entrepreneur or a digital startup. Where can they get an edge in this brutal competitive environment? How can they "hack" their respective growth processes with effective strategies under the constraints of limited capital?

1.2. Background of the Study

This is perhaps where the area of behavioral economics can lend a hand. Decision-making theories have evolved over years from the classical expected utility theory, which assumes a completely rational and economic profit-maximizing human, to approaches like the prospect and nudge theories, which have inspired research into the *predictably* irrational elements of human behavior. Ever since Tversky and Kahneman's (1979) prospect theory was introduced, cognitive biases such as loss aversion have been identified and empirically proven, and effects such as the fear-of-missing-out (FOMO), zero-price and endowment effects have provided much insight into how humans react to various stimuli. Such insights have shaped public policies and strategies over the past few decades in one way or another, and gained popularity in the early 2000s stemming from research by the work of other titans from the field of behavioral economics such as Shampanier et al. (2007), Thaler and Sunstein's (2008) and Ariely (2008) in the early 2000s. Such an evolution of research is briefly summarized in the following Figure 1 . My research will contribute to the nascent bodies of literature in the freemium and digital nudging fields, whereas the proposed managerial implications will add to the growing body of literature in the growth-hacking realm, which seeks to differentiate itself from traditional marketing literature.

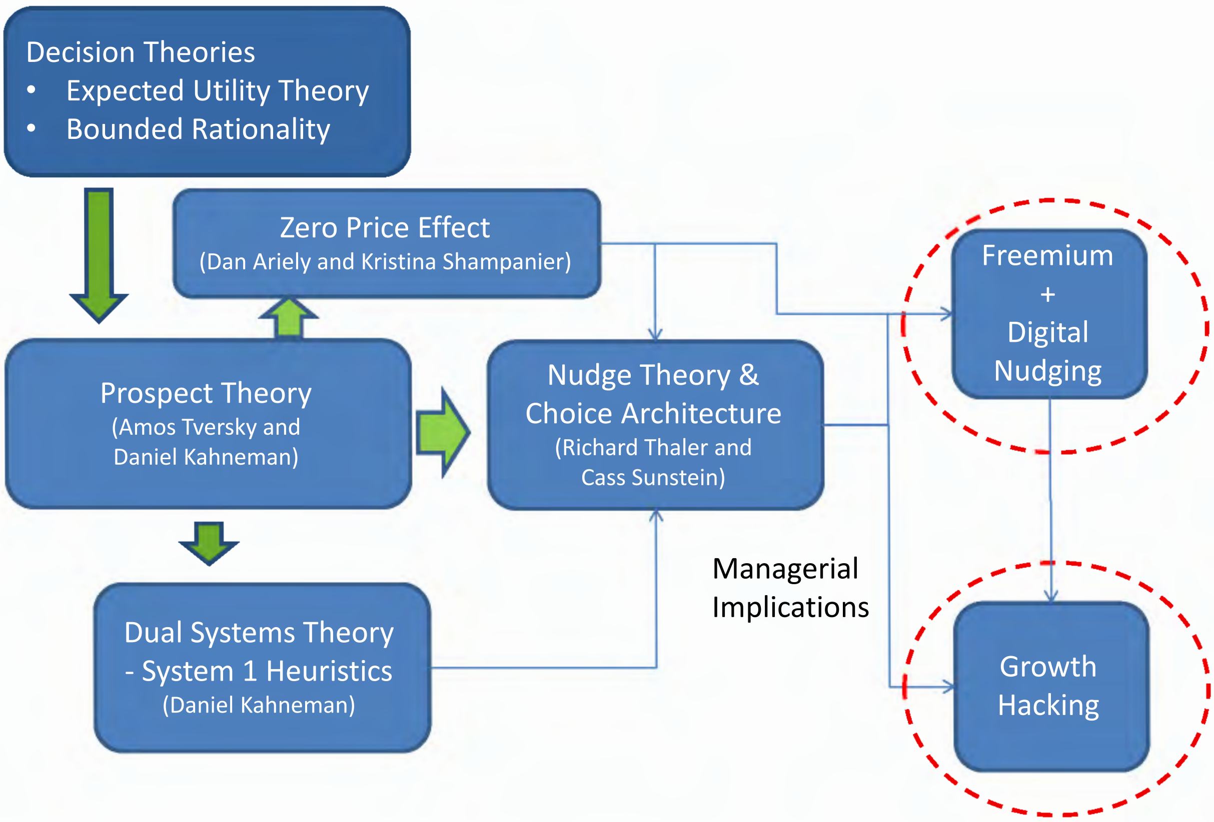

Figure 1: Diagrammatic summary of the evolution of decision making theories

The linearity bias in extrapolating their observations and experiences in most humans – the assumption that proportional changes occur due to variances of the input variable – is an entrenched cognitive bias that limits our ability to wrap our heads around exponential growth. Yet, we cannot deny that it is precisely the subtle workings on individuals' minds and behavioral dynamics that drive virality or effective technology diffusion and, consequently, network effects, leading to the dominance of the "Big Tech" platform companies of today as asserted by Eyal (2014). The human mind is thus a fertile ground for us to research and potentially unlock any previously untapped capacities for digital practitioners.

1.3. Research Problem and Proposed Conceptual Framework

In view of the abovementioned, I find it particularly interesting and useful to explore deeper on how the nuances in the digital consumer behaviors can be discovered and exploited in a non-intrusive way to achieve the success in the marketplace. As we herald in this new age of rethinking the business models for the digital economy, we wish to elide business and marketing strategies with such unique insights from behavioral economics, with a particular focus on understanding the zero-price effect (ZPE) and the free mentality, in order to formulate useful and effective growth hacking strategies for the budding entrepreneurs of tomorrow.

As described in Chapter 1.1, there exist key differences between the digital context and the physical retail context, and as such, it is fathomable that the consumer decision-making process will defer as well. Extant literature seems to group consumers' awareness of a product together with the purchase decision, thereby constituting a person's willingness to pay. In the physical goods retail context, awareness is very much curated by the store's procurement department or staff member and limited by the store or malls' physical space, but in the digital context, particularly in mobile app stores where there are literally millions of apps available, there is a constant need to compete for a consumer's attention and corresponding awareness of any digital offerings. This sets the stage for my research problem, given that there is such a genuine difference in the tangible physical retail context and the digital context which my research will be situated, I believe that a lot of pre-existing assumptions including the experiments conducted by Shampanier et al. (2007) or Ariely (2008) need to be re-tested and examined in this research.

As such, I propose a new framework involving *two stages of consideration* especially in the context of the business-to-consumer (B2C) mobile application digital context, comprising the consumer's *willingness to download (WTD) and willingness to pay (WTP)*. The goal is to explore deeper some of the key behavioral effects in play during these two stages of consideration for consumers making decisions within the digital context. Furthermore, given the digital context, I also propose to adopt the quantitative measure of the 11-point Net Promoter Score (NPS) as opposed to the previous 5-point scale to measure the level of affect by prior researchers in the tangible physical context in order to better simulate the digital context and situate the research participants more comfortably during the quantitative study. I believe that firms need to consider and understand these two stages well and insights derived from this research can help them to design better non-intrusive "nudges" or other choice architecture to execute a successful and sustainable business strategy in the digital context.

1.4. Research Question and Objective

My research extends prior research on the ZPE such as the seminal one by Shampanier et al. (2007) as well as on the endowment effect by Kahneman et al. (1991), which have focused primarily on tangible goods and services. Using the proposed new conceptual framework as introduced in the prior chapter 1.3, I seek to study how categories moderate the ZPE, which in turn, moderate the level of affect experienced by consumers, leading to their willingness to download in the first awareness stage.

In the second conversion stage, I also seek to study how the categories as well as the type of free-related strategies (specifically, a limited-feature freemium or a full-feature free-trial strategy) moderate the endowment effect, which in turn moderate the level of affect experienced by consumers as they proceed to make a decision to convert into premium-paying customers on a digital app store. This new revised framework will be particularly helpful as I seek to contribute to the growing body of digital nudging literature.

The research objectives and questions are further elucidated in Chapter 2.6 whereas the respective hypotheses for both the awareness and conversion stages are detailed in Chapter 2.7.

1.5. Research Method and Analysis

A quantitative survey in a two-stage scenario-based quasi-field experiment was conducted with a series of questions to situate respondents in various scenarios. Instead of using Shampanier et al.'s (2007) single-item 5-point scale to measure "affect", I used the popular 11-point Net Promoter Score or NPS, widely used by most digital practitioners to mirror the conditions of the digital context more closely and increase familiarity with my survey participants.

A total of 381 complete responses were collected from a target audience based in Singapore. In essence, my research shows that both the ZPE and endowment effect do extend to the digital context. Furthermore, categories and the type of free-related strategies do moderate both effects, as well as the corresponding level of affect as measured by NPS in both the awareness stage 1 and conversion stage 2. The results are detailed in Chapter 4.

1.6. Major Areas of Contribution

My dissertation includes a few areas of contribution, notably theoretical contribution to nudge theory and the corresponding zero-price theory. The quantitative survey results detailed in Chapter 4 also contribute substantially to understanding the relationship between the consumer's choice and affect (as measured by NPS) with the various independent variables such as categories within a digital context as well as the type of free-related strategies. My contribution from a qualitative perspective includes a systematic literature review of the various decision-making processes preceding nudge theory, as well as the various heuristics and cognitive biases relevant to the digital context. The main research will also contribute to the nascent but growing body of digital nudging literature as shown in figure 1.

The managerial implications section of the dissertation under Chapter 5 also includes an introduction to the famous Benson and Manoogian's (2018) cognitive bias codex where I make a formal proposal to include the ZPE into this codex. Chapter 6.3 also includes a descriptive review of the notable growth hacking examples adopted by practitioners in the digital context. Recognizing the difficulty practitioners face in drawing on the ocean of literature in the cognitive psychology space focusing on various behavioral effects, I also propose a framework in the penultimate chapter of this dissertation to link the cognitive behavioral biases codex to Berger's (2013) STEPPS framework, for designing more surgical and targeted campaigns to drive virality, as well as to Berger's (2020) REDUCE principle to design better "nudges" for effective conversion.

1.7. Thesis Outline

Following this introduction chapter is Chapter 2 where an extensive literature review is conducted to frame my research questions. Chapter 3 will detail the main quantitative study whereas I will discuss the results and analysis in Chapter 4. We will then talk about the managerial implications from the findings of the study, and I will introduce a purpose-driven framework for growth hacking in the digital context Chapter 6. Finally, the conclusion and key contributions are summarized in Chapter 7 followed by the list of references. The quantitative survey questions, participant consent form as well as the comprehensive tabled version of the cognitive biases codex are also included under the Appendices located at the end of the dissertation.

Chapter 2: Literature Review

This chapter of the thesis focuses on the literature review of the various fields that help to frame my research questions. I have also provided a quick history and overview of the evolution of various major decision-making theories leading to the nudge theory and corresponding zero-price theory which I believe will help any new researchers in the field of behavioral economics to better navigate how this nascent field of research has evolved over the years. The chapter also includes a descriptive review of the heuristics and cognitive biases literature relevant to the digital context. I have also conducted a critical review of the literature surrounding the zero-price effect including freemium and free-trial related literature, which sets the stage for framing the research objectives and finally proposing my key hypotheses in the last section of this chapter.

2.1. Introduction to Humans' Decision-Making Processes

A literature review on this cross-disciplinary topic is a substantial undertaking given that it covers extant literature across various fields, primarily in economics, psychology, marketing, strategy and management, and information systems. However, as we herald in a golden age of digital disruption for various business models, it is essential to have a good understanding of the various pioneering studies in these fields prior to formulating suitable business and operational strategies with insights gleaned from such a review. Thaler and Sunstein's (2008) seminal book, *Nudge: Improving Decisions About Health, Wealth, and Happiness,* introduced several new terms which have proven to be influential in shaping the business and marketing strategies of different industries, particularly those that interface with retail consumers. However, I will discuss more about these terms later, because this book is also widely considered as Thaler and Sunstein’s tribute to the many other pioneers in the field of decision theory as well as in cognitive and mathematical psychology. It is therefore important to examine the epistemology of this field of behavioral economics right from the beginning, as we look at the different models of how consumers make their decisions. This chapter thus has several primary objectives:

1. A brief descriptive review of previous literature on major decision-making theories developed primarily in the 20th century.
2. A descriptive review of previous literature on behavioral economics and the major cognitive biases, such as loss aversion, anchoring and reciprocity biases, in order to understand the potential explanatory factors for variance in how humans treat the various products and service offerings in the digital context.
3. A critical review of the ZPE given its major influence on freemium-based strategies adopted by many companies in the digital economy, including underscoring some limitations and gaps in existing literature which will serve as the basis for further examination within the scope of this dissertation.

Section 2.2 will provide a brief descriptive review of the major decision-making theories, including expected utility theory, bounded rationality theory, prospect theory and nudge theory, as well as a cursory introduction to the dual-system theoretical framework from the social psychological domain. This will serve as an introduction to Section 2.3, where a table of the major heuristics and cognitive biases relevant to the digital context is presented based on a brief descriptive review of extant literature. I then focus more closely on the ZPE and the free mentality in Section 2.4, with a critical review of the seminal paper by Shampanier et al. (2007) that introduced this effect, thereby identifying some of the key limitations and areas for further research. Section 2.5.1 provides a critical review of subsequent research surrounding the "freemium and free-trials" business models underpinned by the ZPE, and seeks to consolidate the empirical findings and conceptual foci that evaluate this "free" mentality. Key gaps in the literature related to the ZPE and freemium were identified in this subsection, setting the stage for the framing of the research questions in Section 2.6.

2.2. Descriptive Review of Major Decision-Making Theories

The main purpose of this section is to provide a brief descriptive review of the major decision-making theories developed over the years, with a particular focus on the chronological order of development, to best illustrate how subsequent theories seek to address the major gaps and limitations of prior theories.

2.2.1. A Brief History of Expected Utility Theory

Ever since *expected utility theory* was formally and mathematically introduced by Von Neumann and Morgenstern (1944), it has been fundamental for much research pertaining to how individuals make decisions rationally, with the key word being *rationally*. Interestingly, the concept of expected utility was first posited by Daniel Bernoulli, a Swiss mathematician and physicist in 1738, to solve his cousin's, Nicolas Bernoulli's, St. Petersburg Paradox, which is a theoretical lottery game of chance where the participants seem to attribute a disproportionately low value to an expected pay-off that is potentially infinite. The discrepancy between what participants are willing to pay to play the game and its potentially infinite pay-off sets the stage for the paradox. Bernoulli made a clear distinction between expected value and expected utility that year in 1738, henceforth setting the stage for a whole new domain of decision-making under uncertainty. While expected value focuses on weighted outcomes, expected utility uses weighted utility multiplied by probabilities.

Von Neumann and Morgenstern (1953) re-introduced the expected utility theory and elaborated it further by listing four underlying axioms to define the typical rational decision maker: completeness, transitivity, independence and continuity. Instead of formulaically presenting the axioms, and to align with this dissertation's spirit of practical application, the four main axioms underpinning expected utility theory are described in simple English as follows:

1. Completeness refers to clearly defined preferences of the decision maker.
2. Transitivity refers to the consistency of choices made by the decision maker.
3. Independence refers to the condition where each preference shown is independent of the possibility of another outcome, also sometimes known as the "substitution" axiom.
4. Continuity refers to a potential "tipping point" of each preference being better than and worse than a given middle option.

Expected utility theory really suggests that our decisions are the result of a considered weighing of costs and benefits. Becker (1976) also elucidated pillars of "rational choices", assuming that we have stable preferences and engage in utility-maximizing behavior. He applied this *rational choice theory* to various fields, including crime and the institution of marriage, to illustrate that the neoclassical economists' assumption of the homo economicus is valid, suggesting we are all rational, economic profit-maximizing agents with stable preferences.

However, there have been multiple criticisms of and improvements to expected utility theory. A notable example is the Allais paradox, which is a choice problem designed to illustrate an inconsistency of actual observed choices with the predictions from expected utility theory, as demonstrated in Allais (1953), and specifically posited as an exception to the independence axiom listed above. Allais (1953) observed a phenomenon known as the certainty effect, or the *common ratio effect*, in which participants irrationally change their preferences among a set of choices when the probability of the incentive system in each choice is reduced by a common factor. This was substantiated subsequently by Loomes and Sugden (1982) through their *regret theory*, which states that if one makes certain assumptions about regret anticipation following an actual outcome, then expected utility theory can still be valid, reconciling some of the violations uncovered by Allais. Laciana and Weber (2008) also provided an explicit version of a regret-corrected and disappointment-corrected utility function that produces the stated preferences without posing the said paradox. All these indicated that there is a clear gap in the ability of expected utility theory to mirror actual decision-making by humans.

2.2.2. Bounded Rationality

The Allais paradox discussed in the previous subsection truly set the ground for much deeper discussion and further research into people's irrational behavior, particularly in the context of decision-making. Several other studies and developments on decision theory followed, such as Simon's (1955) work focusing on the effects of limited cognition as well as the implications of such bounded rationality on the design and performance of organizations. This concept of *bounded rationality* suggests that the rationality of human beings is limited by three main factors: the limited information one possesses; the limited cognitive powers of one's mind; and the limited time one has to make a decision. Herbert Simon believed that because of uncertainty about the future and potential costs of acquiring information in the present, a decision maker may not be able to be fully rational in decision-making. These decision makers thus possess only bounded rationality, ending up with suboptimal but "acceptable" choices which will make them just happy enough. Simon's concept of bounded rationality is widely considered to be a pre-cursor to the eventual development of the field of behavioral economics. Selten and Berg (1970) also documented much experimental evidence on deviations from rational economic decision-making, and Selten (1990) provided a good overview, pointing out that the limits of rationality are not just cognitive but motivational in nature, and that bounded rationality is not just a variation of utility maximization, thus encouraging deeper research into the intricate ways that humans make their decisions.

However, while bounded rationality truly represents a logical and reasonable deviation from the classical model represented by expected utility theory in the context of decision-making, there is limited explanation and empirical evidence provided by extant bounded rationality literature on the cognitive limitations of the mind. This paves the road ahead for deeper research and closer scrutiny.

2.2.3. Prospect Theory

As discussed previously, expected utility theory, as with any mathematical model, is an abstraction and simplification of reality, lending some credence to Leonard's (2008) view that homo economicus is essentially fiction. Therefore, building on the bounded rationality theory first proposed by Simon (1955), Tversky and Kahneman's (1979) seminal paper on *prospect theory* sought to describe the actual behavior of individuals when making decisions, empirically showing how the preferences of decision makers are inconsistent among the same choices, depending on how those choices are presented. This paper served as a major critique of expected utility theory. The authors' key claim was that real people are not simply fallible, but that real people make mistakes systematically, due to their inherent tendency to embrace irrelevant information, process this information erroneously, and draw conclusions and see patterns from data which do not really exist. Also, Tversky and Kahneman's (1979) work on gambling probabilities forms the basis for several cognitive biases and heuristics that will be elaborated in subsequent sections of this chapter. For example, they found that people perceive zero probability considerably differently than they perceive smaller positive probabilities; they proved that an individual's perception of zero probability is accurate or, in lay terms, absolutely certain, but that the individual tends to magnify the perceived value of choices with smaller positive probabilities. This provides an important and practical insight in the current age of digital business model disruption, where the freemium model is considered as a key pricing option in the boardrooms of most global software companies and startups.

As a brief summary, Tversky and Kahneman's (1979) prospect theory comprises four main areas:

- An individual derives utility from gains and losses relative to a reference point.
- An individual is more sensitive to losses than to gains, exhibiting a unique cognitive bias known as loss aversion.
- An individual will exhibit diminishing sensitivity to gains and losses. For example, a person will feel happier when they gain $200 from an original $100 given, but their measure of happiness or utility is not as much when the amount is increased from $10,100 to $10,200.

- The probabilities or decision weights attached to different outcomes vary from person to person, but there is an observable tendency to overweight low probability events and underweight high probability events.

The aggregate of the four main observations described by Tversky and Kahneman's (1979) indicates a value function that exhibits concavity for gains and convexity for losses, as illustrated in the following diagram (Figure 2).

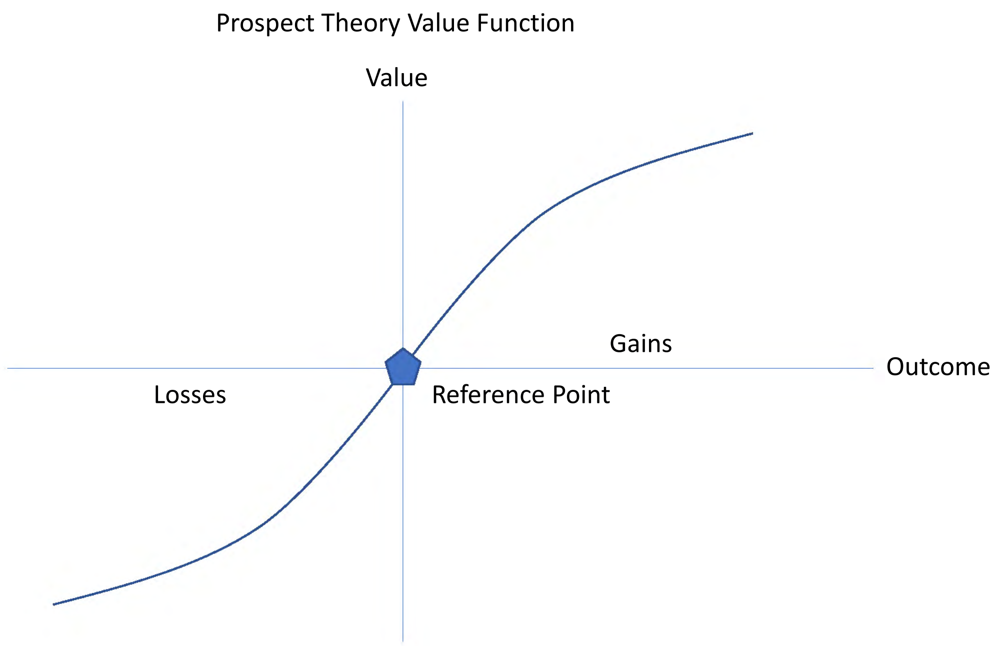

Figure 2: Prospect Theory Value Function Diagram

In addition, Tversky and Kahneman (1981) also explored how framing affects decision-making. A good example would be to consider how an individual will decide if given a choice between a medical procedure that has a 70 percent chance of success, or if presented with a medical procedure that has a 30 percent failure rate resulting in certain fatality. This paper also discussed the framing of acts, contingencies and outcomes, further illustrating that seemingly small changes in the options presented to participants will cause big shifts in preferences, with particular examples of loss aversion first described in Tversky and Kahneman's (1979) earlier paper.

A later paper by Tversky and Kahneman (1992) provides a further development, introducing *cumulative prospect theory*. Their essential argument here was that the weighting should be applied to the cumulative probability distribution function instead of just the probabilities of the events. This modification presented a substantial improvement on theoretical grounds.

One of the key contributions of prospect theory in general is not the belief that modern economists are naïve to think that decision-making is as simple and straightforward as the neoclassical economic model suggests, but that advocates of prospect theory sought to change the perpetuation of such neoclassical models in universities, governments and business, where they were applied with a corresponding hubris about their exactitude, only to be proven wrong time and time again when empirically tested in real-life contexts. Prospect theory's advocates' humble approach towards incorporating contextual variables was admirable, fully recognizing that the old classical model, such as expected utility theory, which assumes the absence of psychology, cultural contexts, ethical considerations and trust among various stakeholders, was simply not practical.

Prospect theory has been commended for laying out the theoretical foundations for the various cognitive biases, For example, interesting observations were made by Medvec et al. (1995), who used the theory and corresponding concept of loss aversion to explain why bronze medalists at Olympics award presentation ceremonies often seem happier and smile more than silver medalists. They argued that bronze medalists perceive a "gain" as opposed to not winning any medal, but silver medalists perceive a major "loss", seeing themselves as the "first loser". However, despite this seemingly irrational real-world phenomenon being explained, the real-world application of the theory since 1979, with corresponding frameworks to shape business strategies or public policy, was not really explored in detail, thereby setting the stage for *nudge theory* and its corresponding choice architecture framework.

2.2.4. Nudge Theory and Choice Architecture

Nudge theory is a concept grounded in behavioral science that suggests that positive reinforcement and indirect suggestions can influence people's decision-making and behaviors without them even realizing it. Thaler and Sunstein (2008) defined a nudge as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (p. 6). The term *choice architecture* from the above definition was coined by Thaler and Sunstein (2008); it refers to the practice of influencing consumers' choice by "organizing the context in which people make decisions" (p. 3). They particularly highlighted that to qualify as a nudge, the intervention should be easily and cheaply avoided, given that it is easy to confuse the intervention as mandating or manipulating. Such an influence without coercion is known as libertarian paternalism, another term coined by Thaler and Sunstein (2003), and implementers of such nudges are known as "choice architects" (Thaler & Sunstein, 2008, p. 3).

Examples of nudges in action include putting healthier food choices at eye level in the fridge or near cash registers and including an image of a housefly on men's urinals to improve “aim”. Other tools used by choice architects include defaults; this was demonstrated by Pichert and Katsikopoulos (2008), who found that more people chose the renewable energy option for electricity when it was offered as the default option. Thaler and Benartzi (2004) also illustrated how behavioral economics was applied and a number of nudges (though the term is not yet coined in 2004) were deployed in the “Save More Tomorrow” or “SMarT” program to help employees save more money. Nudge theory has indeed had a strong role in shaping policies in the United States and the United Kingdom, as illustrated by McSmith (2010). In Singapore, Lew and Leong (2009) also demonstrated how behavioral economics and nudges have shaped Electronic Road Pricing policies to manage traffic congestion. Thaler et al. (2013) provided still more examples of how behavioral economics and choice architecture shapes human behavior through public policies globally. They identified six main principles on which this is based: incentives, understanding of mappings, defaults, feedback, error-expectation, and structuring complex choices.

In summary, it is clear that Thaler and Sunstein have indeed developed on Tversky and Kahneman’s prospect theory specifically, and behavioral economics in general, to a “more pragmatic and applicable” level with their *nudging* and choice architecture framework. Considering that most of nudge theory’s initial application has been in the health and public policy arena, another important development in nudge theory is the nascent but growing body of literature surrounding *digital nudging.* More recently, “digital nudging” has come to the fore given that technology adoption has become more prevalent in our lives. Weinmann et al. (2016) defined digital nudging as “the use of user-interface design elements to guide people’s behavior in digital choice environments” (p. 433) whereas Lembcke et al. (2019a) argue for a more thorough foundation with an extended definition factoring its analog roots.

Digital nudge theory, as a subset of Thaler and Sunstein's (2008) nudge theory is based on the idea that small, non-intrusive and non-coercive interventions can have a significant impact on the choices that people make. Finally, Sunstein (2015) and Lembcke et al. (2019b) also extensively discussed the ethics of digital nudging, which I will discuss in greater detail in a later subsection, given its considerable importance and relevance to business ethics. Furthermore, Berger et al. (2022) also extends the application of effective digital nudging elements to promote environmentally sustainable behavior, helping to shape policies that addresses the global climate change concerns. Schneider et al. (2020) demonstrated how digital nudges like defaults and popularity signals (social proof bias) effectively increase electronic identification (eID) adoption. Schneider et al. (2018) provided a five-step process to guide the design of digital websites or software applications, such as radio buttons, for default options. Mirsch et al. (2017) also proposed several tactical changes to user interface designs to shape user behavior in the digital environment. Djurica and Figl (2017) focused their digital nudge recommendations on e-commerce platforms, such as the effective application of defaults and customer reviews to nudge consumer behaviors. Mathias and Jannach (2021) studied deeper into the use of digital nudging strategies within recommender systems for other digital platforms such as the media streaming services. They have also conducted a comprehensive literature review of the various studies on the effects of nudging mechanisms on user behavior in the context of recommender systems. Valenčič et al. (2022) examined various nudging strategies on the online grocery stores context, such as the changing of grocery store's user interface by incorporating different label(s), including a default option, having a pop-up sway suggestion or increased salience to achieve optimal results. Plak et.al (2022) have also studied how various digital nudging strategies can be formulated in the context of education by identifying ways tailoring to the level of motivation in order to raise student engagement. They found that motivational nudges were particularly useful in fostering high level of students' engagement, leading to better academic outcome. Kroll and Stieglitz (2021) also examined the social network context, to examine how self-disclosure on social network sites constitutes a potential privacy risk, further proposing the application of digital nudging as an intervention to improve the awareness of such risks among the digital users. Aside from examining just the digital context, Bammert et al. (2020) have also conducted an extensive research into how digital nudging can help to improve various business process, Primarily using process deviance as the theoretical lens to conduct an online experiment, concluding that digital nudging does indeed influence decisions of the process participants, thereby leading to optimal business process improvements.

In spite of the abovementioned developments in the growing body of research surround nudge theory and digital nudging, given that Van Kleef and Van Trijp (2018) have suggested that all nudges are supposed to appeal to the heuristics and biases in consumers' decision-making, it is appropriate to review the existing literature on heuristics and cognitive biases so that we can identify further which are the suitable phenomena for me to dive deeper into for further examination and research.

2.2.5. Dual-System Theory as an Introduction to Heuristics and Cognitive Biases

Following his profound contributions to prospect theory, Nobel Prize winner Daniel Kahneman developed another theoretical psychological framework involving a dual-system process that guides decision-making, culminating in a *New York Times* bestseller, *Thinking, Fast and Slow*, published in 2011. This book documented considerable research in heuristics and other major decision theory and psychological research over the previous few decades. Kahneman (2011) talked about *dual-systems theory*, and explained that *System 1* consists of thinking processes that are intuitive and automatic. Individuals make mental rules-of-thumb or cognitive shortcuts known as *heuristics*, which are experience-based, and mostly done automatically and unconsciously. *System 2* is relatively more reflective, deliberative and analytical. This system of effortful, controlled reasoning serves as a check and balance on mental operations and corresponding outward behaviors due to the habitual tendency, given readily accessible mental content, to form quick judgments (influenced by System 1). In fact, Thaler and Sunstein (2008) elaborated at great length on how heuristics are formed as a result of the cognitive biases stemming from System 1 thinking. Their nudge theory and choice architecture framework suggests that the choice architectural changes are meant to "nudge" consumers towards certain predictable decision-making patterns, habits or biases, more commonly known as heuristics. The focus of this dissertation is also to explore the mental processes of System 1 more deeply when it comes to attributing value to products and services offered in the digital context.

2.3. Heuristics and Cognitive Biases

The dual-system framework has developed a large following, particularly among psychologists, and has inspired researchers to explore many cognitive biases or systematic errors, as highlighted in Kahneman (2011). This stems very much from the need for humans (and even animals) to make decisions under the constraint of time and with limited informational resources. Duhigg (2012) stated that the formation of habits, also known as automatic behavioral patterns, is the result of repetition and associative learning. Tversky and Kahneman (1974), Gilovich et al. (2002), and Gigerenzer and Goldstein (1996) have provided a substantial list of such biases, as well as fast and frugal algorithms or heuristics that violate the principles of classical rationality as suggested by the classical expected utility theorists.

However, to the best of my knowledge, I have been unable to locate any journals within the extant literature that have comprehensively consolidated such findings with a special focus on applications within the digital context. This is what I hope the following subsection can seek to accomplish.

2.3.1. Descriptive Review of Key Biases and Heuristics Relevant to the Digital Age

This section also seeks to contribute to existing literature on cognitive biases and heuristics through providing a table of brief descriptive reviews of extant literature on various types of bias, effects and heuristics (see Table 1). This table is certainly not an exhaustive list of all relevant research, but represents some of the key studies identified and which are relevant to the digital age's business models.

Table 1: Descriptive Review of Key Biases and Heuristics Relevant to the Digital Age

Serial Number	Types of Bias, Effect or Heuristic	Brief Summary and Descriptive Review of Relevant Literature	Key Findings
1	Loss aversion, risk aversion, regret aversion, endowment effect and fear-of-missing-out effect (FOMO)	Perhaps the best-documented cognitive bias, loss aversion is aptly explained by Tversky and Kahneman (1979) with the summary line "losses loom larger than gains" (p. 270). Their empirical study indicated that the pain of losing has approximately twice the effect as the utility derived from gaining.	The empirical study by Tversky and Kahneman (1979) on loss aversion is one of the earliest and most salient examples of cognitive biases and irrational decision-making behavior. Many similar, related terms

		Loss aversion also sets the stage for other well-known biases and effects, such as framing, the endowment effect, the status quo bias and the sunk cost fallacy as described by Thaler (1985, 1999), paving the road for much research in this domain of decision-making under uncertainty. A more detailed literature review on the endowment effect, which is driven largely by loss aversion, will be covered in the next section 2.4. A similar bias known as regret aversion was further explained by Brewer et al. (2016), who suggested that "anticipated regret" plays a big part in decision-making and is potentially a better predictor of intentions and behavior than other kinds of anticipated negative emotions and evaluations of risk.	were introduced subsequently by various researchers, though suggesting similar impact. In the context of the digital economy, loss aversion plays an extremely pivotal, albeit subtle, role given it is so entrenched in our psyche, and contributes greatly to the FOMO culture that drives much of digital social media and e-commerce behavior.

		The cognitive biases of loss aversion and regret aversion are also the main reasons driving the more widely known “fear of missing out” (FOMO) effect, as Anderson (2011), Collins (2017) and McGinnis (2020) have explained.	
2	Framing and reflection effect	Tversky and Kahneman (1979) also explained that choices can be presented in ways that highlight their relative positive or negative aspects, shaping preferences in different ways. This was formally termed *framing* in Tversky and Kahneman (1981), and was illustrated with the famous Asian disease problem where participants were asked to imagine that the United States was preparing for the outbreak of an unusual Asian disease, which was expected to kill 600 people and to choose between two differently worded options with objectively identical outcomes. When the options were presented in terms of “lives saved”, a majority chose the option which was worded with more certainty, whereas when the programs were	Originally introduced by Tversky and Kahneman (1981) as a policy choice for addressing the “Asian disease”, the framing effect has seen substantial adoption within the socio-political policy-making domain.

		presented in terms of "expected deaths", the majority chose the option which was worded to "gamble or take a chance", lending more credence to the loss aversion fallacy elaborated in the preceding section. The *reflection effect* was also introduced in Tversky and Kahneman (1979) and was often assumed to be similar to framing. The reflection effect posits that we actually have opposite risk preferences for uncertain choices, contingent on whether the outcome is perceived as a possible gain or loss. However, Fagley (1993) suggested that, unlike framing, reflection effects do not involve the same gamble or the same domain. Reflection and framing effects are both predicted in prospect theory by the S-shaped value-function curve even though framing is a perceptual phenomenon similar to optical illusions, whereas reflection is not. (Fagley, 1993, p. 451).	Given the profoundly useful insight that framing, and the reflection effect contribute, suggesting that humans are risk averse when they have something to gain, but risk-seeking when they have something to lose, framing becomes a useful digital tool or nudge for entrepreneurs and marketers to craft their sales pitch and marketing message to their target audience.

3	Availability and numerosity heuristics, recency bias	Tversky and Kahneman (1973, 1974) highlighted the *availability heuristic* as one where people make judgments about an event's probability based on how "available" a similar instance or case is, or how easily such an instance or case comes to mind. A clear application of this in the medical field was documented by Poses and Anthony (1991), who found that a doctor's recent experience of a condition increases the probability of diagnosing the said condition subsequently. This article also illustrated the recency bias, which is considered a smaller but still fairly well-known subset of the availability heuristic. In the context of retail and consumer marketing, Ofir et al. (2008) also showed how the availability heuristic plays an important part in shaping a less knowledgeable customer's overall perception towards a mall, given the ease of recall of information. More knowledgeable customers are	Extant literature focuses on empirical studies of physical malls and tangible goods, though I argue that availability heuristics and recency bias are even more applicable in the digital mobile app context, given that new products and offerings need to cross the hurdle of "awareness" amidst the plethora of similar options on the digital "supermalls", such as Apple's App Store and Google Android's Play Store.

		affected more by the *numerosity heuristic*, demonstrated by Pelham et al. (1994). They found that people judge the amount or likelihood of occurrence based on the presented number of units composing the stimulus, therefore, the more low-priced items on display, the more the customer will attribute a “good value” perception towards a mall.	Understanding such effects thus plays an especial role in achieving maximum visibility, such as, for example, spacing out marketing advertisements, or having digital advertisements that feature heavily during particular periods of the user journey.
4	Representativeness heuristics	This is another major heuristic; Kahneman and Tversky (1972) describe *representativeness heuristics* as assessing similarity of objects or events	Again, existing research on representativeness heuristics

		and organizing them based around the category or class. Representativeness is at work even in lotteries, where gamblers prefer lottery tickets with random-looking sequences over those with a patterned sequence, as evident from afield experiment conducted by Krawczyk and Rachubik (2019). Kardes et al. (2004) demonstrated this clearly in the retail context, suggesting that the consumer may note how similar the generic store brand's package is to that of the more expensive name brand (given that such similarity exists) and infer that the generic product will perform similarly to the name-brand product. This is a common merchandizing strategy in retail stores, used to great effect.	and salience bias is seen mostly in the physical goods domain, although it can be argued that in the digital context, many consumers also form "labels" that are deeply entrenched in their psyche, to assist in their decision-making process. The representativeness heuristic is particularly relevant in the digital age; as the adage goes, the wealth of

		In the domain of corporate finance and trading, Chen et al. (2007), using brokerage account data from China, provided several examples of how investors make poor trading decisions by preferring to buy a stock that had abnormally high recent returns, wrongly extrapolating future potential high returns from past performance.	information leads to the dearth of attention. The rise of influencers on various social media platforms will likely see this representativeness bias taking center stage in any new digital age rethinking of business models.
5	Affect heuristic	The *affect heuristic* is another major heuristic which is so entrenched in most of our System 1 thinking that we seldom use our System 2 to reflect about it. Originally attributed to Tomkins (1962), Tomkins (1984) highlighted that "affect is the primary innate biological motivating mechanism, more urgent than drive, deprivation and pleasure, and more urgent even than physical pain" (p. 163). Slovic et al. (2002) explains this	One of the key findings of this review of the affect heuristic literature is that this heuristic drives most of the "impulse-buying" behavior we see in today's consumerism, given

		affect heuristic as quick and automatic evaluations rooted in experiential thought that is activated prior to reflective judgments. This is the heuristic where emotional response or *affect* plays an important role. Affect is also responsible for binary black-or-white thinking tendencies, especially in circumstances where there is time pressure to make decisions. Positive affect thus refers to the extent to which a person experiences positive moods and emotions subjectively. This is particularly critical because, according to the System 1 thinking that Kahneman (2011) explained, positive affect plays a special role in tilting a consumer into such a binary exactitude, thereby making the ultimate purchasing decision. In the clinical context, Slovic et al. (2000) found in an empirical study that people are more influenced with a negative affect by risks framed in frequency (e.g. 20 out of 100) as opposed to probability (e.g. 20%	the binary black-or-white tendencies it drives in our minds. In the digital context, many features and effects contribute to the affect heuristic, either positively or negatively, to contribute eventually to a final decision, whether a consumer or user forms a good opinion or impression of the offering or not.

		likelihood), when it comes to clinicians viewing patients with potential to commit acts of violence. Finucane et al. (2000) illustrated the affect heuristic at play, finding that when a person is in a positive emotional state, they are more likely to perceive an activity as having high benefits and low risks; conversely, when their emotional state is negative, they are more inclined to see the activity as being low in benefits and high in risk. This study also highlighted that this inverse relationship between risk and benefit judgments was strengthened when time pressure was introduced. King and Slovic (2014) lent further credence to this inverse relationship in the context of product innovation, where affect is used to infer judgments about the attributes of product innovations, which are often marked by uncertainty both about the risks and benefits offered by the product.	Digital entrepreneurs and mobile developers and marketers will do well to follow through with an appropriate call to action once a summarily positive affect can be identified along the customer/user journey.

		In the corporate context, Park and Lee (2007) used the affect heuristic to explain the linear relationship between number of online comments and the positive perception towards a company's corporate reputation. This was also further substantiated by Ravaja et al. (2015), finding that corporate reputation does affect emotional and motivational processes and that the emotional tone of messages and reader comments in online news affects the corporate reputation. Murphy and Zajonc (1993) also showed how affect can be an effective priming tool, as it is elicited outside of conscious awareness, diffuse and non-specific. Their study also supported the affective primacy hypothesis, first asserted by Zajonc (1980), that positive and negative affective	

		reactions can be evoked with minimal stimulus input and virtually no cognitive processing.	
6	Empathy gap (hot-cold) vs (cold-hot) gaps	As a potential subset of the affect heuristic, Loewenstein (2005) introduced two forms of empathy gaps, explaining that *empathy gap* is the inability for people to appreciate fully the effect of emotional and physiological states on preferences or behavior. The "hot" visceral states include negative emotions such as anger or fear, feeling states such as pain, and "drive" states such as hunger, thirst and cravings due to addictions or sexual arousal as detailed by Loewenstein (2000). In regard to the "cold-hot" gap , "people who are in "cold" states tend to underestimate the motivational force of their own future hot states, they often fail to take measures to avoid situations that will induce such states, or to prepare to deal with those that are inevitable" (Loewenstein, 2005, p. S49).	In the digital context, I argue that the visual cue is especially important given the dominance of mobile devices, where digital offerings are mostly delivered, lending further credence to the phenomenon of "addicts glued to their mobile screens". As such, sexual cues, relying on the hot-cold empathy gap

		Ariely and Loewenstein (2006) illustrated this best in the context of decision-making during sexual intercourse, whereby men in the “cold” unaroused state tend to state that they will use contraceptive measures in the subsequent encounter but often fail to do so in their “hot” aroused state. Sayette et al. (2008) also showed that relative to the “hot” group, smokers in a “cold” group under-predicted how much they would value smoking in a subsequent session; these authors thus used the cold-hot empathy gap to explain poor decisions among smokers attempting to quit and why people underestimate their risk of becoming addicted in the first place. However, discussions around this empathy gap still predominantly focused in the medical and psychology fields, and there is a clear gap in existing literature on applying this understanding in the business or marketing	effect, are heavily deployed to stimulate arousal and achieve a maximum awareness effect, thereby driving impulsive social media and consumerism behaviors, potentially explaining the rise of the social influencers industry through various social media platforms.

		context. In the digital context, empathy gap heuristics can be used to design the user interface of software applications, to place potential users in arousal states to trigger further positive affect towards the use of digital services.	
7	Status quo bias	Samuelson and Zeckhauser (1988) defined *status quo bias* as the preference for doing nothing or sticking to decisions previously made. Madrian and Shea (2001) also associated inertia with the status quo bias in their paper about 401(k) plan participation of employees in the United States. They found that the participation rate was higher under automatic enrolment and that the default contribution rate and investment allocation chosen by the company had a strong influence on the savings behavior of the participants.	A key finding is that, given the immensity of options and information made possible by the digital revolution, a modern-age consumer needs "help" and appropriate "nudges" to evaluate and decide.

		Samuelson and Zeckhauser (1988) also noted that this status quo bias is consistent with Tversky and Kahneman's (1979) introduction of loss aversion. In today's digital context, where consumers and internet users are flooded with information from a wide plethora of sources, Dean et al. (2017) explained that the status quo bias is the result of "choice overload", and that, unlike the suggestion of many economists, status quo bias is actually rational given the high uncertainty and deliberation costs identified by Nebel (2015). According to Goldstein et al. (2008b), status quo bias is also the basis for a powerful tool for marketers known as *default*, which has been used in many other contexts, including the digital economy.	As such, startup entrepreneurs and digital app developers and marketers will do well to employ defaults; driven predominantly by this bias, these can be used to great effect.
8	Present bias and temporal/	As the wise adage from John Capgrave's *The Life of St Katharine of Alexandria*, written in 1450, goes: "a bird in the hand is worth two in the	The instant gratification effect, underpinned by present bias,

	time/delay/future discounting, instant gratification effect	bush". O'Donoghue and Rabin (1999) defined *present bias* as the tendency for people to give stronger weight to payoffs that are closer to the present time when considering trade-offs between two future moments. The present bias is closely related to *temporal discounting*, otherwise known as time or delay discounting. Frederick et al. (2002) provided further evidence, supporting O'Donoghue and Rabin's (1999) findings, that humans are impatient and that present rewards are weighted more heavily than future ones. However, Laibson (1997) highlighted that this temporal discounting effect is not linear, nor does it occur at a constant rate. Laibson's paper introduced *hyperbolic discounting theory* applied to the context of an illiquid asset whose sale must be initiated at one time period before the proceeds are received. The theory states that values placed on rewards decrease very rapidly for small delay periods and then fall more slowly for longer delays.	as highlighted by Eyal (2014), is often found in the post-digital revolution world, and many digital products and services are designed around this effect. Variable rewards, coupled with an investment of effort – whether in the form of time, capital, attention or data, such as comments – trigger the release of dopamine. As explained by D'Amato (2019),

		As with Sayette et al. (2008), Bickel et al. (1999) also used the smoking context to examine impulsive behavior, and found that the tendency towards immediate gratification can be used to explain delay discounting. As a remedy to mitigate this temporal discounting effect for smokers, Stein et al. (2018) suggested *episodic future thinking* (EFT) as an intervention exercise, to simulate future events mentally. In another noteworthy paper that involved several researchers, Sheffer et al. (2016) also introduced priming tasks to substantially reduce the effect of this delay discounting effect. In the marketing context, Hershfield et al. (2011) indicated in a study of examining saving behavior that people who saw age-progressed avatars of themselves tended to have a smaller temporal discount and were more likely to accept future financial rewards as opposed to more immediate rewards.	dopamine is a chemical compound released by neurons that creates a pleasurable sensation, perpetuating the "hooked cycle" that Eyal (2014) suggested, and which increases the habitual propensity to use the product repeatedly. The digital entrepreneur and developer should consider embedding an understanding

		As such, this cognitive bias has a material impact in shaping business and marketing strategies for the digital context, which has a substantial focus on instant gratification.	of present bias and its corresponding effects to develop habit-forming products.
9	Priming, anchoring/ focalism and salience bias	Weingarten et al. (2016) defined *priming* as a phenomenon in which exposure to a stimulus, such as a word or image, influences how one responds to a subsequent, related stimulus. In the retail marketing context, Chartrand et al. (2008) used two key words, such as “prestige” and “thrift”, to prime participants in a study of perceptions towards shopping malls in the United Sates. It was clear from the results that higher preference ratings were given to the malls which were primed with the word “prestige”. The same study also noted that subliminally evoked retail brand names can serve as cues to activate consumer purchasing goals. In another study, Chartrand and Bargh (1999) also introduced the *chameleon effect*,	Priming and anchoring are effective tools employed by many in the retail context. The underpinning biases of salience and focalism have driven many entrepreneurs and developers to begin adopting “simple, clean and lean” designs in their user

		referring to nonconscious mimicry of the postures, mannerisms and other behaviors of one's interaction partners as being an effective prime towards others, thereby gaining social acceptance in a mechanism known as the perception–behavior link. *Anchoring* or *focalism* is a cognitive bias observed and discussed by Tversky and Kahneman (1974), where initial exposure to a piece of information, such as a number or an event, serves as a reference point and influences subsequent judgments. It is a particular form of priming which is heavily used in various recent contexts, as illustrated in a comprehensive literature review by Furnham and Boo (2011). One notable example in the consumer retail context is a study by Wansink et al. (1998), which found that anchor-based, point-of-purchase promotions such as nudge slogans, purchase quantity limits or expansion anchors could be effective strategies to	interfaces and messaging to achieve maximum effect. Furthermore, in the digital context, particularly with software applications available on various online stores such as Apple's App Store and Google's Play Store, where the prices of comparable products of a particular category or genre are typically the same (e.g. free, US$0.99 or US$4.99), the anchoring effect

		potentially increase consumer purchase propensity and sales output quantities. Another frequently discussed bias is *salience*, which underpins most heuristic judgments relying on external cues. In essence, in the context of public policy, Dolan et al. (2010) asserted that information that stands out has a higher probability of affecting our thinking and actions. Maheswaran et al. (1992) noted clearly that brand names serve as an effective salient cue to infer quality and shape consumer preferences, while Coulter and Coulter (2005) concluded that consumers are not consciously aware of the role of magnitude representations in influencing price perceptions. In their study of the degrees of visual salience, they found that a lower sales price in a smaller font size relative to the regular price resulted in greater purchase propensity than presenting the price in a larger font size.	is likely to be stronger, although there is no existing literature to examine how an startup can overcome such bias with a new price offering.

10	Social and cultural norms, social proof effect, fairness/ reciprocity bias	Dolan et al. (2010) defined “social and cultural norms as the behavioral expectations, or rules, within a society or group, or alternatively a standard, customary, or ideal form of behavior to which individuals in a social group try to conform” (p. 268). Chartrand and Bargh (1999) showed evidence of this in their social mimicry study described earlier. Akerlof and Kranton (2000) noted that such norms are essential components of identity economics, a theoretical approach which suggests that economic actions and behaviors are the result of both monetary incentives and people’s concepts of themselves. Cialdini (2008) also highlighted that social norms play a key role in social interactions, because when people are uncertain, they will tend to look for social proof, and collectively they form a norm. Particularly relevant in this post-#MeToo era, Bhattacharyya (2018) and Tippett (2018) argued that many existing social norms need to	One key finding is that social and cultural norms are particularly applicable in the digital economy, given the prevalence of social networks, where many digital offerings rely on network effects, which further enhance technology diffusion. Digital startup entrepreneurs, developers and marketers will do well to understand these

		be revisited and revised. Descriptive normative feedback can be useful in behavioral change programs, as evident in a study by DiClemente et al. (2001), which found that the comparison of a person's alcoholic drinking level with the national average was effective in nudging for lower general consumption levels. Furthermore, Allcott (2011) clearly illustrated that normative feedback on how the individual household's energy consumption level compared to the regional average shaped energy conservation habits effectively, in a large-scale pilot program run by OPOWER, a US-based company acquired by Oracle in 2016. The same effect has been documented by Farrow et al. (2017) and Goldstein et al. (2008a), who also concluded that the social norm bias has been particularly effective in inducing environmental conservation behaviors.	biases in order to achieve maximum awareness, particularly in the user base ramp-up and growth phase. Given the prevalence of online falsehoods, there exists a clear trust deficit between the masses and the prevailing institutions of societies. Many people have thus turned to friends, family, other relatives and even social influencers for validation, for everything from

		However, in light of the COVID-19 global pandemic spreading during the preparation of this dissertation, and the corresponding elevation in awareness of climate change and the woeful conditions of the global health security infrastructure, Cohen (2020) also argued that this is the ideal time to revise our social norms towards a more sustainable consumption pattern to elevate our global health security preparedness. It is also noteworthy that the COVID-19 pandemic has proven Cialdini's (2008) finding about pre-recorded audience laugh tracks serving as the "social proof" to elicit TV audience's laughter in situation comedies, as we can observe how awkward late-night shows can be when superstar hosts in the United States, like Stephen Colbert or John Oliver, had to deliver their monologues without a live audience or accompanying laugh tracks during the quarantine periods of 2020 and 2021.	digital offerings to lifestyle choices.

		Gouldner (1960) referred to *reciprocity* as a generalized moral norm. As defined by Fehr and Gachter (2000), it involves in-kind exchanges between people, which can be both positive (such as returning a favor) or negative (such as retaliation). Cialdini (2008) explained that this is entrenched in our human nature, since our ancestors had to share resources in early societies. However, Ariely (2008) stated that social norms of exchange, such as reciprocity, are different from market exchange norms. Cialdini et al. (1975) expanded on Freedman and Fraser's (1966) foot-in-the-door technique to develop a reciprocal concessions procedure for inducing compliance. This is a powerful tool adopted by many organizations in various contexts. It is also commonly seen in charitable organizations and was well documented by Falk (2007). In that study – a large field experiment involving gift exchange compared to a no gift condition – donations increased by 17 percent if a small gift was included and by a	

		massive 75 percent for a large gift. Chuan et al. (2018) also found similar conclusions in a large field study involving former patients of a hospital, though they also identified that reciprocal behavior decays rapidly as times passes, suggesting the importance of capitalizing quickly on opportunities to benefit from a quid pro quo. In today's digital context, Hopcroft et al. (2011), Zhu et al. (2014) and Song et al. (2017) have shown how reciprocity links have been effective in information diffusion processes on various social media platforms such as Twitter, YouTube in the United States, and Sina Weibo and Douban in China, although strategic networking among the network participants is particularly important for them to gain a larger audience respectively.	
	Literature on the zero-price effect is critically reviewed in greater detail in the next section.		

2.4. Zero-Price Effect – A Critical Review

The *zero-price effect* (ZPE) is an empirically tested phenomenon where the demand for a product is substantially higher at a price of zero as opposed to any other prices, even including prices that are just slightly higher than zero. The *endowment effect*, as explained by Kahneman et al. (1991), is the phenomenon that people tend to overvalue something that they already own, even if it is only owned temporarily. Such insights have driven strategies in the tangible product context, such as test-driving for luxury cars to increase conversion rates. However, in the digital context, these effects also play interesting roles, because the combination of these two supposedly different and isolated phenomena can lead to favorable business outcomes. The importance of ZPE and the closely related endowment effect cannot be emphasized enough, given their major influence on freemium-based strategies adopted by many companies in the digital economy. One salient example of such strategies is the use of free or zero-pricing to achieve greater user traction via downloads, allowing more users to temporarily own or experience a product. This allows the endowment effect to have an influence when it comes to making an eventual decision to pay more for subsequent premium offerings or continued usage. Therefore, I feel that discussion of the ZPE warrants an entire subsection as part of this dissertation's critical review of existing literature.

2.4.1. Zero-Price Effect and Corresponding Endowment Effect

Seminal research by Shampanier et al. (2007) introduced the ZPE. This study suggested that decisions about free products differ from traditional linear cost-benefit models where people will choose the option with the highest cost-benefit difference. Shampanier et al. (2007) essentially asserted that the traditional linear models, which assume that benefits deemed by a consumer stay constant with changes in "cost" at all price levels, are untrue. They empirically established that the intrinsic value of a tangible product is disproportionately increased when it is priced at zero due to various psychological factors. They also suggested that positive affect, along with social exchange norms and mapping difficulty, are the key drivers of this ZPE. Hossain and Saini (2015) further validated this non-linear relationship, with studies indicating that the relative preference for hedonic products (e.g. entertainment), as opposed to utilitarian products (e.g. food and other necessities) as defined by Khan et al. (2005) is disproportionately enhanced when they are offered for free.

It is indubitable that Shampanier et al.'s (2007) study has influenced other seminal works, such as Anderson's (2009) *Free: The Future of a Radical Price*. Anderson asserted that the 20th century concept of "free" was very much a marketing gimmick, with a corresponding cost. However, the 21st century heralded in the Web 2.0 digital revolution, which has led to digital products and services that are genuinely free, given that the marginal cost of production and distribution has reduced substantially, forcing a rethink of business strategies and pricing models. The digital context, according to Chris Anderson, is one where content is free and value is determined primarily by the attention the product/service or potentially the brand, company or its associated persona gets. Anderson's (2009) recommended approach of offering a free version for marketing and mass exposure, with a corresponding premium version of the product which can be charged for, has been the primary strategy for most digital businesses. The entire social media influencer industry and the modern music industry post-Napster and iTunes were birthed from such a strategy. Ariely's (2008) popular book, *Predictably Irrational,* also elucidated the idea of "free" further, explaining that people tend to overvalue what they already own, illustrating this with a basketball tickets experiment. This overvaluing is known as the endowment effect, which Kahneman et al. (1990, 1991) have documented in detail with studies on *tangible physical items* such as coffee mugs and sports cards (List, 2011). Kahneman et al. (1990, 1991) also used loss aversion as the main paradigm to explain such an effect, and this was substantiated further by Marzilli-Ericson and Fuster (2014). Ariely et al. (2018) expanded further on Shampanier et al. (2007), suggesting that, due to social norms, people behave differently when faced with a price of zero. For example, if a chocolate is priced at a lower nominal price relative to its normal average market price, demand for it will increase in accordance with classical economic theory. However, social norms mediate this effect when the chocolate is priced at zero (i.e. it is free), and people begin to limit their demand to only one or two items, so as not to appear greedy or desperate. This led Ariely et al. (2018) to suggest that if hotel operators were to price supposedly free amenities at a nominal or "bargain" price, rather than offering them for free, this could potentially increase the demand for these items. Therefore, it is demonstrated that while the ZPE does result in a disproportionate increase in demand for most tangible goods from prior research, there may be other effects such as social norms that will mediate this effect.

2.4.2. Key Limitations of This Seminal Paper

Shampanier et al.'s (2007) work has certainly been widely cited in various marketing and business journals. However, beyond the authors' fascinating introduction of the concept of "zero" since the Babylonian age, there is only a cursory reference to Tversky and Kahneman's (1979) prospect theory. The limited literature review within the paper presents a challenge for readers or subsequent researchers to identify which theory or paradigm guided the research, and the gap in the theoretical or framework evolution of consumer decision-making processes is what the preceding literature review section in this dissertation sought to bridge. Aside from that, Shampanier et al. (2007) examined consumer behavior only with *tangible physical goods* such as chocolates and truffles. This provides a unique opportunity to explore how similar work can be done with *digital* products and services, given their increasing relevance in the 21st century. Therefore, I seek to examine the psychology of "free" in the context of today's application software, which has been made so prevalently available via Apple's App Store and Google's Android Play Store, as well as the efficacy of freemium business models, and whether cognitive biases like ZPE and the endowment effect still apply in this digital age.

Another study within Shampanier et al. (2007) involved nominal/bargain pricing versus free pricing pertaining to Amazon's delivery services in Europe, and also provides a good basis for further exploration in the digital context. Relative to the "free shipping of parcels" introduced in other European nations, the price of shipping in France was reduced to a nominal 1 French franc (rather than free), which corresponded to a negligible price of only US$0.10, or 10 cents. The authors reported that the order quantity increased substantially in the countries with free shipping, while the quantity changes in France were immaterial. This finding about zero-pricing of delivery services in Europe, except France, clearly substantiates the ZPE that Shampanier et al. (2007) asserted. However, while the French anomaly seems to support classical economics theory predictions, it is contradicted by the findings of Ariely et al. (2018), where the demand for chocolates and snacks dropped when they were provided for free in a hotel/hospitality context. Ariely et al. (2018) suggested that social norms mediate such effects, and that, fearful of being perceived as desperate or greedy, consumers limited themselves to only one or two free products; in contrast, a nominally priced option or items priced at a bargain level relative to their average market price actually substantially increased the demand for such products. Given such a unique contrasting phenomenon, it is worth exploring whether such a disproportionate and irrational bias and value attached to goods with a zero price or free is still applicable in the digital economy, or if nominal or bargain pricing of US$1 has a similar effect to a deep-value proposition like “zero”.

In summary, despite my critical review of this seminal paper on the ZPE and the well-documented endowment effect on tangible physical goods, to the best of my knowledge there is an obvious gap in the literature around examining the impact of the endowment effect for *digital* offerings. I am seeking to bridge that gap in this dissertation. This is then an opportune place to segue to the next segment of this literature review, which focuses on the digital context within which I am situating my research, and more specifically the mobile applications digital context.

2.5. Review of the Digital Context Literature – Mobile Applications

As Lytras et al. (2008) have explained, the software industry has gone through enormous changes over the decades since the days of the massive IBM mainframes, and the mobile applications (hereafter “apps”) sub-segment, being my dissertation’s focused context, has certainly matured substantially since the introduction of the first iPhone in 2007, as described by Hsu et al. (2015). Extant literature on apps is quite extensive, and growing substantially, particularly in the realms of information systems as well as electronic commerce research and applications. However, as Tang (2019) opined, the various streams of research remain inconsistent and fragmented.

First, in considering a definition of apps, numerous definitions exist. Roma and Ragaglia (2016) defined apps as simply software developed for mobile phones, distributed primarily through mobile portals, which are in turn managed by mobile network operators. Chang (2015) defined apps as software or applications that perform specific tasks for the users and are suited to run on mobile devices. Hsu and Lin (2015) indicated that escalating user demand and ubiquitous developer tools have driven an exponential increase in the categories of apps. They defined apps as mobile application software for mobile devices for general productivity and information retrieval purposes including:

1. contact management, calendar, email, stock market information and weather
2. games, social networking platforms, e-books and utilities
3. others offering access to information and content such as entertainment, media and lifestyle.

For the purpose of my research, I align my work to Hsu and Lin’s (2015) more granular definition. Furthermore, to situate my behavioral economics research within this digital context requires an understanding of the existing theories that underpin research into the universe of apps. Among the multiple theories that guide existing apps-related research, I have found the most common to be the theory of planned behavior, diffusion of innovations theory, the technology acceptance model, and the theory of uses and gratifications.

Yang (2013) integrated Ajzen’s (1991) seminal paper on the theory of planned behavior, the technology acceptance model and the theory of uses and gratification to guide his research into app consumers’ attitudes, intent and use, identifying perceived enjoyment, usefulness, ease of use and subjective norms as the significant predictors of consumers’ attitude to apps. Carter and Yeo (2016) also adopted the theory of planned behavior to guide their research on apps usage by Malaysian business school undergraduates and postgraduates, concluding that while there were nuanced differences in subjective norms and perceived behavioral control norm constructs, there was limited difference in the perceived attitude towards the apps construct.

Kim and Baek (2018) used the diffusion of innovation theory (DIT), first introduced by Rogers (1962, 1983), as a conceptual basis for identifying innovative traits of a new technology, in order to examine the complex patterns of technology adoption. They found that time convenience, interactivity, and compatibility with existing values, past experiences and needs of potential consumers were the key factors influencing mobile app engagement. Similarly, Karjaluoto et al. (2019) also used “personal Innovativeness”, a term derived from DIT by Rogers (1962), along with self-congruence and new product novelty to explain the popularity of the mobile financial services apps industry in Finland. Kang (2014) also used both this classic communication theory, DIT, and the theory of planned behavior (Ajzen, 1985) to reinforce the explanatory potential of the theory of acceptance model, particularly in the realm of apps adoption. Hew et al. (2015) also adopted the unified theory of acceptance in their study concerning the reasons catalyzing apps usage intention.

Rauschnabel et al. (2017) anchored their research into the recent and wildly popular mobile augmented reality game Pokémon GO with the uses and gratification theory (U&GT) to address the fundamental question of why consumers adopted the app, as U&GT (Rubin, 2002) proposes that consumers are goal-oriented and proactively select media that satisfy particular needs. They found that hedonic, emotional and social benefits and social norms drive consumer reactions whereas physical risks, given that Pokémon GO involves interaction with physical surroundings, hinder consumer behavior. Tang (2017) used the telepresence theory, which, according to Steuer (1992), refers to the experience of presence in an environment by means of a communication medium, as well as social capital theory to explain the critical success factors of Pokémon GO. Using telepresence theory was a particularly surgical approach, given that Steuer (1992) developed this theory specifically for the virtual reality environment, which has special relevance in the case study of Pokémon GO. Tang (2017) saliently highlighted the app's ability to tap into nostalgia, and the adoption of technologies such as augmented reality (AR) and global positioning systems (GPS) to execute a unique transmedia storytelling, and asserted that these, alongside the establishment of a cult-like following, underpinned by social capital theory, contributed to the success of this AR video game app.

There are, of course, some other theories applied to apps which are also noteworthy. Hsiao and Chen (2016) adopted the perceived value theory in their research, concluding that loyalty among players of gaming apps and perceived values of the game measured by playfulness, connectedness, access flexibility and reward, will influence consumers' purchasing intention. Chang (2015) also used perceived value theory to assess satisfaction and loyalty, noting that the "high level of perceived value for e-commerce and m-commerce warrant exploration of the effect of satisfaction and its impact on mobile application loyalty" (p. 687). Oyedele and Simpson (2018) adopted both perceived value and identity theory to examine the adoption of media-streaming apps, finding that there was a strong relationship between the streaming apps' values and consumers' self-identity, and that such identity salience will likely contribute substantially to the probability of recommendation and propagation.

Aside from the key guiding theories that assist in navigating the widening ocean of the apps body of literature, I refer to Tang (2019), who presented a comprehensive classification of the key themes of this literature, grouping them into primarily three categories (see Figure 3):

1. branded apps as business supportive tools
2. revenue-generating apps
3. consumer motivation, attitudes and behaviors toward mobile apps.

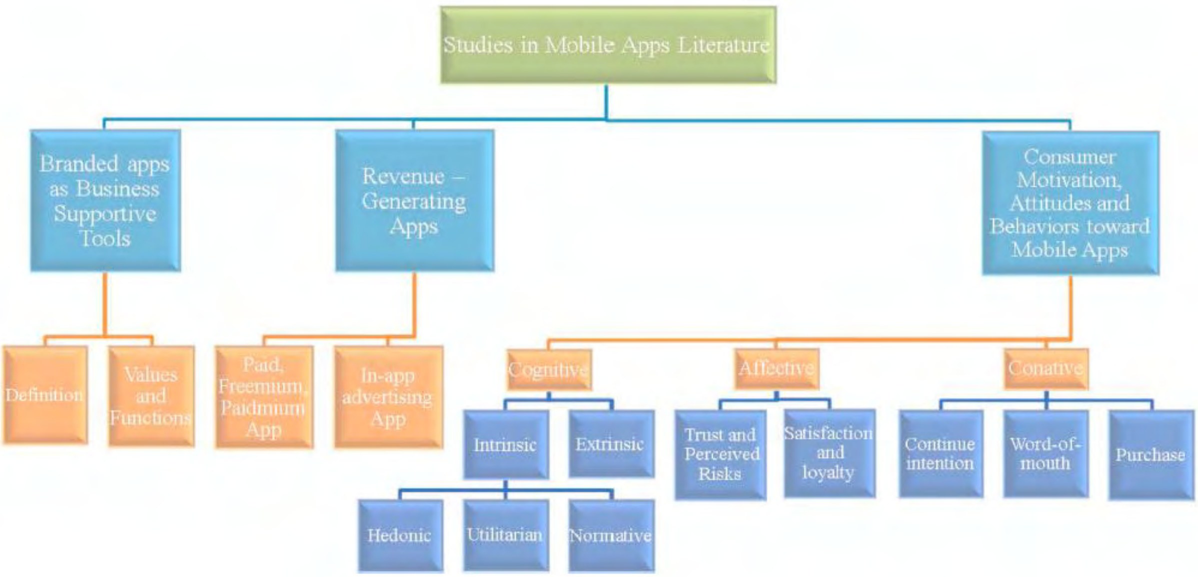

Figure 3: Tang's (2019) Thematic Classification of Apps Literature

As Tang (2019) explained, branded apps differ from revenue-generating apps in that they serve to support existing business operations, including brand-building, promotions and online channel purchases, whereas revenue-generating apps are made for the purpose of earning profit. It is the goal of my research to focus on the latter two categories. My explicit aim is to elide the insights from the behavioral economics literature expounded in the preceding sections of this chapter, which play an especial role in reinforcing understanding of the third category of the apps literature, with a review of various business and revenue-generating models in Tang's second category, focusing predominantly on the freemium business model, because Tang (2016) indicated that freemium apps account for the highest percentage of sales in the major app stores.

Drilling deeper into the broad theme of consumer motivation, attitudes and behaviors, Tang (2019) underscored that there is a growing body of literature grounded on three further dimensions: the cognitive (think), affective (feel) and conative (do) perspectives. The cognitive dimension is further broken down into intrinsic and extrinsic factors. The intrinsic subjective factors are examined by various researchers, including Kang (2014) for hedonic motivations and Martinez-Lopez et al.'s (2014) empirical research on the utilitarian motivations. Rauschnabel et al.'s (2017) study focused more on the social normative element in their famous augmented reality Pokémon GO case study, finding eventually that consumers' self-concept drives positive attitudes, although social norms only show moderate effects on the intention to continue playing. Cheung and To (2017) also identified that social norms can reinforce trust and positively moderate both consumers' tolerance to in-app advertisements and consumer behavior. As we move on to the more objective extrinsic factors, Gu et al. (2017) studied how contextual cues, such as permission justification and app popularity, affect consumers' behavior. Urban and Sultan (2015) also noted that apps that show a higher propensity towards benevolence and generosity in sharing information and promoting trust tend to positively moderate consumers' behavior and attitudes. This finding was echoed by Cheung and To (2017), who highlighted that trust is a powerful antecedent of app users' attitudes. The conative dimension corresponds primarily to the behavioral outcomes of app usage. Xu et al. (2015) provided a salient example with their research into word-of-mouth recommendations by users, finding that satisfaction with apps (affect) and the hedonic benefits (utilitarian) were strong intrinsic antecedents of the desired conative outcomes of continuing usage and (word-of-mouth) recommendations. Hsu and Lin (2015) found that value for money, the app rating itself, and free alternatives to paid apps had a direct impact on the intention to purchase, another desired conative outcome. Tarute et al. (2017) also found that consumer engagement positively shaped the conative outcome – consumers' intention to continue using the app – with an explicit focus on the use of visuals in design and navigability of the app. In addition, Hew et al. (2015) found that habit was a major factor for positively shaping consumers' intentions.

Evidently, there are a plethora of theories that guide various studies into the apps universe. Notwithstanding this, the inconsistent findings from the different streams of research present an issue for practitioners, as it may seem that researchers tend to "miss the forest for the trees" when they focus narrowly on just the respective factors, and thus aggravate the academic research–practice gap, as suggested by Porter and McKibbin (1988). Particularly in the apps universe, where there are millions of apps on the Apple's App Store and Google Android's Play Store, as illustrated in DotNek (2020), practitioners need to identify ways to breach the awareness barrier. Furthermore, as Tang (2019) noted, the "cognitive, affective and conative components are interrelated and the sequence may vary" (p. 8). Thus, a particular focus of my research is to use nudge and zero price theory, as described in the preceding section, to examine whether the realm of behavioral economics can provide further insights (beyond the information systems and electronic commerce contributions) into how consumers' attitudes towards zero price can help practitioners cross the awareness chasm for the modern apps of the digital economy. Therefore, it is appropriate to dive deeper into the specific thematic business model subcategory of freemium literature in order to get a better understanding of this study's context.

2.5.1. Freemium and Free Trials

Among the various digital business models listed by Veit et al. (2014), the freemium business model is a popular one, especially among companies that develop *information goods* such as computer software, online games, apps and services, as defined by Shapiro and Varian (1998). *Freemium*, which is a portmanteau word combining "free" and "premium", refers to a business model that involves offering a free, scaled-down basic version of the product, with the anticipation of converting users into paid users of a premium, value-enhanced version of the product.

Shapiro et al. (1998) as well as Deubener et al. (2016) provided a comprehensive classification scheme for the various kinds of freemium business models, using theoretical sampling of 40 apps from the App Store in an attempt to derive a typology; they used two key themes "relationship between free and premium offering" and "premium revenue stream" as the main differentiating variables of the typology. Heier (2015) also highlighted that the difference between "pay-to-play" versus "pay-to-win" models adopted by most mobile gaming developers has various impacts with regard to consumer criticism, given that the latter model provides spenders with unfair advantages vis-à-vis skilled players and does not provide a good basis for competitive electronic gaming. In essence, extant research has indicated that not all freemium apps and their corresponding business models are the same.

Brockmann et al. (2015) conducted an extensive study on around 254 successful apps from Apple's App Store to categorize them appropriately and seeking to identify the prevalent business models. Content-based freemium business models were identified as the most popular, adopted by most independent software developers or production and development studios, lending further credence to Heier's (2015) observations about the precipitous rise of the freemium model. Within the content-based distribution business model explained by Brockmann et al. (2015), the games (e-entertainment), media-streaming (e-infotainment) and productivity-related (e-information) sub-categories were broadly the most popular. Most of the extant literature focuses on games, given the relatively extensive availability of information on these apps. Evans (2016) conducted an in-depth examination of three freemium games, exploring the relationships between commercial motivations and game designs. This study also highlighted that the freemium model often dictates a never-ending game world, so as to prolong the engagement period with the user and thus increase the chances of their conversion into paying customers. Evans (2016) also underscored the fact that freemium as a strategy serves objectives beyond just revenue generation, also acting as a potential branding strategy to introduce adjacent or related products. Winestock and Jeong (2014) provided a good overview of the dictionary application market in their research, highlighting the bleak outlook for revenue generation given multiple sources of competition, including device manufacturers embedding free versions in their operating systems and voice-activated assistants. They suggested that the freemium model is only viable for dictionary app developers and publishers if there are other ways to monetize via other services such as exam preparation or native pronunciation coaching.

Freemium-based mobile apps are usually downloaded for free from Apple's App Store or Google Android's Play Store. There are plenty of examples in the mobile software application market, including well-known names like Dropbox, a file-sharing platform;

LinkedIn, a social networking platform for professional networking and job-matching; casual puzzle video games like Candy Crush or Angry Birds; as well as Spotify, a music streaming services platform. This limited feature freemium model is thus similar to the definition of *freeware*, a term more commonly used in the Web 1.0 era during the dot-com boom of the late 1990s until just prior to the introduction of the Apple's App Store in 2008. Freeware refers to a version of the software with basic features and without a time lock, as explained by Lee and Tan (2013). Free trials however, often referred to as *trialware*, involve the full functionality of focal software with a time lock (Lee & Tan, 2013, p. 213). Both models are underpinned by the same loss aversion mentality and endowment effect, as described in the previous sections.

There is a growing body of empirical literature on the efficacy of both the freemium and free-trial strategies. However, existing literature contributes findings that contradict each other. Lee and Tan (2013) suggested that both freemium (freeware) and free-trial (trialware) are similar in terms of impact on user conversion, basing this contention on data observed from Download.com. Liu et al. (2014) supported the hypothesis that "free" is effective, finding that the freemium strategy was positively associated with increased sales of the paid version of mobile apps, using a large data set of 711 ranked mobile apps from Google Android's Play Store. Koch and Benlian (2015) demonstrated that this freemium strategy, coupled with scarcity and personalization, is particularly effective to drive viral marketing campaigns and increase a user base rapidly. Niemand et al. (2015) also stated that free services are perceived to provide more value than the premium paid services, based on results from experimental studies.

However, Koch and Benlian (2017) found that the "PremiumFirst" model, which is their definition of trialware, significantly increased conversion propensity compared to "FreeFirst", which corresponds to the freemium/freeware strategy. According to these authors, this is largely explained by the loss aversion cognitive bias. Furthermore, in a study examining the trade-off between network effects (which enhance the propagation of the technological offering) and the cannibalization effect (which suggests that a product or service offering from one firm can potentially decrease the adoption or consumption of another product or service offering from the same firm), Cheng and Tang (2010) found that when network intensity is strong, it is more profitable for a software monopoly to offer free-trial products (trialware) than to segment the market with two versions of different quality (i.e. to introduce a freemium version on top of the main product version). In an earlier study, Ye et al. (2004) also found that the "free mentality" and the expectation of online offerings is well-entrenched and that many people believe that previously free online services should remain free. Studying consumers' willingness to pay for various online services, such as email, travel, news, weather, sports and auction information, they further suggested that the perceived importance of convenience and usage are important factors, and that older consumers are more willing to pay for online services than younger ones. In a more recent study, Rietveld (2018) also showed that users of freemium digital PC games actually played less, and that the freemium models generated correspondingly less revenue than their premium paid alternatives (even factoring in the in-game purchasing options after an initially free download). Rietveld also found that greater variety in games' menus of paid items was associated with higher revenues. He used the sunk cost fallacy, rooted in loss aversion bias, to explain such a phenomenon observed with Toki Tori, a game developed by the Dutch game developer Two Tribes, which was released on the Steam digital publishing platform in 2010. A more recent research by Wang et al. (2018) showed how the availability of free substitutes on the app store for a productivity app like the GPS navigation app actually drives user's intentions to purchase a productivity app, given relative advantage and perceived enjoyment post purchase. Another recent study by Fang et al. (2019) sought to address the monetization of social freemium gamers from a social influence lens, and found that a *pure-friend* relationship was much stronger than a *Simmelian-tie* friendship, leading to a higher propensity to be converted into a paying customer. This implies that previously held beliefs that technology diffusion through existing users' mutual connections might not be that effective after all. Hamari et al. (2017), in a study involving 869 user responses, interestingly found that while all service dimensions, such as assurance, empathy, reliability and responsiveness, positively increased the willingness to continue the freemium usage of mobile apps, increasing the quality of such a freemium service had surprisingly limited impact on the willingness to pay for additional premium services.

These contradictory findings lend credence to what Niemand et al. (2019) have suggested: that despite certain evidence that "free" is useful and effective, many companies in the digital world, particularly startups, struggle to employ the freemium business model due to low conversion rates. Pauwels and Weiss (2008) also highlighted a number of key challenges and various sources of long-run revenue losses as companies attempt to shift from freemium to fee-based or hybrid offerings. Boudreau et al. (2021) made a particularly relevant finding when their research uncovered that the prior, overly simplistic assumption that freemium models and network effects will benefit every participant in the market is false, as their empirical findings suggest that only the market leader benefits, whereas followers tend to suffer from adopting freemium strategies. In fact, if incumbents achieve market leadership through the freemium strategy, they encourage creative exploration of revenue or conversion models within the incumbents, making it even more difficult for followers to compete with them.

Huttel et al. (2018) asserted that the ZPE, ever since its introduction by Shampanier et al. (2007), has remained a black box, especially in the context of the digital economy. They proposed a model suggesting that the positive affect resulting from the ZPE is moderated by two factors: a benefit-inflation effect and a cost-deflation effect. They suggested that non-monetary value contributions or non-monetary costs (NMCs) are substantially factored in by consumers amidst other factors, as suggested by Schumann et al. (2014), Kumar et al. (2010) and Van Doorn et al. (2010). These NMCs may include costs associated with advertising intrusion and data privacy. Huttel et al. (2018) focused solely on advertising intrusion and essentially found that the free version of a fictional video-streaming platform, Netstream, reduced the NMC or cost-deflation effect from advertising intrusion but reinforced the benefits-inflation effect. However, it is important to note that while Huttel et al. (2018) suggest that advertising is a fundamental source of revenue and conclude that companies should offer service for free and benefit from the cost-deflation effect by selling more advertising, Thiel and Masters (2014) indicated that this only benefits the tech titans – Google, Facebook and Amazon. These companies dominate the online advertising market, with ~70% market share according to the Interactive Advertising Bureau (2019). Selling online advertisements is simply not a viable or sustainable strategy for mobile app startups.

Niemand et al. (2019) developed a framework to explain the ZPE using two central System 1 impulse intuitions that moderate the ZPE: the *free mentality* as adapted from Dou

(2004) and previously highlighted by Lin et al. (2013); and the *price-quality inference*, identified by Lichtenstein et al. (1993) as the tendency to expect a positive relationship between price and quality. Schreiner and Hess (2013) conducted an empirical study to examine consumers' willingness to pay for privacy with a web survey involving 160 German-speaking users to identify the optimal pricing for a premium version of Google, the popular online search engine, and Facebook, another titan in the social networking space. Both of these companies make the bulk of their revenue from monetizing user data through selling advertisements. Schreiner and Hess identified the optimal price for the fictional premium version of Facebook to be ~1.67 euro per month, while the optimal price for the premium version of Google varied between ~1.00 euro and 1.50 euro per month. Schreiner and Hess (2015) expanded on their prior research, recruiting 553 online survey participants. However, they found that while perceived usefulness and trust significantly affected willingness to pay, perceived internet privacy risk did not seem to have a material impact. They concluded that consumers will only be willing to pay for the premium versions of these digital services if there was a substantial value improvement and if the brands were trustworthy. They also identified the theory of planned behavior (TPB), as proposed by Ajzen (1991), as an adequate theory to explain willingness to pay for privacy behavior.

Ku et al. (2017) developed a value-based adoption model applied to a social media instant-messaging application called Line, the file-sharing platform Dropbox and a music streaming platform known as KKBox which suggested that the perceived value of the application, derived from perceived risk, effort, usefulness, assurance and trustworthiness of the developer, strengthens the positive affect of the freemium strategy, which in turn greatly enhances the user's intention to pay. Li and Cheng (2014), through an empirical study on the

Chinese music streaming platform, Douban FM, found that perceived value enhanced the positive affect stemming from the ZPE more significantly than perceived costs or sacrifices. They also substantiated Shih's (2012) finding that cognitive lock-in decreases the willingness to pay, and further added that cognitive biases like loss aversion elevate the perceived costs, whereas social norms mainly increase the perceived benefits. Building on the assertions of Dou (2004) and Ye et al. (2004), suggesting that the free mentality towards any offerings online is highly entrenched, Lin et al. (2013) confirmed such assertions with a study of data collected from 268 online music users, primarily of KKBox and ezPeer, two popular Taiwanese online music streaming platforms.

Shi et al. (2015) focused their research on how social dynamics, whether formally developed within the game or informal social connections, influence purchase decisions. Their research work targeted massively multiplayer online role-playing games (MMORPGs), and freemium social network games, which allow users to play a fully functional game but are designed to encourage multiple purchase opportunities, known as microtransactions, to enhance their gaming experience, such as levelling up their game character or avatar faster. This research implied that social norms, social proof and reciprocity bias play a large role in elevating purchase intent for MMORPGs or other social network games, but the authors did not examine the extent of the ZPE further. Oestreicher-Singer and Zalmanson (2013) also come to the same conclusion: that is, that consumers' willingness to pay increased as they climbed the so-called "ladder of participation" on another music streaming website founded in the United Kingdom and known as Last.fm. Their study also found that the social element and community participation were found to have a much greater influence on the willingness to pay.

Finally, Hossain and Saini (2015) highlighted that the ZPE works differently in different types of products: whereas level of affect on hedonic products were disproportionately enhanced, the ZPE on utilitarian products was more subdued. It is this particular insight from Hossain and Saini (2015) that I seek to explore further in this dissertation, examining whether or not the category of digital offerings available on software application stores makes a difference to the ZPE, thereby seeking to contribute further to the zero price theory that Shampanier et al. (2007) introduced.

2.5.1.1. Key Gaps Within the Freemium Literature

In addition to the key gaps in Shampanier et al.'s (2007) work on the ZPE discussed earlier, I will now explore the key gaps in the freemium literature amidst the ocean of existing apps-related literature. Many prior researchers have tended to lump freemium/freeware together with free-trial/trialware, despite these being different strategies; this has made it difficult to come to a congruent explanation of the ZPE or to align the different approaches we observe practitioners of ZPE employed, especially in the startup domain. Only two notable studies, including Cheng and Tang (2010) and Koch and Benlian (2017), provided key insights into this differentiation, as elucidated in the previous section. Another important practical point to note is that there is often a resource challenge for startups in developing more differentiating and value-enhancing features in order to widen the user's perceived value gap between the free basic and premium paid version of an app, so as to achieve successful conversion. As Berger (2020) also highlighted, the freemium strategy's success is contingent on how much is given away. If too much is given away for no immediate revenue, the startup can run the risk of spending too much of its precious early resources and capital to maintain a base of early, entitled users without any prospect of converting these into paying customers.

Furthermore, unlike the case of a free-trial/trialware strategy, without exposure to an app's full features or functionality in the freemium/freeware version, it is difficult for the user to extrapolate the value gap appropriately in making a final purchasing decision. Also, most of the prior research has focused on the more rational, reflective System 2 processes as described by Kahneman (2011), and only Niemand et al. (2019) have attempted to explore the System 1 intuitions, such as how the "free mentality" and "price-quality inference" moderate the positive affect, which is an inherent cognitive bias of consumers, in purchasing decisions. Besides, while Shampanier et al. (2007) suggest that nominal or bargain prices of $1 (especially in the context of the French delivery services elucidated previously) do not seem to have any material impact on the "positive affect" of the ZPE, Niemand et al. (2019) suggested that in the context of Netflix, which is a frequently used video-streaming platform, the positive affect arising from a deemed "bargain" price might be strong, and even comparable to the positive affect arising from a free offering. This sets the stage for further exploration into whether the category/genre as well as the frequency of use of a mobile application affects the perceived value gap needed to constitute a good deal or bargain. Within the digital context, my interest is in identifying whether different reference points exist for consumers to make their decisions. In addition, Ariely et al. (2018) also indicated that social norms mediate the ZPE, and I believe it is worthwhile to explore whether different digital application categories equate to the different categories of physical goods, such as chocolates and hotel amenities, leading to different consumer demand outcomes. Moreover, Stocchi et al.'s (2017) research also suggested that apps that are branded independently are more likely to attract more users and achieve better brand image if offered at a price other than zero, juxtaposed with apps linked to existing online or offline brands, which their research indicated are better off priced for free. Such variances in the findings pertaining to free/zero-price versus bargain/nominal price motivate me to explore these issues deeper through a behavioral lens.

Finally, extant literature seems to group consumers' awareness of a product together with the purchase decision, thereby constituting a person's willingness to pay. In the physical goods retail context, awareness is very much curated by the store's procurement department or staff member and limited by the store or malls' physical space, but in the digital context, particularly in mobile app stores, there is a constant need to compete for a consumer's attention and corresponding awareness of any digital offerings. Through my dissertation, I seek to address this major gap (i.e. as a result of grouping together both the awareness and purchase decision) in order to better reflect the digital context for the purpose of formulating better and more expedient business strategies.

As such, I would like to submit that there are ***two stages of consideration*** especially in the context of the business-to-consumer (B2C) mobile application digital context, comprising the consumer's ***willingness to download (WTD) and willingness to pay (WTP)***. Given that there are so many "free" options on both Apple's iTunes App Store and Google Android's Play Store, I believe that firms need to consider both stages in order to execute a successful and sustainable business strategy in the digital context.

2.6. Framing the Research Objectives and Questions

In line with the pragmatism spirit of this dissertation, it is crucial to explore the various antecedents and factors that ultimately influence the consumer's decision to be converted from a freemium or free-trial user into a paying customer. Huttel et al. (2018) placed a particular focus on positive affect, given its binary, black-or-white decision-making effect on consumers, when they conceptualized a framework to determine the eventual impact on irrational demand, thereby reflecting the importance of Kahneman's (2011) System 1 automatic thinking (see Figure 4).

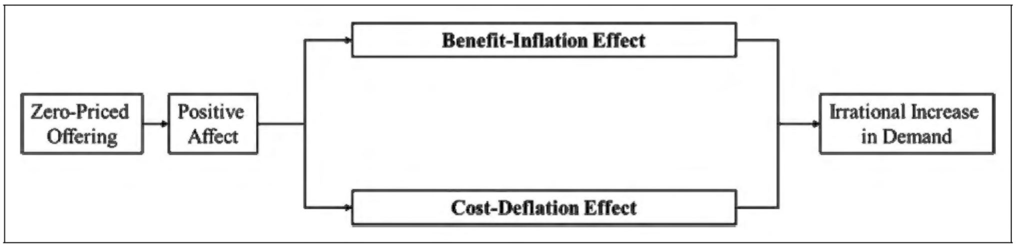

Figure 4: Original Conceptual Framework of Huttel et al. (2018)

Drawing inspiration from their conceptual framework, as shown in Figure 4, I seek to more deeply explore the behavioral effects that may influence positive affect, specifically the zero-price effect (ZPE) and the endowment effect.

As defined in Chapter 2.4, the ZPE is an empirically tested phenomenon where the demand for a product is substantially higher at a price of zero as opposed to any other prices, even including prices that are just slightly higher than zero. The endowment effect is the phenomenon that people tend to overvalue something that they already own, even if it is only owned temporarily. I believe that they play especial roles in moderating the level of affect experienced by consumers in both the first awareness and subsequent conversion stage of decision-making process in the digital context.

Therefore, I have modified the referenced framework by Huttel et al. (2018) to include both stages as shown in Figure 5.

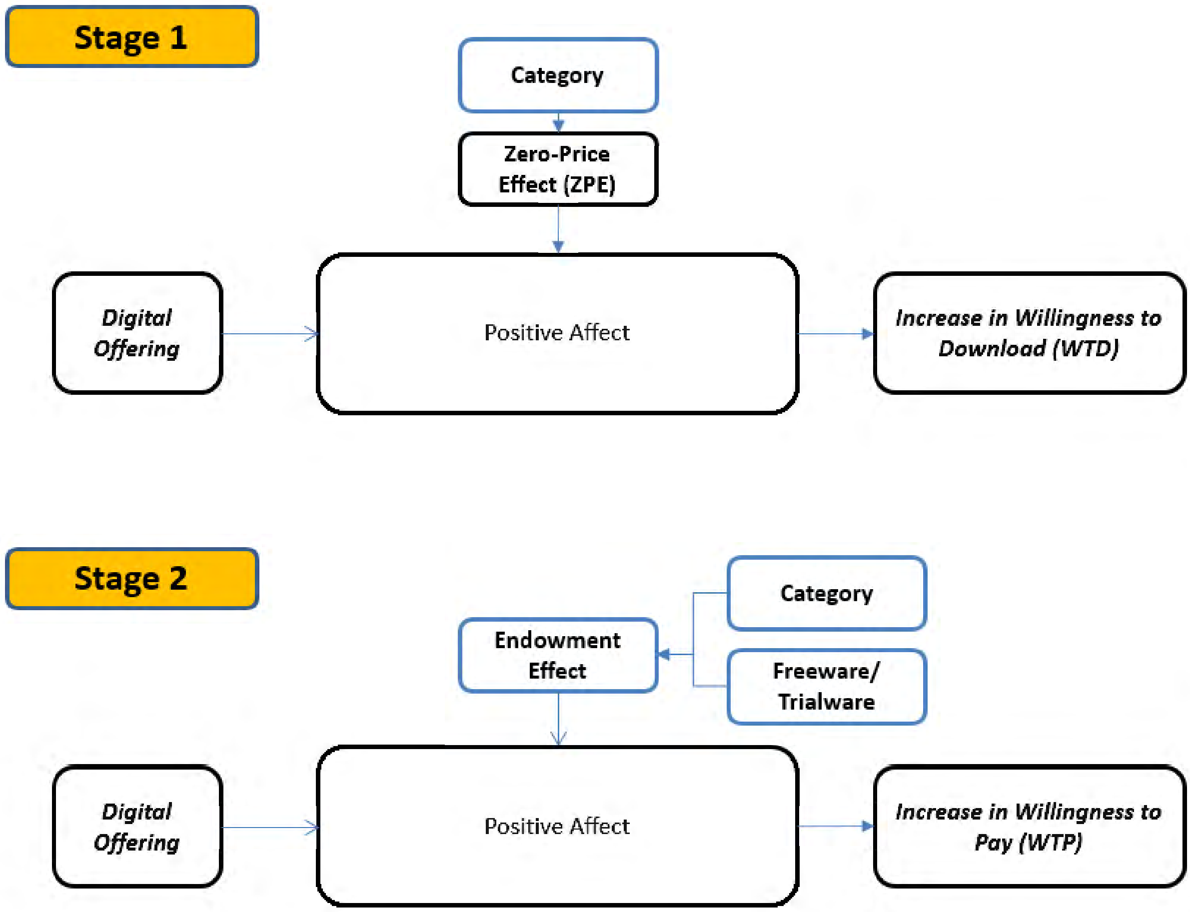

Figure 5: Conceptual Framework for This Dissertation

In this framework, I propose that there are two stages in a digital consumer's purchasing decision. In the first, awareness stage, a digital offering will trigger a positive affect that is influenced by the ZPE. This framework suggests that the category of a digital offering may play a part in determining the strength of the respective effects influencing the positive affect, which may ultimately lead to the consumer's willingness to download. It is important to highlight that an individual can only evaluate an app after they are made aware of it and have downloaded it for evaluation. Therefore, I also note that in the case of a bargain-price offering, the willingness to download in Stage 1 also implies a willingness to pay the nominal/bargain price for the download and that the willingness to pay in Stage 2 refers to the willingness to pay for the additional premium offering in the app.

For Stage 2, which is the conversion stage, I will also explore whether the endowment effect holds for digital offerings, and whether the endowment effect has a different impact if executed with a free-trial/trialware or a freemium/freeware strategy.

Within this conceptual framework, I will examine the following research questions:

1. For Stage 1, with the objective of achieving maximum willingness to download, how do consumers perceive zero-priced vs bargain-priced digital offerings?
    a. Is this homogenous across the three main differing categories/genres of *games*, *media-streaming applications*, such as music streaming platforms (e.g. Spotify), and *productivity*, such as cloud-storage solutions (e.g. Dropbox).
2. For Stage 2, does the endowment effect apply for mobile applications?
    a. Is this effect homogenous across the aforementioned three main categories?
    b. Does the endowment effect impact the freemium/freeware model to the same extent as the free-trial/trialware model with respect to willingness to pay?

2.7. Key Hypotheses

Using my guiding conceptual framework which is developed on top of the framework introduced by Huttel et al. (2018) and the focused research questions 1 and 2, I have derived the following hypotheses for the two different stages.

Given that in Stage 1, the goal for any digital practitioner is to overcome the awareness hurdle faced by many marketers and entrepreneurs as explained by Berger (2013); and to ensure that their digital products or offerings are made known to the target audience who faces a myriad of applications for them to choose from, we want to examine whether ZPE can help to moderate the level of positive affect, leading to an effective nudge to download the app for the user to try out.

For Stage 1's awareness stage, examining a modern digital consumer's willingness to download:

- Hypothesis 1: The zero-price effect (ZPE) generalizes to the digital context, and is observed for digital offerings across all three categories, namely games, media-streaming mobile applications and productivity.
- Hypothesis 2: The zero-price effect (ZPE), as measured by the choice proportions and the level of affect, varies across different digital application categories
- Hypothesis 3: At the bargain/nominal price, the choice proportions and the level of affect vary across different digital application categories
- Hypothesis 4: Digital consumers prefer to download the full-feature free-trial option for evaluation at this stage as opposed to the limited-feature freemium version for all three digital application categories.

For stage 2, where the user already has the chance to evaluate the digital product or service, the overarching goal for the digital practitioners is thus on conversion, i.e. persuading or convincing the user who has already downloaded the app previously, to convert into a premium-paying customer. As Berger (2020) highlighted, this is also the stage that determines whether the idea, product or service will take root, contributing to a sustainable revenue model for the business enterprise. As such, we want to study whether the endowment effect can help to moderate the level of positive affect, leading to an effective nudge for the user to become a paying customer.

For Stage 2's conversion stage, measuring a modern digital consumer's willingness to pay for the premium offering:

- Hypothesis 5: An endowment effect exists for consumers who are being endowed with a limited-feature freemium basic offer or with a full-feature free-trial period basic offer for all three digital application categories
- Hypothesis 6: Consumers who are endowed with the full-feature free-trial period basic offer are more likely to pay for the premium offer than consumers who are endowed with the limited-feature freemium basic offer after a predetermined period of time for all three digital application categories.

With insights gleaned from such studies, I hope to contribute to existing literature on applied behavioral economics in the context of the digital economy, including digital nudging as well as free-related strategies in the marketing and information systems domain.

Chapter 3: Research Design and Methods

To more deeply understand the affective mechanisms driving the consumer's willingness to download in Stage 1 of the conceptual framework, as well as their willingness to pay in Stage 2, I have undertaken a quantitative study in my research and the details of the research design and methodologies are documented in this chapter.

3.1. Objective of the Study

The purpose of this main study is to test the hypotheses laid out for the two stages of the digital consumer's purchasing journey.

3.2. Guiding Research Paradigm

The debates about which paradigm is superior have existed since time immemorial, during the age of Socrates and Plato from the West and Lao Tzu and Confucius from the East. However, the scientific revolution in the 16th century, following the Renaissance era, saw the rise of science as a branch of philosophy, and scientists were referred to as "natural philosophers", as described in Manicas (1987). The 19th century truly revealed how philosophy and scientific research are connected, beginning with a philosophy titan, Georg Hegel (1770–1831). Hegel introduced the concept of idealism, which ascribes priority to the mind, and incorporates the idea that the external world does not exist without the mind perceiving it. It was not until the dawn of the 20th century that scholars like Bertrand Russell (1872–1970) and George Edward Moore (1873–1958) began to challenge idealism as a dominant paradigm with their common-sense realism. They even went so far as suggesting that sophistry and hypocrisy were associated with idealism because idealists entering a room will approach and sit on chairs, even though they believe such chairs are *not* real and do *not* exist. The movement against idealism's philosophical hegemony gained momentum with the Vienna Circle, including Moritz Schlick (1882–1936) and Richard von Mises (1883–1953) in the first score of years of the 20th century, contributing to the rise of logical positivism. In fact, Moritz Schlick led the logical positivists in a very overt alliance with the realists, declaring that anyone who acknowledged the Vienna Circle's fundamental principle must also be an empirical realist.

In the world of the sciences, the positivistic theoretical perspective founded on objectivistic epistemology and corresponding foundationalist ontology has long enjoyed much influence, given its confidence in claims of "objectivity" and empiricism. The promise of exact and accurate knowledge of the world, derived from data collected from sensory experience, truly appeals to humanity's need for certitude. Such data will form the basis for establishing relationships between social phenomena that can be observed with "objective and unprejudiced eyes", and with an empirical rather than normative mindset found within the questioning, according to Houghton (2011). However, as Houghton concluded, such claims do not stand up to scrutiny when used in both social and natural sciences. The discovery of quantum by Max Planck in 1900 and subsequent research in the field of quantum mechanics throughout the 20th century by physics titans like Niels Bohr, Ernest Rutherford, Werner Heisenberg, Max Born, Erwin Schrödinger and Albert Einstein dealt a strong blow to the claim of certainty made by the positivists and championed by the Vienna Circle. Busch, Heinonen and Lahti (2007) clearly explain Heisenberg's (1927) seminal publication which introduced the Heisenberg uncertainty principle to the then nascent field of quantum theory. This was most clearly manifested by the Schrödinger's Cat thought experiment (Schrödinger,

1935) which illustrates that the mere act of observation by the researcher alters the experiment, and that it is simply impossible to accurately determine subatomic dynamics with absolute certainty. Moritz Schlick, who was also a student of Max Planck, worked with Niels Bohr to develop the "Copenhagen interpretation", essentially suggesting that the Heisenberg uncertainty principle does not mean that positivists are ignorant of the laws of nature, but that uncertainty is a law of nature itself; therefore, what we can know about the quantum world is only the effects we can observe after the researcher's intervention.

Notwithstanding this, as Harari (2014) asserts, our existence involves repeated nuanced programming, which is manifested in the form of habitual tendencies of the body and the mind. He underscored Bodhi's (2005) recounting of the ancient Indian philosophers and teachers, including the Buddha, that one's mind is consistently shaped by every possible thing we experience. For things that we like, the mind breeds different levels of greed; for things that we don't like, the mind breeds different degrees of aversion, and when brought to an extreme, it breeds fear, anger and potentially hatred; and for things that we neither like nor do not like, such as breath or the sensation on our soles, the mind breeds ignorance. The last of these characteristics is what has propelled the renaissance of the *mindfulness practices* we see in the 21st century and which are evangelized by many technology entrepreneurs and modern psychologists. However, the issue behavioral economists face in achieving mainstream recognition is that the logical positivists, as mentioned earlier in this subsection, consider only the five main sense organs – eye, ear, nose, tongue, skin – for the collection of empirical data, while the ancient thinkers, especially in the East, have often considered the mind as the sixth key sense organ. As the literature review has highlighted, it was not until the 1970s, when the pioneering work of Tversky and Kahneman (1979) began to adopt the quantitative method, that recognition of the “mind” as a sensory organ for which quantitative data can be collected began. It is this tradition that guides my research methodology and the main quantitative portion of this dissertation will be aligned with this approach. This is, in my opinion, a band-aid solution, albeit the best one currently available, to the qualia measurement problem.[2]

However, my research broadly adopts the pragmatism paradigm, which, according to Morgan (2014), has often been associated with the mixed-methods research approach. This pragmatism paradigm is less interested in the philosophical debate and abstract concerns of the positivists and the interpretivists, or the dualistic views of the realists and the idealists. At the end, to my target audience of digital entrepreneurs, my study is really about “what works”, which effectively sums up what pragmatism’s early proponent, John Dewey, said about the paradigm, as highlighted by Crotty (1998). As Matsuda (1989) notes, pragmatism is attractive to the “subordinated” class as it is their indigenous method to adapt strategies for daily living, and for resource-strapped early-stage startup entrepreneurs, I do believe it is most appropriate. Pragmatists are concerned with the human experience. Crotty (1998) highlighted another important criticism of pragmatism – the sense that it seems to accommodate the Holocaust – and this relates to the topic of ethics. As Sunstein (2015) explains, “nudging” and use of cognitive biases in policy shaping or business strategies can

[2] Qualia is a unit of measurement of a subjective experience perceived by a person; it lies at the core of the mind–body problem that psychologists, neuroscientists, philosophers and theoretical physicists over the last century have been contending with. Behavioral economists since the 1950s have used affect scale measurement as a “proxy” to quantify this level of “subjective” experience.

constitute a perception of "manipulation", and one must thread the fine line to ensure the target's decision-making powers are not subverted or insulted. As an aspiring behavioral scientist, I find myself in agreement with this philosophy, and pragmatism's continuous reflection of beliefs and actions is applicable. While on the one hand, our human experiences are constrained by the natural world at large, *quantitative* approaches such as experimental surveys (which is clearly guided by a post-positivist perspective and objectivism epistemology), can help us collect data and develop better understanding and knowledge via an inductive reasoning process; on the other hand, adopting *qualitative* methodologies guided by the interpretivism epistemology such as literature reviews or case studies, which are essentially, detailed accounts of individuals' or companies' experiences and perspectives within their localized setting can also strengthen the said inductive reasoning process.

Pragmatists felt that the use of both quantitative and qualitative methods even within one research project is not only permitted but potentially necessary to have a better picture of the truth, and seeks primarily to achieve practical and applicable results. As such, the first part of my research project involves this main quantitative online survey, guided by the positivistic epistemological position, whereas my literature review of the various heuristics and behavioral effects in the preceding section as well as the subsequent literature review of online blogs for novel growth hacking techniques using the various ideas of "free" is guided more by an interpretivist paradigm.

In summary, as contemporary astrophysicist, Neil deGrasse Tyson said of the natural world, "The universe is under no obligation to make sense to you"; Gayatri Spivak, an Indian scholar from Columbia University also once said, "Relieving anxiety is not the object of academic work". While the epistemological and metaphysical debates will continue, I feel that

Pragmatism as a research paradigm will guide me to avoid a binary, either-or thinking that favors exactitude and caution me to remain open-minded while embarking on this mixed-methods research project. And particularly in the context of a nascent field like behavioral economics in the digital context, I find it especially important.

3.3. Procedure

I deemed that a quantitative survey in a two-stage scenario-based quasi-field experiment to be most appropriate. In this case, I focus my experimental design around a discrete choice experiment, which as explained by Mangham et al. (2009), is a quantitative research technique for identifying individual preferences, and allows researchers to uncover how individuals choose between hypothetical alternatives. I also adapted the useful framework provided for the study of discrete choice modelling and choice behavior laid out by Louviere et al. (2000), as this has been a preferred choice to empirically measure consumer preferences, particularly in the field of marketing. Green and Srinivasan (1978, 1990) also stated that discrete choice experiments are particularly useful in measuring a consumer's or individual's utility level according to a particular set of configurations. Referencing the famous Shampanier et al. (2007) experimental setup, I employed a 2 by 2 matrix mixed design as per a categorical scenario, with "cost" and "offering" as the key dimensions to observe. That is, participants go through three different scenarios corresponding to the different mobile application categories/genres (games, productivity and media-streaming) to make their respective choices. Within the "cost" dimension, there are "free" and "paid" conditions; within the "offering" dimension, there is a "basic" and a "premium" condition.

Focusing on the cost dimension, in the “free” condition, participants are introduced to a basic offering priced at zero or free, and a premium offering priced at S$10.00 (Singapore dollars). For the “paid” condition, participants are introduced to a basic offering priced at a bargain/nominal price of S$1.48 and a premium offering priced at S$11.48. One thing to note is that the most basic paid tier in the United States and Singapore AppStore/PlayStore is priced at US$0.99 and S$1.48 respectively. As such, the nominal or bargain price in the Singapore context, which I am examining, was thus set at S$1.48, to ensure familiarity for the Singapore-based participants. I maintained a consistent price differential of S$10.00 between the basic and premium offering for both the free and paid conditions to ensure there was at least a double-digit monetary unit difference in the prices, to delineate the options presented. This deliberately accentuated the difference between the basic and premium offering that a digital consumer will likely face, which would otherwise be difficult to replicate in a hypothetical scenario. I also included an option of “do nothing” to allow survey participants to have a fallback option if neither the basic or premium offerings seemed to satisfy them. Participants who chose this option were *not* asked to rate their “affect” level.

Instead of using Shampanier et al.’s (2007) single-item 5-point scale to measure “affect”, I used the popular 11-point Net Promoter Score® or NPS®, widely used by most digital practitioners today in the e-commerce context. The wider point scale as opposed to the previously used 5-point scale allows me to better measure the nuances of how participants feel about their respective choices. More importantly, using this NPS metric will mirror the conditions of the digital context more closely and increase familiarity with my survey participants, given that they will most likely have received emails or experienced such survey before in their daily lives while using various digital services online.

3.4. Introduction to Net Promoter Score® or NPS®[3] (NPS)

The Net Promoter Score® or NPS® is a popular metric introduced by Reichheld (2003) that measures customer experience. It is widely used as a predictor for business growth, serving as a core measurement for customer relationships and experience management programs globally.

Using an 11-option, 0–10 scale, respondents are asked the following question:

"How likely is it that you would recommend the stated digital mobile application to a friend, colleague or relative?"

Digital entrepreneurs or marketers then group respondents into the following categories for actionable follow-up:

1. A score of 9–10 is defined as *"Promoters"*, who are loyal enthusiasts who display high willingness to buy and will encourage further buying and refer others, evangelizing the product and fueling growth and user adoption.
2. A score of 7–8 is defined as *"Passives"*, who are merely satisfied but not considered zealous enough to evangelize, and who are vulnerable to sourcing other competitive products.

[3] Please note that both Net Promoter Score® and NPS® are registered trademarks of Bain & Company, Inc., Satmetrix Systems, Inc., and Fred Reichheld, and although, in practice, the ® trademark sign is seldom indicated. For proper referencing, I have included this explanation here, but will be using NPS as an abbreviation for Net Promoter Score for the rest of this dissertation.

3. A score of 0–6 is defined as *"Detractors"*, who are considered unsatisfied customers who can potentially damage the company or brand's reputation and impede growth through negative word-of-mouth.

Normally, the Net Promoter Score® or NPS® is obtained by subtracting the percentage of Detractors from the percentage of Promoters. In this case, I am using the 11-point, 0–10 scale in lieu of the Shampanier et al. (2007) 5-point scale to measure the level of affect, given that it is a much more familiar metric faced by digital consumers today. Furthermore, this NPS level is particularly useful in my empirical analysis to measure affect (i.e. the emotion elicited after a survey respondent made a choice for every hypothetical scenario presented). This differs slightly from the 5-point scale, but the NPS registered on this wider 11-point scale for the different choices makes for a better discrimination and statistical comparison in my analysis.

3.5. Target Audience

Setting the context of the mobile applications to the business-to-consumer (B2C) segment, the target audience for this research is the adult digital consumer in Singapore over 18 years old. In Singapore, citizens over 18 years old are considered as young adults, which is also why all male Singaporeans are required to fulfil their National Service duties at that age, as per the NS (Amendment) Act of 1967.[4] Aside from that, given that compulsory education in Singapore involves six years of primary school as mandated by the Compulsory Education

[4] The National Service (Amendment) Act was passed on the 15 March 1967.

Act of 2000,[5] and that 99% of Singaporeans have also completed four years of secondary school,[6] with more than half the population achieving a post-secondary diploma or above,[7] I chose to avoid including individuals under 18 years in my sample. People below this age would still be considered largely as school students, whereas my research aims to examine the more general digital consumer. Moreover, I also chose the over-18 adult population in order to examine more accurately the adult digital consumer. In particular, this helps avoid confounding variables such as affordability, as people in this age group have a much higher probability of having sufficient discretionary income to make it unlikely that the nominal price of S$1.48 and even the premium-priced digital service offering of S$11.48 would be deemed extravagant for their consumption. Furthermore, according to the Singapore government's statistics (SingStat), as of 2019,[8] Singapore's mobile population penetration rate was 159.1%, suggesting that the entire country's population owns at least one mobile phone device. According to the Statista Research Department, a global leading provider of market and consumer data, the rate of internet penetration was 88.4%[9] in Singapore as of mid-2020, and among the internet-using population, 93% accessed the internet for personal reasons every day. This makes Singapore an ideal location to examine the adult digital consumer's behavior.

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[5] Compulsory Education Act - https://sso.agc.gov.sg/Act/CEA2000.
[6] https://www.moe.gov.sg/docs/default-source/document/publications/education-statistics-digest/esd-2015.pdf.
[7] https://ncee.org/what-we-do/center-on-international-education-benchmarking/top-performing-countries/singapore-overview-2/singapore-learning-systems/ .
[8] https://www.singstat.gov.sg/find-data/search-by-theme/industry/infocomm-and-media/latest-data.
[9] https://www.statista.com/topics/5852/internet-usage-in-singapore/#:~:text=As%20of%20mid%2D2020%2C%20Singapore,4.8%20million%20were%20internet%20users
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3.6. Operationalization

I used a snowball sampling methodology, specifically the exponential non-discriminative snowball sampling method, in order to reach the target number of 300 participants promptly. This method, also regarded as the chain-referral method with a network propagated mechanism, is well-known in the researcher community as cheap, simple and cost-efficient as explained by Goodman (1961), Handcock and Gile (2011). Furthermore, we find that this is potentially a better way to reach out to a larger audience compared to prior research methodology adopted by Shampanier et al. (2007) and Ariely (2008) where they focus only on the visitors to the canteen within their local varsity context as a sample to conduct statistical inference. Working within the constraints of the Covid-19 pandemic, the quantitative survey can also be more readily propagated and accepted by the participants with this method, as it is particularly challenging to gather them together physically into a specific compound to conduct the experiment. Using the online survey URL weblink to propagate on social media platforms such as WhatsApp, Facebook, Reddit forums in Singapore, makes it relatively easier to forward along the links to participants' respective contacts. The online surveys were created using Qualtrics, which is an online survey-creation platform that generate useful reports in the form of Excel spreadsheets or .csv data files for further analysis.

I aimed to reach a target of around 300 participants for a two-stage experiment. A set of four different surveys was developed and sent to the initial targeted participants of each group. From this beginning, the propagation described above was carried out. The four different surveys attempt to capture responses for the two-stage experiment, with one stage focusing on the ZPE, requiring two major groups of participants, and the second stage focusing on the endowment effect, requiring the target population to be divided into three different groups. As such, the set of questions targeting the second stage had to be split up in order to achieve the objectives. It is perhaps best to visualize the operationalization in the following diagram (Figure 6).

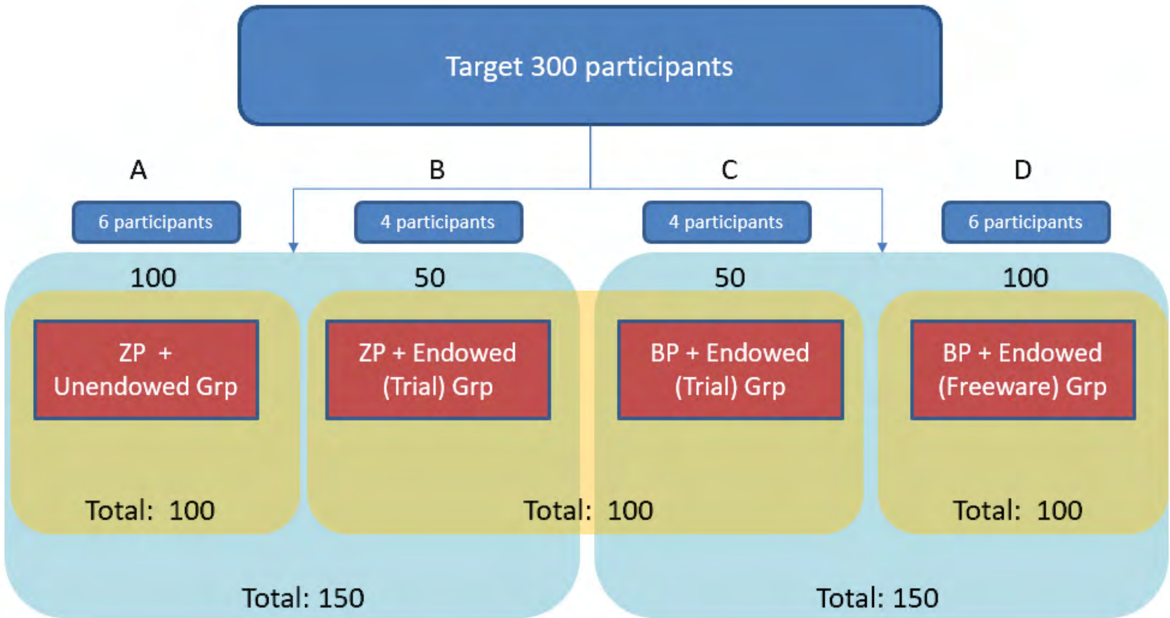


Figure 6: Operationalization Target Size of Each Group

The four groups are described as follows:

A. Free Condition Survey Group (free vs S$10), measuring zero-price effect (ZPE) for Stage 1, as well as surveying the unendowed group, totaling approximately 100 participants.

B. Free Condition Survey Group (free vs S$10), measuring zero-price effect (ZPE) for Stage 1, as well as surveying part of the group for Stage 2, endowed with the free-trial (full-feature limited trial period) option, totaling approximately 50 participants.

C. Paid Condition Survey Group (S$1.48 vs S$11.48), bargain-price group (BP) for Stage 1, as well as surveying part of the group for Stage 2, endowed with the free-trial (full-feature limited trial period) option, totaling approximately 50 participants.
D. Paid Condition Survey Group (S$1.48 vs S$11.48), bargain-price group (BP) for Stage 1, as well as surveying part of the group for Stage 2, endowed with the freeware (or limited-feature freemium) option, totaling approximately 100 participants.

Six targeted individuals were sent the survey weblinks for Groups A and D, whereas four targeted individuals were sent the survey weblinks for Groups B and C. Each of this first tier of referred participants was asked to refer the link to five other contacts, where I advised them to send it to five other contacts. The referred contacts were also asked to refer to five other contacts. I have set the data collection period for another two weeks, to ensure that there is ample time for the survey links to be propagated to others.

In the first stage, online respondents for the Free Condition Survey Group were given a series of hypothetical scenarios, making a choice between the free basic offering, S$10 premium offering or "do nothing", whereas online respondents for the Paid Condition Survey Group were asked to make a choice between the nominally priced S$1.48 basic offering, the S$11.48 premium offering or "do nothing". Following each choice (except for "do nothing"), survey participants were asked to give an NPS score, so that the level of affect or satisfaction could be measured.

In part two of this first stage, the participants were also asked to make a choice about whether to download a full-feature but limited time period version *or* a free limited-feature freemium version. Following each choice, survey participants were asked again to give an NPS score, so that the level of affect or satisfaction could be measured.

This procedure was repeated in scenarios for the three digital mobile application categories of games, productivity and media-streaming.

For Stage 2, measuring endowment effect, the respondents in the respective groups were asked to imagine a scenario where they would be unendowed or endowed with the particular option, and to make a choice between doing nothing *or* paying the extra S$10 for the premium version. "Doing nothing" in the first unendowed group simply means doing nothing, whereas "doing nothing" in the endowed group of the limited-feature freemium group means continuing to use the limited-feature basic version; finally, doing nothing in the full-feature free-trial period group means essentially not paying for premium access and deleting the application to free up space, given its uselessness after the accessible time period. Following each choice, survey participants were asked to give an NPS score to allow for measuring the level of affect or satisfaction.

Given that the survey respondents would be answering the questions for both stages, I estimated that the data collection period would be approximately two to three weeks, before they are organized and processed for further evaluation. These data collected are discussed extensively in Chapter 4, under Results and Analysis.

3.7. Contingencies

Using Qualtrics, I was able to track the completion rate and the number of respondents for each of the four surveys sent out. To complement the snowball sampling method for the experiment and to mitigate the risk of a possible shortfall of responses in each group due to variances in the propagating propensities of each of the initial contacts sent out, I also sent the survey link to various social media platforms, including WhatsApp, Reddit and Facebook groups, that support online consumer behavior research used by various Singapore entrepreneurship interest group communities, with separate survey links and similar questions used for the snowball sampling method. I particularly targeted those groups which seemed to fall behind in the snowball propagation or that were further away from the targeted number for each group (i.e. 100 in Group A, 50 in Group B, 50 in Group C and 100 in Group D). This was my primary mitigation method, as a shortfall of data responses would have been a critical hurdle for the completion of my research.

In the event that I was still not able to achieve the 300 respondents through the snowball sampling method within the three-week period, my intention was to extend the data collection period by another month. This option was important given there is limited control of whether the first-tier participants truly forwarded the survey link to all five contacts, and that it may not be realistic to anticipate all of the contacts would respond accordingly, as well as the fact that even the primary mitigating method of sending out survey links to the social media platforms could be ignored. I planned to extend my sample by reaching out to (300 – x) participants until at least 300 responses were received, where x is the total number of respondents achieved in the first data collection phase of three weeks. These remaining respondents would be sourced within the National University of Singapore, potentially targeting staff and students over 18 years old.

However, it should be noted that I did not need to activate the above-mentioned contingency plan to extend the data collection period by another month as I was able to obtain more than the target number of respondents in the original three-week data collection period. Under the advisement of my supervisors, the survey links were left open for an additional week before we closed the survey just in case there were any new responses from earlier snowball propagation, such that the total data collection period is exactly one month. (Though the original data collection period before any contingency is planned is meant to be only three weeks.) The results and analysis are detailed in Chapter 4 and the total number of respondents are described further specifically in Chapter 4.1.1.

3.8. Ethical Considerations, Biases and Mitigation

Given the contextual difficulties posed by the COVID-19 pandemic, it was particularly challenging to gather 300 participants to participate in a quasi-field experimental survey. As such, the snowball sampling method was chosen as the preferred method as discussed in Mujere (2016) given its quicker and simpler operationalization procedures. However, fully cognizant of the biases that the snowball sampling method would introduce, given that the representativeness of the sample is not guaranteed, I took some measures to mitigate the risks:

- In the original 20 (6+4+4+6) respondents for the different groups that I select to send to, I attempted to select individuals from different ethnic and occupational/professional backgrounds, but as closely representative to Singapore's demographics, gender and ethnic distribution as possible.[10] However, I could not limit which five contacts they would refer to, nor who the five new contacts would reach out to.

[10] https://www.singstat.gov.sg/find-data/search-by-theme/population/population-and-population-structure.

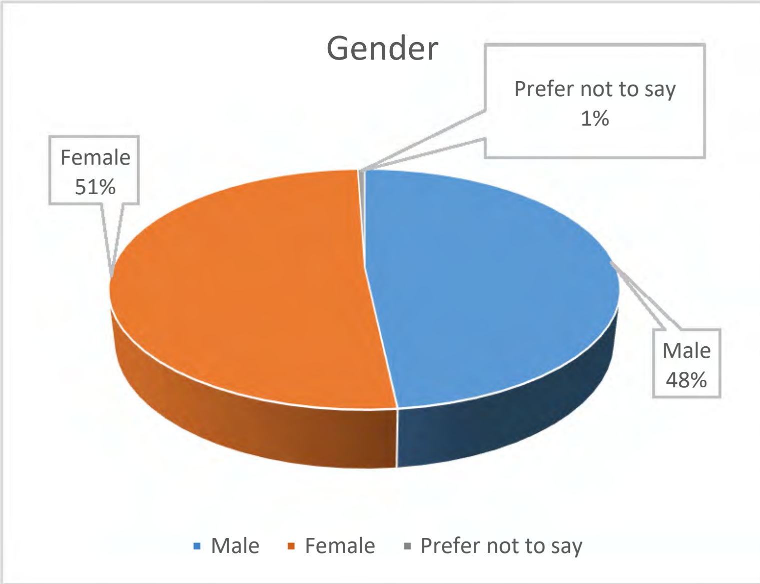
- I ensured that if a respondent had answered one set of survey questions (e.g. the free-condition questions), they would not be able to do the other survey (e.g. the paid-condition questions).
- To adhere to the Personal Data Protection Act (PDPA) of Singapore, and to protect the privacy of the respondents, I did not collect data on specific names, or on identity or contact information; I did collect age data (in order to disqualify individuals from participation if they were less than 18 years old) and gender information.
- To mitigate for the potential that the first and second tier survey participants might not propagate to enough participants to achieve the target 300 sample population for both experiments, I aimed to monitor the number of responses during the three-week data collection period and, if necessary, to identify additional participants for the first tier propagation level (i.e. in addition to the initial 20 (for Experiment 1) or 30 (for Experiment 2)) two weeks into the data collection phase.
- Recognizing that different people have different levels of value attributed to their "perception" of a category, I attempted to generalize this by using generic language such as "moderate" and "substantial" to describe the level of utility or productivity described in the hypothetical scenarios.

Finally, given that these experiments fall within the behavioral science realm, where I am examining the preferences of adult digital consumers at large at an intrinsic human behavioral level, the observations and preferences can likely be generalized to a larger context, even potentially beyond just the Singaporean context. This is similar to the way in which the Shampanier et al. (2007) studies or the experiments of Thaler and Sunstein (2008) on American consumers, or even Huttel et al.'s (2018) findings on the German population extend more generally to human behavioral biases. The whole point of my research in behavioral economics is to identify the various reference points that apply generally to humans of different nationalities in the digital context.

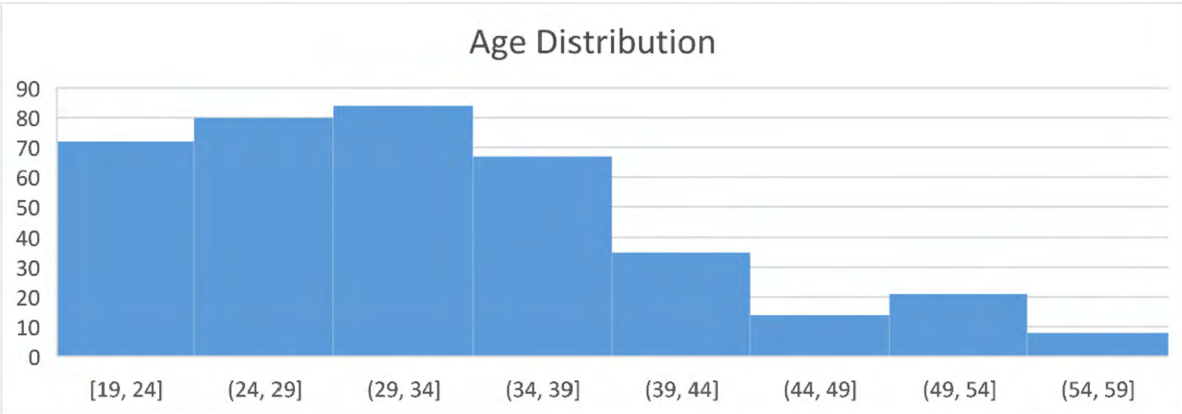
Chapter 4: Results and Analysis

Following the month-long data collection phase, which began in June 2021 and ended in July 2021, a total of 477 responses were recorded. There were 95 incomplete responses; most of which had less than 50% of the total number of questions answered, and which I excluded from the analysis. Among the incomplete responses, most of them quitted the online participation even before they answered any of the actual survey questions. Approximately one thirds of the 95 responses are those that only answer a couple of the personal particular information, without actually answering any of the survey questions. There was one response, which was categorized as survey preview, that I also excluded from the analysis, given that no due consideration was given to the questions, as it was meant test the user-interface (UI) flow of the survey on a mobile device. Using Qualtrics, I adjusted the settings to ensure that a survey respondent could not submit the survey more than once. In the end, I collected a total of 381 complete responses, which was substantially more than my initial target of 300 respondents. This was a pleasant surprise, as we end up with more data to evaluate from. The charts in Figure 7 illustrate the profile of the respondents. The gender mix is considered balanced in this randomized sample (M_{age} = 32.8, 48.3% Male, 51.2% Female, 0.5% Prefer not to say). However, most of the respondents were below 40 years of age, with a median age of 32 years, and a mode of 33 years. Note that "(…]" was used for histogram intervals.[11]

[11] Please note that the "(…]" represents an interval/class, where the first, round bracket suggests that the interval does not include the beginning data referenced by the starting point and the second, square bracket suggests that the interval/class includes data referenced by the end point. For example (24,29] represents the number of people aged 25 to 29 (inclusive) within the interval/class.



Descriptive Statistics	
Age Profile of Participants	
Mean	32.84777
Standard Error	0.46217
Median	32
Mode	33
Standard Deviation	9.021199
Sample Variance	81.38203
Kurtosis	-0.06083
Skewness	0.647363
Range	40
Minimum	19
Maximum	59
Sum	12515
Count	381



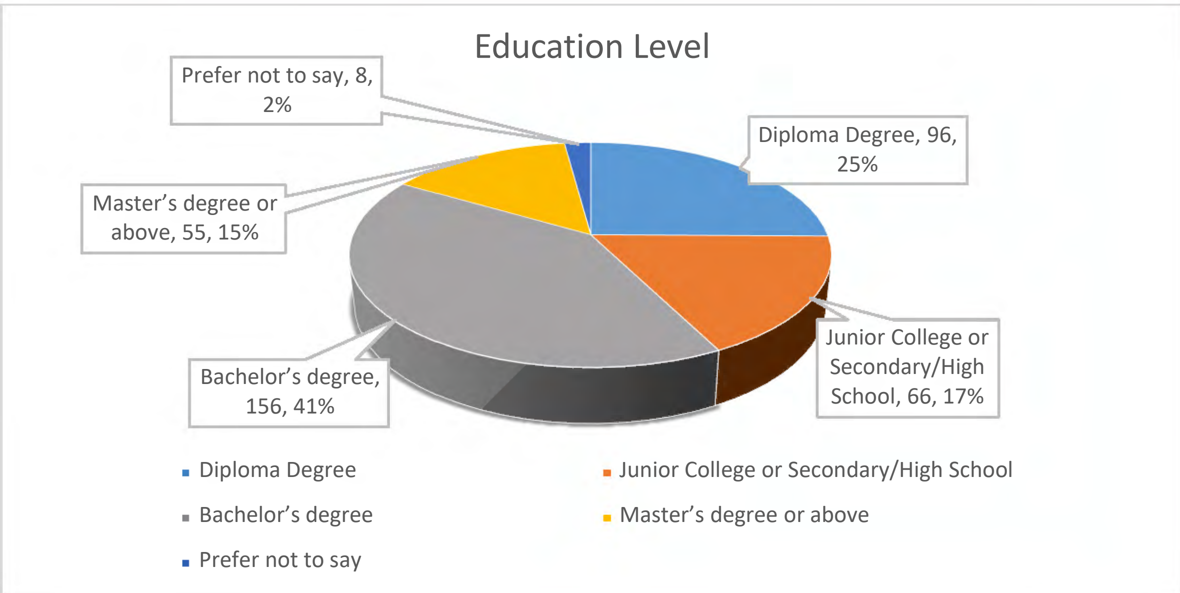


Figure 7: Demographic Data of the Sample

As noted in the operationalization section of Chapter 3 (section 3.6), four different participant groups were targeted. This was shown in Figure 6, which I have reproduced below.

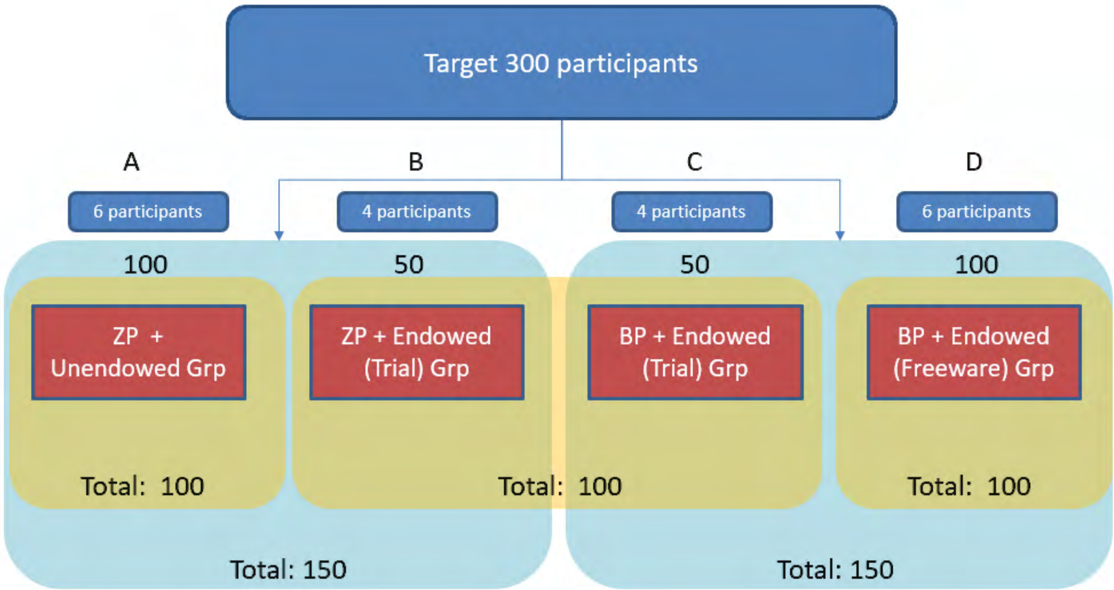


Figure 6: Operationalization Target Size of Each Group

Following data collection, the breakdown of the different groups (A, B, C and D) was as follows:

Total number of respondents	
Group A Total	120
Group B Total	65
Group C Total	64
Group D Total	132

As such, for the "awareness" Stage 1, where I examined the ZPEs and respondents' corresponding level of affect or satisfaction via the Net Promoter Score (NPS), I had a sub-total of 185 (Group A + Group B) respondents in the zero-price (ZP) group and a sub-total of 196 (Group C + Group D) respondents in the bargain-price (BP) group. For the "purchasing" Stage 2, examining the endowment effect and the corresponding NPS, I had a sub-total of 120 respondents (Group A) for the "unendowed group", a sub-total of 129 (Group B + Group C) respondents for the “endowed with full-feature free-trial group” and a sub-total of 132 (Group D) respondents for the “endowed with limited-feature freemium group”.

4.1. Data Organization

Given that the respondents were asked several questions and that their responses were captured and grouped into different “buckets” as shown in Figure 6, I have manipulated the data accordingly to ensure that they are comparable. Given that the samples’ sizes were random and sufficiently large, and that I was examining differences between the proportions, I intended to conduct a two-sample z-test, where the standard normal distribution models the sampling distribution of the difference between proportions. Edwards (1962) stated that the assumption of normality holds in the examination of human behaviors, in the context of behavioral sciences, allowing us to apply the central limit theorem, as long as the sample size is above 30, and in the case of examining proportions, as long as the number of successes and failures exceeds 15 each; in such circumstance, statistical inferences can be made. I perform hypothesis testing on the two population proportions and empirically test the hypotheses specified for the awareness stage (Stage 1). For Stage 1, comparing the effects between the ZP and BP groups will involve data collected for questions 1–12 in Group A and B, which will be compared with the data collected for questions 1–12 in Group C and D. For the conversion stage – Stage 2 – comparing the impact of the “endowment effect”, the data collected for questions 13-18 will be compared among Group A (unendowed group), Group (B+C) (endowed with full-feature free-trial version) and Group D (endowed with limited-feature freemium version).

Given that the choices made by the respondents are discrete, and to perform a good statistical comparison using SPSS, and referencing Shampanier et al.'s (2007) and Huttel et al.'s (2018) methodologies, I have manipulated the data to derive a mean value. I did this by attributing a numerical figure of "1" to the desired choice to be tested (i.e. free vs paid conditions) and "0" for the other options (inclusive of "do nothing"). This also allowed me to test the statistical significance between the difference of proportions measured in the ZP or BP group. The proportions in this case are represented as a mean in order to make it possible to compare the data with t-tests and ANOVA. Furthermore, there was a need to consolidate and stack the responses for questions 1 to 12 from both the ZP and BP groups across all three categories (i.e. games, media and productivity) on top of each other in order to make the data recognizable and comparable in SPSS statistical analysis packages.

Please note that according to Ateş et al. (2019), given that a population is considered normal and balanced, any of the test statistics (Pillai's Trace, Wilks' Lambda, Hotelling's Trace or Roy's Largest Root) generated by SPSS can be used and will be considered similar. These results are demonstrated in Results Table 1B. Also, the reporting convention for the F-statistic value that I have adopted in this dissertation is F (degree of freedoms between groups, total degree of freedoms). In specific multivariate F-tests, the reporting convention will be F (degree of freedoms between groups/ hypothesis degree of freedoms, error degree of freedoms).

To generate additional insights (other than comparing the proportions, which are represented with a mean using the abovementioned method of data manipulation), I also analyzed the corresponding NPS data collected, which is a measure of the level of affect the respondents register after making a particular choice. In this case, the mean values for the NPS for various choices made are appropriate for the various statistical analysis.

4.2. Stage 1 – "Awareness" Stage

In this stage, I am testing several hypotheses. For hypothesis 1, I am replicating Shampanier et al.'s (2007) and Huttel et al.'s (2018) experiments:

> **Hypothesis 1:** The zero-price effect (ZPE) generalizes to the digital context and is observed for digital offerings across all three categories, namely games, productivity, and media-streaming mobile applications.

I established the null and alternative hypothesis as follows, and the test on the basic segment (i.e. Option of S$0 or S$1.48) was repeated for all the three categories:

$$H_0 : \rho_1 = \rho_2$$

$$H_a : \rho_1 \neq \rho_2$$

Where ρ_1 refers to the proportion of the respondents who select the basic option in the ZP group ($0) and ρ_2 refers to proportion of the respondents who select the basic option in the BP group ($1.48).

The respective choice proportions are displayed in Figure 8a, 8b and 8c:

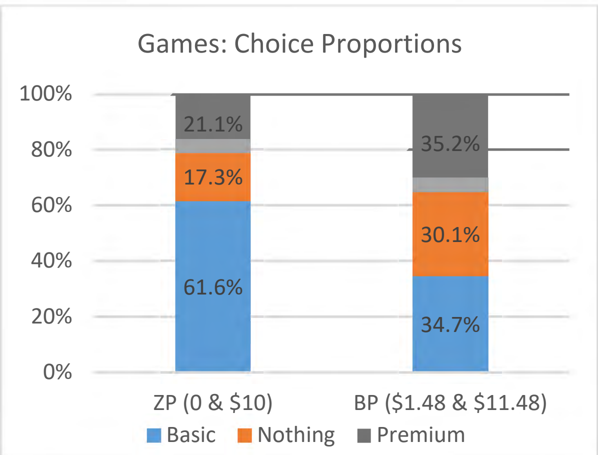


Figure 8a: Game Category – Choice Proportions

For the games category, the robustness of the ZPE is demonstrated, with substantially larger proportion of respondents willing to download the application compared to the paid condition in the BP group. I applied an independent samples t-test, using the mean, μ, as the proxy for the respective proportions within the basic segment (i.e. respondents who chose either \$0 or \$1.48 in their respective groups). These results ($M_{\$0}$ = 61.6% vs $M_{\$1.48}$ = 34.7%), t(5.443), ρ< 0.05 suggest a significant difference in the results. We can thus reject the null hypothesis for the games category.

To explore this in more depth, I replicated the test for the premium segment (i.e. respondents who chose either \$0 or \$1.48 in their respective groups). These results ($M_{\$10}$ =21.1% vs $M_{\$11.48}$ = 35.2%), t(-3.101), ρ< 0.05 also indicate a significant difference.

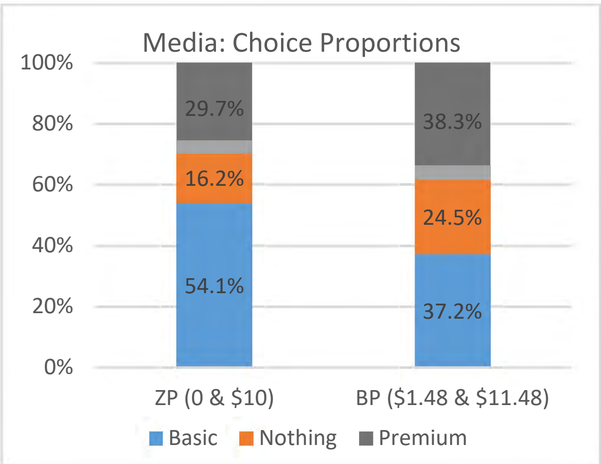


Figure 8b: Media Category – Choice Proportions

For the media category, focusing on the basic segment, there is also a substantial difference ($M_{\$0}$ = 54.1% vs $M_{\$1.48}$ = 37.2%), t(3.330), ρ< 0.05. We can thus also reject the null hypothesis for the media category. However, for the premium segment, ($M_{\$10}$ =29.7% vs $M_{\$11.48}$ = 38.3%), t(-1.762), ρ> 0.05, the results do not indicate a significant difference.

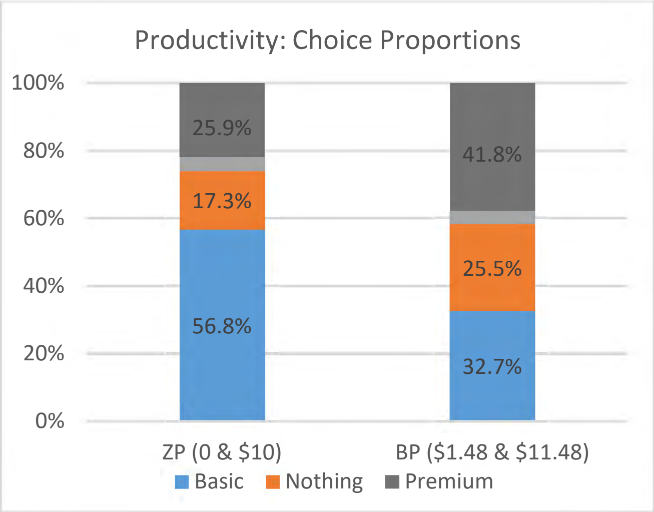


Figure 8c: Productivity Category – Choice Proportions

Finally, for the productivity category, focusing on the basic segment, there is also a substantial difference ($M_{\$0}$ = 56.8% vs $M_{\$1.48}$ = 32.7%), t(4.858), $\rho < 0.05$. We can thus reject the null hypothesis for the productivity category. For the premium segment, ($M_{\$10}$ =25.9% vs $M_{\$11.48}$ = 41.8%), t(-3.319), $\rho < 0.05$, it was also evident that there is a significant difference between the two proportions. The results are summarized in Results Table 1A and clearly suggest that the ZPE extends to the digital offerings across all three categories – games, media and productivity.

Next, I drilled deeper into the ZP group and examined the second hypothesis:

Hypothesis 2: The zero-price effect (ZPE), as measured by the choice proportions and the level of affect, varies across different digital application categories.

To test this hypothesis, I established the following null and alternative hypothesis.

$H_0 : \rho_1 = \rho_2 = \rho_3 :$

There is no difference in the proportions of those who choose the basic option in the games, media and productivity categories.

H_a : $\rho_1 \neq \rho_2 \neq \rho_3$:

There is a difference in the proportions of those who choose the basic option in the games, media and productivity categories.

Using repeated measures analysis of variance (ANOVA), the result of this hypothesis testing was: $F(2,183) = 5.736$, $\rho < 0.05$. This lends further support to the hypothesis that there is a significant difference in the proportions of respondents in the three different categories. For the second hypothesis, we can thus reject the null hypothesis.

When I replicated the test for the premium options, the three proportions across the categories were also shown to be statistically different, $F(2, 183) = 7.688$, $\rho < 0.05$. We can thus say that there is sufficient evidence to suggest that “category type” did play a part in influencing choice, particularly when a choice was provided between the basic and premium options in the ZP group across all three categories.

I also decided to test whether the level of affect, as measured by the corresponding NPS, differs for respondents choosing the basic option for the three categories:

H_0 : $\mu_1 = \mu_2 = \mu_3$:

There is no difference in the means of NPS for those choose the basic option in the games, media and productivity categories.

H_a : $\mu_1 \neq \mu_2 \neq \mu_3$:

There is a difference in the means of NPS for those choose the basic option in the games, media and productivity categories.

The various means of the NPS scores across "cost x offering type" are summarized in the tables consolidated in Figure 9.

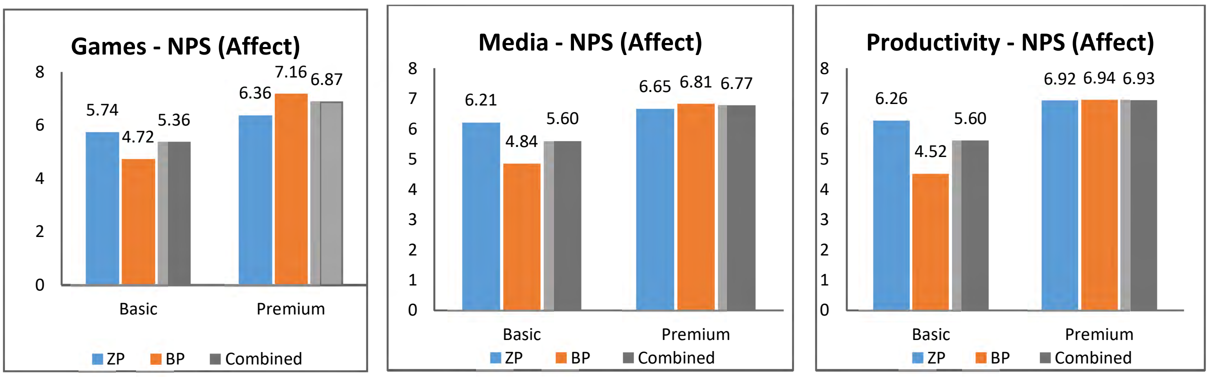


Figure 9: Mean NPS of Basic vs Premium Group for Various Categories

I conducted an ANOVA on the NPS, and found that using NPS as the basis for analysis, with a test result of $F(2, 318) = 4.232$, $\rho<0.05$, we can also reject the null hypothesis that the mean NPS or level of affect for the three different categories is similar. However, the post-hoc analysis suggested that within the ZP group, the mean NPS of games was statistically significantly different to the NPS of productivity ($\rho<0.05$) but not significantly different to the NPS of the media category ($\rho > 0.05$). In addition, the mean NPS of media was also not statistically significantly different to the NPS of productivity ($\rho >0.05$). These results are presented in Table 1C.

Shifting gear to the BP group, let us examine the third hypothesis:

Hypothesis 3: At the bargain/nominal price, the choice proportions and the level of affect varies across different digital application categories.

To test this hypothesis, I again established the following null and alternative hypothesis, similar to those for hypothesis 2:

$H_0 : \rho_1 = \rho_2 = \rho_3 :$

There is no difference in the proportions of those who choose the basic option in the games, media and productivity categories.

$H_a : \rho_1 \neq \rho_2 \neq \rho_3 :$

There is a difference in the proportions of those who choose the basic option in the games, media and productivity categories.

Using repeated measures analysis of variance (ANOVA), the result was as follows: $F(2, 194) = 5.293$, $\rho<0.05$. This indicates that there was a significant difference in the proportions of respondents in the three different categories for the BP group as well. We can thus reject the null hypothesis. The Results Table 1D summarizes the results of the ANOVA test from a choice perspective.

In repeating for this BP group the abovementioned test on whether the level of affect, as measured by the corresponding NPS, for respondents choosing the basic option for the three categories, I propose the following hypothesis regarding the mean NPS.

$H_0 : \mu_1 = \mu_2 = \mu_3 :$

There is no difference in the means of NPS for those choose the basic option in the games, media and productivity categories.

$H_a : \mu_1 \neq \mu_2 \neq \mu_3 :$

There is a difference in the means of NPS for those choose the basic option in the games, media and productivity categories

Results Table 1E summarizes the results of the ANOVA test from the NPS/affect perspective. Using this NPS as a measure of affect, with a test result of $F(2, 204) = 0.426$, $\rho > 0.05$, we cannot reject the null hypothesis.

Therefore, it is important to note that while for the ZP group the proportions of respondents who choose the basic offer and the corresponding affect/NPS are significantly different across the three categories, for the BP group, only the proportions are deemed significantly different. For the BP group, the level of affect/NPS for the people who choose the basic offer is not significantly different across the categories.

4.3. Choice Between Freemium vs Free Trial

The fourth hypothesis within this "awareness" Stage 1 is as follows:

> **Hypothesis 4:** Digital consumers prefer to download the full-feature free-trial option for evaluation at this stage as opposed to the limited-feature freemium version for all three digital application categories

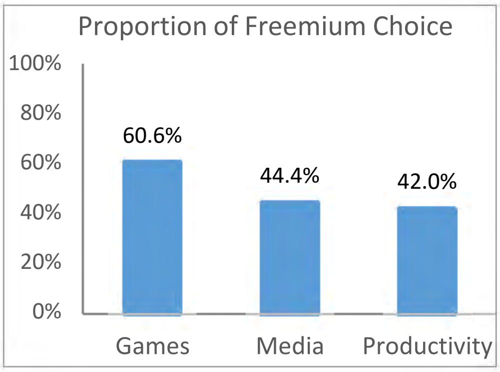
To test this, all the respondents were asked to make a choice between free-trial or freemium for the three categories and to provide a corresponding NPS rating for their choice. I established the following null and alternative hypothesis to be tested across the three categories, with the various proportions laid out in Figure 10.

$H_0 : \rho_1 = 0.5$

The same proportion of people will choose the full-feature free-trial version vs the limited-feature freemium version of the application for the games, media and productivity categories.

H_a : $\rho_1 \neq 0.5$:

Different proportions of people will choose the full-feature free-trial version vs the limited-feature freemium version of the application for the games, media and productivity categories



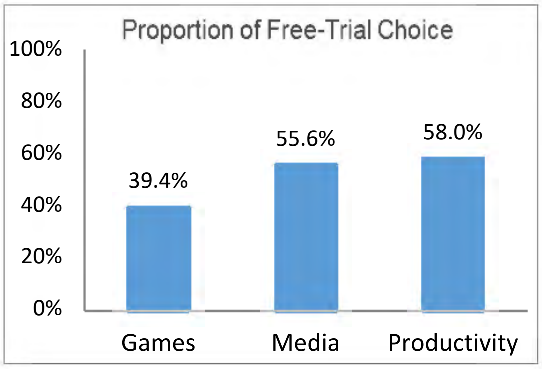


Figure 10: Proportion of Choices for Freemium and Free-Trial Strategies

Running t-tests on the respective datasets for all three categories' yielded the following results, summarized in Results Table 1F and Table 1F(i):

- For games, 39% chose the free trial, and the finding of T(381) = -4.241, $\rho < 0.05$, suggests that this is significantly different from the assumed 50%–50% split. We can reject the null hypothesis.
- For media, 56% chose the free trial, and the finding of T(381) = 2.214, $\rho < 0.05$ suggests that this is significantly different from the presumed 50%–50% split. We can also reject the null hypothesis.
- For productivity, 58% chose the free trial, and the finding of T(381) = 3.162, $\rho < 0.05$, suggests that this is significantly different from the assumed 50%–50% split. We can also reject the null hypothesis for this category.

Table 1F(i): Summary of Hypothesis 4 results

		N	Mean	Std. Deviation	Std. Error
Choose_Freemium	1 Games	381	0.61	0.489	0.025
	2 Media	381	0.44	0.497	0.025
	3 Productivity	381	0.42	0.494	0.025
	Total	1143	0.49	0.500	0.015
Choose_FreeTrial	1 Games	381	0.39	0.489	0.025
	2 Media	381	0.56	0.497	0.025
	3 Productivity	381	0.58	0.494	0.025
	Total	1143	0.51	0.500	0.015

Running an ANOVA on the dataset also suggested that there is a significant difference of proportions between the three categorical groups in the freemium segment – $F(2,1142) = 16.096$, $\rho < 0.05$ as well as in the free-trial segment: $F(2,1142) = 16.096$, $\rho<0.05$.

Diving deeper into the difference of mean NPS/affect among the respondents for each of the three categories in the respective freemium or free-trial segments, I established the following null and alternative hypothesis.

$H_0 : \mu_1 = \mu_2 = \mu_3$:

There is no difference in the mean NPS in the games, media and productivity categories for the stated strategy (freemium/free-trial) segment.

$H_a : \mu_1 \neq \mu_2 \neq \mu_3$:

There is a difference in the mean NPS in the games, media and productivity categories for the stated strategy (freemium/free-trial) segment.

The respective mean NPS or affect scores are presented in the chart shown in Figure 11.

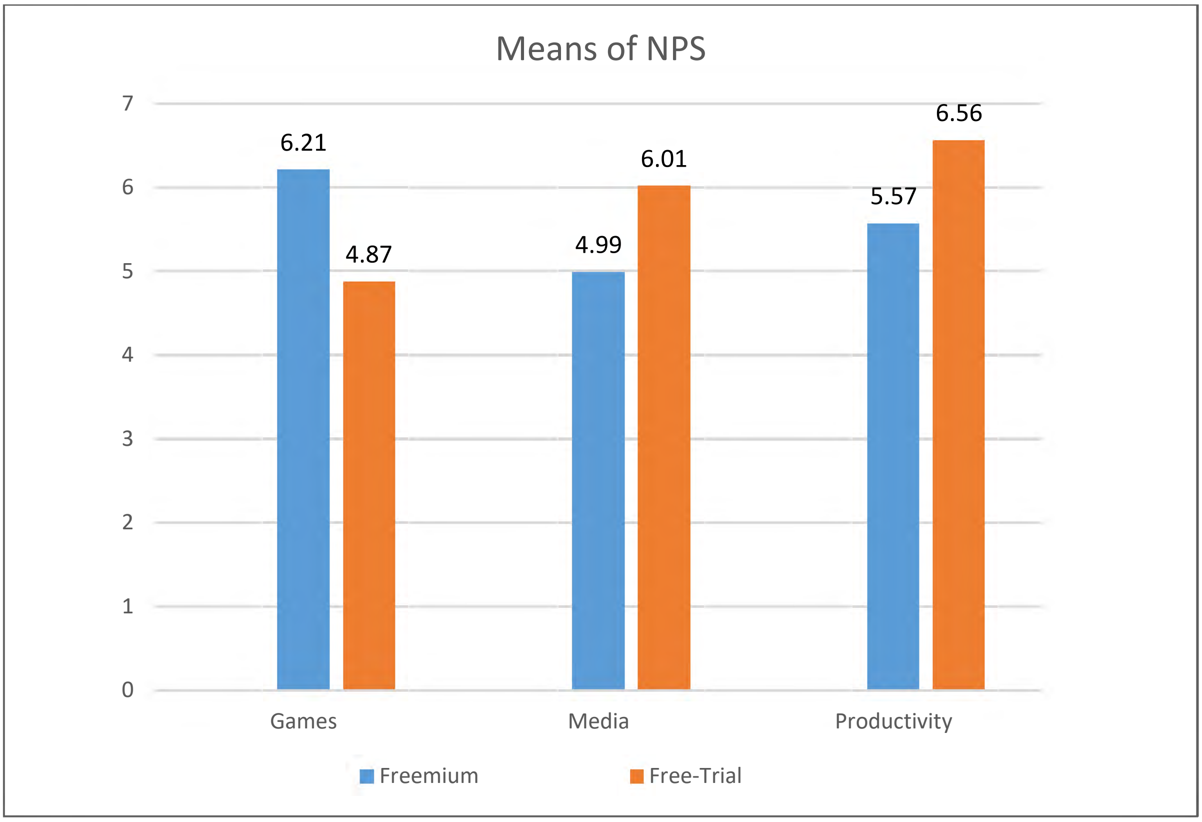


Figure 11: Mean NPS for Freemium and Free-Trial Strategies for Various Categories

Focusing on respondents who chose Freemium option, I conducted a one-way ANOVA of the NPS score across the three categories. The ANOVA results of F(2,559) = 11.269, $\rho < 0.05$ indicated a statistical difference in the mean NPS recorded between the three different categories. However, drilling deeper into the post-hoc multiple comparisons within the freemium group dataset, I identified that the mean NPS for the games category was significantly different from both media and productivity, although the mean NPS for the media category was *not* significantly different from the productivity category. The results for the population that chose freemium are summarized in Results Table 1G.

For the respondents who chose the free-trial option, I repeated these tests, performing a one-way ANOVA of the NPS score across the three categories. The ANOVA results of F(2,582) = 29.412, $\rho < 0.05$ indicated a statistical difference in the mean NPS recorded between the three different categories. We can reject the null hypothesis in this case. For the free-trial group dataset, I also found that the means of the NPS of all three categories were significantly different from each other. The results are summarized in the Results Table 1H.

4.4. Stage 2 – "Conversion" Stage

For Stage 2, the main focus is to empirically test for the existence of an endowment effect, and whether a difference in how a user is being endowed impacts their decision to pay for the upgrade to the premium version. The total group of 381 respondents was comprised of three main sub-groups, as follows:

- unendowed group – 120 respondents
- endowed with free-trial version – 129 respondents
- endowed with freemium version – 132 respondents.

To address **Hypothesis 5** – An endowment effect exists for consumers who are being endowed with a limited-feature freemium basic offer or with a full-feature free-trial period basic offer – I established the following null and alternative hypothesis:

$$H_0 : \rho_1 = \rho_2$$

$$H_a : \rho_1 \neq \rho_2$$

Here, ρ_1 refers to the proportion of the respondents who opt to pay for the upgrade in the unendowed group and ρ_2 refers to proportion of the respondents who opt to pay for the upgrade in the endowed group (either free-trial or freemium).

It should be noted that the dataset is organized such that the mean is used as the proxy for the proportions of the sample population that opt to pay for the premium option for the unendowed group and that opt to pay the upgrade to the premium version for the endowed group.

Firstly, running an independent t-test between the unendowed group vs the limited-feature freemium endowed group, the results are as follows:

- games category: T(252) = -3.295, $\rho < 0.05$
- media category: T(252) = -3.617, $\rho < 0.05$
- productivity category: (252) = -3.536, $\rho < 0.05$.

This gives a strong indication that there is a significant difference between the proportions of the unendowed group and the freemium endowed group for all three categories. We can therefore reject the null hypothesis and establish that an endowment effect does exist in this scenario.

Next, I ran another independent t-test between the unendowed group vs the full-feature free-trial endowed group. The results are as follows:

- games category: T(249) = -3.965, $\rho < 0.05$
- media category: T(249) = -4.199, $\rho < 0.05$
- productivity category: (249) = -5.903, $\rho < 0.05$.

This gives a strong indication that there is a significant difference between the proportions of the unendowed group and the free-trial endowed group for all three categories. We can therefore reject the null hypothesis and establish that an endowment effect does exist in this scenario, with a higher proportion of the free-trial endowed group choosing to pay for the upgrade to the premium version. The results of the independent tests are summarized and captured in Results Table 1I.

> **Hypothesis 6**: Consumers who are endowed with the full-feature free-trial period basic offer are more likely to pay for the premium offer than consumers who are endowed with the limited-feature freemium basic offer after a predetermined period of time for all three digital application categories.

From a choice proportion perspective, I set up the null and alternative hypotheses as follows:

$H_0 : \rho_1 = \rho_2 = \rho_3$:

There is no difference in the proportions of those who choose to convert to the premium option in the games, media and productivity categories.

$H_a : \rho_1 \neq \rho_2 \neq \rho_3$:

There is a difference in the proportions of those who choose to convert to the premium option in the games, media and productivity categories.

I also conducted a one-way ANOVA test on the dataset, and the results are detailed as follows:

- games category: $F(2, 380) = 8.541$, $\rho < 0.05$
- media category: $F(2, 380) = 9.991$, $\rho < 0.05$
- productivity category: $F(2, 380) = 16.770$, $\rho < 0.05$.

The above results, illustrated in Results Table 1J, indicate a statistically significant difference among the unendowed, freemium endowed and free-trial endowed groups for all three categories, and lend further credence to the proposition that an endowment effect *does* exist, even for digital offerings. However, the post-hoc multiple comparisons, also illustrated also in Table 1J, do provide interesting insights as well.

While the proportions of respondents who opt to pay for the upgrade to the premium version do vary significantly between the unendowed group and the endowed groups, there is not enough evidence to suggest that there is a larger proportion of people in the free-trial endowed group that will opt to pay for the upgrade relative to the freemium endowed group. The same phenomenon is observed across all three categories. Therefore, there is not enough evidence to reject the null hypothesis if we use the proportions to evaluate it.

However, if we consider the affect perspective (i.e. the corresponding NPS of the respondents who choose the premium option or who upgrade to the premium option) we can potentially generate different insights. The chart in Figure 12 summarizes the mean NPS, which is used as a proxy to measure the level of affect for the different groups across all three categories.

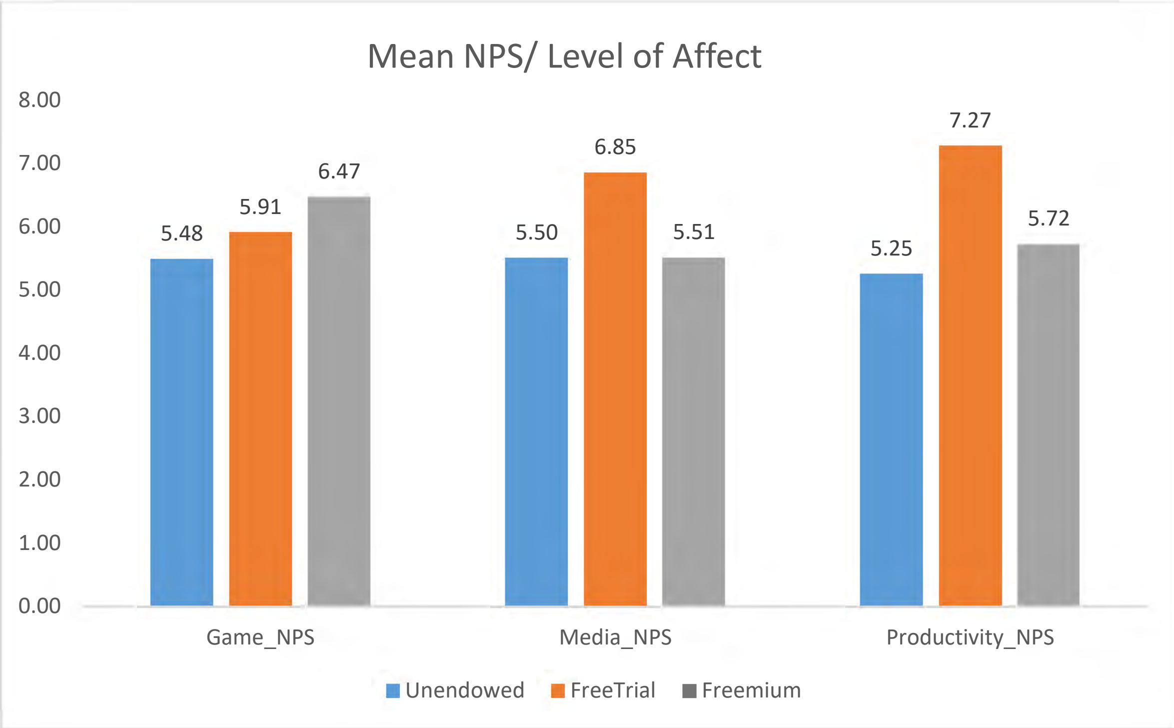


Figure 12: Mean NPS for Various Categories Involving Endowment Effect

Focusing on the games category, I ran a one-way ANOVA and the results are captured in Results Table 1K. Given that F(2, 154) = 1.927, $\rho > 0.05$, there is not enough evidence to suggest that there is any significant difference in the means of NPS for the three groups. Post-hoc multiple comparisons also indicated that there is no significant difference between any two of the three groups as shown in Table 1K(i).

Table 1K(i) Games – NPS/Affect Multiple Comparison

Dependent Variable: Games_NPS

(I) Groupings_Games		Mean Difference (I-J)	Std. Error	Sig.
1 Unendowed	2 FreeTrial_Endowed	-0.422	0.519	0.695
	3 Freemium_Endowed	-0.983	0.524	0.150
2 FreeTrial_Endowed	1 Unendowed	0.422	0.519	0.695
	3 Freemium_Endowed	-0.560	0.426	0.389
3 Freemium_Endowed	1 Unendowed	0.983	0.524	0.150
	2 FreeTrial_Endowed	0.560	0.426	0.389

Moving on to the media category, the ANOVA results are shown in Results Table 1L. Given that $F(2, 154) = 3.916$, $\rho < 0.05$, there is indeed a significant difference in the means of NPS for the three groups, and drilling deeper into the post-hoc multiple comparisons in Table 1L(i), we can see that between the free-trial endowed group and the unendowed group, there is a significant difference between the mean NPS for these groups, whereas there is not any significant difference for the other comparisons.

Table 1L(i) Media – NPS/Affect Multiple Comparison

Dependent Variable:	Media_NPS			
(I) Groupings_Games		Mean Difference (I-J)	Std. Error	Sig.
1 Unendowed	2 FreeTrial_Endowed	-1.220*	0.514	0.049
	3 Freemium_Endowed	-0.248	0.519	0.882
2 FreeTrial_Endowed	1 Unendowed	1.220*	0.514	0.049
	3 Freemium_Endowed	0.972	0.422	0.058
3 Freemium_Endowed	1 Unendowed	0.248	0.519	0.882
	2 FreeTrial_Endowed	-0.972	0.422	0.058

*. The mean difference is significant at the 0.05 level.

For the productivity category, the results shown in Results Table 1M are clearer. With $F(2, 154) = 9.471$, $\rho < 0.05$, there is indeed a significant difference in the means of NPS for the three groups. Drilling deeper into the post-hoc multiple comparisons as shown in the following Table 1M(i), we can see that while there is no significant difference in the mean NPS of the respondents between the freemium endowed group and the unendowed group, there is clearly a significant difference between the free-trial endowed group and the unendowed group as well as between the free-trial endowed group and the freemium endowed group.

Table 1M(i) Productivity – NPS/Affect Multiple Comparison

Dependent Variable: Productivity_NPS

(I) Groupings_Games		Mean Difference (I-J)	Std. Error	Sig.
1 Unendowed	2 FreeTrial_Endowed	-2.025*	0.497	0.000
	3 Freemium_Endowed	-0.790	0.503	0.261
2 FreeTrial_Endowed	1 Unendowed	2.025*	0.497	0.000
	3 Freemium_Endowed	1.235*	0.408	0.008
3 Freemium_Endowed	1 Unendowed	0.790	0.503	0.261
	2 FreeTrial_Endowed	-1.235*	0.408	0.008

*. The mean difference is significant at the 0.05 level.

The following subsection is a consolidation of all the results tables (Tables 1A – 1M), detailing the results discussed in this segment.

4.5. Results Tables

Choice Perspective

4.5.1. Results Table 1A – Hypothesis 1

Analyzing Basic Groups: Group A+B (ZP) vs Group C+D (BP)

Choosing Basic Group

Group Statistics

ZP or BP Grp		N	Mean	Std. Deviation	Std. Error Mean
Games_Basic	1 ZP	185	0.62	0.488	0.036
	2 BP	196	0.35	0.477	0.034
Media_Basic	1 ZP	185	0.54	0.500	0.037
	2 BP	196	0.37	0.485	0.035
Productivity_Basic	1 ZP	185	0.57	0.497	0.037
	2 BP	196	0.33	0.470	0.034

Independent Samples Test

	t-test for Equality of Means						
	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
Games_Basic	5.443	376.621	0.000	0.269	0.049	0.172	0.367
Media_Basic	3.330	376.063	0.001	0.168	0.050	0.069	0.267
Productivity_Basic	4.858	374.237	0.000	0.241	0.050	0.143	0.339

Note: Equal variances not assumed.

Analyzing Premium Groups: Group A+B (ZP) vs Group C+D (BP)

Group Statistics

ZP or BP Grp		N	Mean	Std. Deviation	Std. Error Mean
Games_Premium	1 ZP	185	0.21	0.409	0.030
	2 BP	196	0.35	0.479	0.034
Media_Premium	1 ZP	185	0.30	0.458	0.034
	2 BP	196	0.38	0.487	0.035
Productivity_Premium	1 ZP	185	0.26	0.440	0.032
	2 BP	196	0.42	0.495	0.035

Independent Samples Test

	t-test for Equality of Means						
	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
Games_Premium	-3.101	375.315	0.002	-0.141	0.046	-0.231	-0.052
Media_Premium	-1.762	378.996	0.079	-0.085	0.048	-0.181	0.010
Productivity_Premium	-3.319	377.648	0.001	-0.159	0.048	-0.253	-0.065

Note: Equal variances not assumed.

4.5.2. Results Table 1B – Hypothesis 2

Choice Perspective

Analyzing Basic (ZP) Group: Across Three Different Categories

Descriptive Statistics

	Mean	Std. Deviation	N
Games_Basic	0.62	0.488	185
Media_Basic	0.54	0.500	185
Productivity_Basic	0.57	0.497	185

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Category	Pillai's Trace	0.059	5.736[b]	2.000	183.000	0.004
	Wilks' Lambda	0.941	5.736[b]	2.000	183.000	0.004
	Hotelling's Trace	0.063	5.736[b]	2.000	183.000	0.004
	Roy's Largest Root	0.063	5.736[b]	2.000	183.000	0.004

a. Design: Intercept within subjects design: Category

b. Exact statistic

Analyzing Premium (ZP) Group: Across three different categories

Descriptive Statistics

	Mean	Std. Deviation	N
Games_Premium	0.21	0.409	185
Media_Premium	0.30	0.458	185
Productivity_Premium	0.26	0.440	185

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Category	Pillai's Trace	0.078	7.688[b]	2.000	183.000	0.001
	Wilks' Lambda	0.922	7.688[b]	2.000	183.000	0.001
	Hotelling's Trace	0.084	7.688[b]	2.000	183.000	0.001
	Roy's Largest Root	0.084	7.688[b]	2.000	183.000	0.001

a. Design: Intercept within subjects design: Category

b. Exact statistic

4.5.3. Results Table 1C – Hypothesis 2

NPS/Affect Perspective

Analyzing Basic (ZP) Group: Across three different categories

Descriptives

Basic_NPS

	N	Mean	Std. Deviation	Std. Error
1 Games	114	5.74	1.597	0.150
2 Media	100	6.21	1.358	0.136
3 Productivity	105	6.26	1.421	0.139
Total	319	6.06	1.483	0.083

ANOVA

Basic_NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	18.232	2	9.116	4.232	0.015
Within Groups	680.752	316	2.154		
Total	698.984	318			

Multiple Comparisons

Dependent Variable: Basic_NPS

Tukey HSD

(I) Categories_Basic		Mean Difference (I-J)	Std. Error	Sig.
1 Games	2 Media	-0.473	0.201	0.050
	3 Productivity	-.520*	0.199	0.025
2 Media	1 Games	0.473	0.201	0.050
	3 Productivity	-0.047	0.205	0.971
3 Productivity	1 Games	.520*	0.199	0.025
	2 Media	0.047	0.205	0.971

*The mean difference is significant at the 0.05 level.

4.5.4. Results Table 1D – Hypothesis 3

NPS/Affect Perspective

Analyzing Basic (BP) Group: Across three different categories

Descriptives

Basic_NPS

	N	Mean	Std. Deviation	Std. Error
1 Games	68	4.72	1.744	0.211
2 Media	73	4.75	1.422	0.166
3 Productivity	64	4.52	1.662	0.208
Total	205	4.67	1.605	0.112

ANOVA

Basic_NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.207	2	1.103	0.426	0.654
Within Groups	523.237	202	2.590		
Total	525.444	204			

Multiple Comparisons

Dependent Variable: Basic_NPS

Tukey HSD

(I) Categories_Basic		Mean Difference (I-J)	Std. Error	Sig.
1 Games	2 Media	-0.033	0.271	0.992
	3 Productivity	0.205	0.280	0.745
2 Media	1 Games	0.033	0.271	0.992
	3 Productivity	0.238	0.276	0.664
3 Productivity	1 Games	-0.205	0.280	0.745
	2 Media	-0.238	0.276	0.664

*The mean difference is significant at the 0.05 level.

4.5.5. Results Table 1E – Hypothesis 3

Analyzing Basic (BP) Group: Across three different categories

Choice Perspective

Descriptive Statistics

	Mean	Std. Deviation	N
Games_Basic	0.35	0.477	196
Media_Basic	0.37	0.485	196
Productivity_Basic	0.33	0.470	196

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Category	Pillai's Trace	0.052	5.293[b]	2.000	194.000	0.006
	Wilks' Lambda	0.948	5.293[b]	2.000	194.000	0.006
	Hotelling's Trace	0.055	5.293[b]	2.000	194.000	0.006
	Roy's Largest Root	0.055	5.293[b]	2.000	194.000	0.006

a. Design: Intercept within subjects design: Category
b. Exact statistic

Analyzing Premium (BP) Group: Across three different categories

Descriptive Statistics

	Mean	Std. Deviation	N
Games_Premium	0.35	0.479	196
Media_Premium	0.38	0.487	196
Productivity_Premium	0.42	0.495	196

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Category	Pillai's Trace	0.047	4.825[b]	2.000	194.000	0.009
	Wilks' Lambda	0.953	4.825[b]	2.000	194.000	0.009
	Hotelling's Trace	0.050	4.825[b]	2.000	194.000	0.009
	Roy's Largest Root	0.050	4.825[b]	2.000	194.000	0.009

a. Design: Intercept within subjects design: Category
b. Exact statistic

4.5.6. Results Table 1F – Hypothesis 4

Choice Perspective

Games Category - One-Sample T-Test

One-Sample Test

	Test Value = 0.5					
	t	Df	**Sig. (2-tailed)**	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Choose_FreeTrial	-4.241	380	**0.000**	-0.106	-0.16	-0.06

Media Category - One-Sample T-Test

One-Sample Test

	Test Value = 0.5					
	t	Df	**Sig. (2-tailed)**	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Choose_FreeTrial	2.214	380	**0.027**	0.056	0.01	0.11

Productivity Category - One-Sample T-Test

One-Sample Test

	Test Value = 0.5					
	t	Df	**Sig. (2-tailed)**	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Choose_FreeTrial	3.162	380	**0.002**	0.080	0.03	0.13

Descriptives

		N	Mean	Std. Deviation	Std. Error
Choose_Freemium	1 Games	381	0.61	0.489	0.025
	2 Media	381	0.44	0.497	0.025
	3 Productivity	381	0.42	0.494	0.025
	Total	1143	0.49	0.500	0.015
Choose_FreeTrial	1 Games	381	0.39	0.489	0.025
	2 Media	381	0.56	0.497	0.025
	3 Productivity	381	0.58	0.494	0.025
	Total	1143	0.51	0.500	0.015

ANOVA

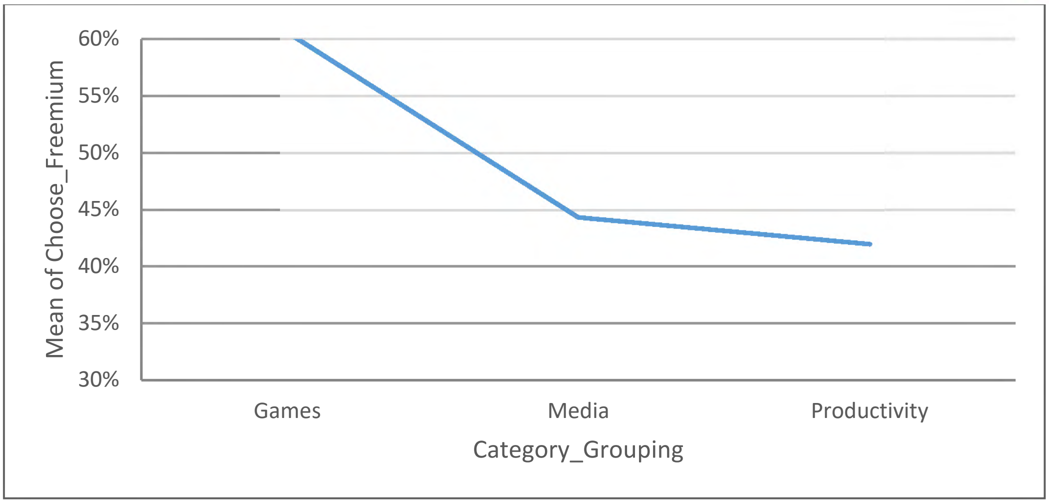
		Sum of Squares	df	Mean Square	F	Sig.
Choose_Freemium	Between Groups	7.844	2	3.922	16.096	0.000
	Within Groups	277.790	1140	0.244		
	Total	285.634	1142			
Choose_FreeTrial	Between Groups	7.844	2	3.922	16.096	0.000
	Within Groups	277.790	1140	0.244		
	Total	285.634	1142			

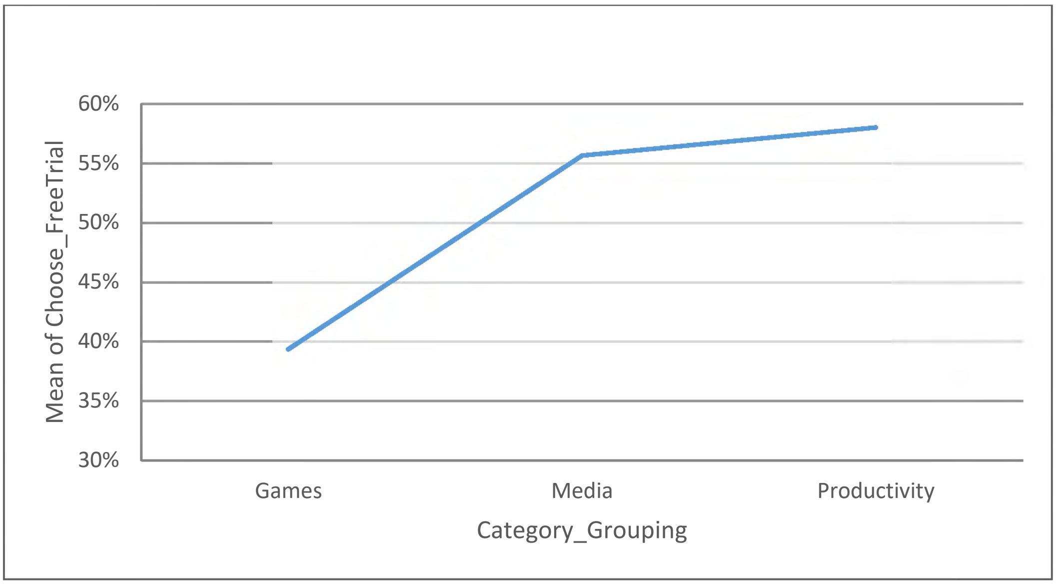
Multiple Comparisons

Tukey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.
Choose_Freemium	1 Games	2 Media	.163*	0.036	0.000
		3 Productivity	.186*	0.036	0.000
	2 Media	1 Games	-.163*	0.036	0.000
		3 Productivity	0.024	0.036	0.786
	3 Productivity	1 Games	-.186*	0.036	0.000
		2 Media	-0.024	0.036	0.786
Choose_FreeTrial	1 Games	2 Media	-.163*	0.036	0.000
		3 Productivity	-.186*	0.036	0.000
	2 Media	1 Games	.163*	0.036	0.000
		3 Productivity	-0.024	0.036	0.786
	3 Productivity	1 Games	.186*	0.036	0.000
		2 Media	0.024	0.036	0.786

*The mean difference is significant at the 0.05 level.





4.5.7. Results Table 1G – Hypothesis 4

NPS/Affect Perspective

Analyzing Choose_Freemium population – All three categories

Freemium

Descriptives

NPS

	N	Mean	Std. Deviation	Std. Error
1 Games	231	6.21	2.313	0.152
2 Media	169	4.99	2.936	0.226
3 Productivity	160	5.57	2.449	0.194
Total	560	5.66	2.600	0.110

ANOVA

NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	146.925	2	73.463	11.269	0.000
Within Groups	3631.246	557	6.519		
Total	3778.171	559			

Multiple Comparisons

Dependent Variable: NPS

Tukey HSD

(I) Category_Grouping		Mean Difference (I-J)	Std. Error	Sig.
1 Games	2 Media	1.220*	0.258	0.000
	3 Productivity	.639*	0.263	0.040
2 Media	1 Games	-1.220*	0.258	0.000
	3 Productivity	-0.581	0.282	0.099
3 Productivity	1 Games	-.639*	0.263	0.040
	2 Media	0.581	0.282	0.099

*The mean difference is significant at the 0.05 level.

4.5.8. Results Table 1H – Hypothesis 4

NPS/Affect Perspective

Analyzing Choose_Free-Trial population – All three categories

Free-Trial

Descriptives

NPS

	N	Mean	Std. Deviation	Std. Error
1 Games	150	4.87	2.862	0.234
2 Media	212	6.01	1.633	0.112
3 Productivity	221	6.56	1.847	0.124
Total	583	5.93	2.190	0.091

ANOVA

NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	256.998	2	128.499	29.412	0.000
Within Groups	2533.976	580	4.369		
Total	2790.974	582			

Multiple Comparisons

Dependent Variable: NPS

Tukey HSD

(I) Category_Grouping		Mean Difference (I-J)	Std. Error	Sig.
1 Games	2 Media	-1.141*	0.223	0.000
	3 Productivity	-1.688*	0.221	0.000
2 Media	1 Games	1.141*	0.223	0.000
	3 Productivity	-.547*	0.201	0.018
3 Productivity	1 Games	1.688*	0.221	0.000
	2 Media	.547*	0.201	0.018

*The mean difference is significant at the 0.05 level.

4.5.9. Results Table 1I – Hypothesis 5

Choice Perspective

(Using individual t-tests for significant differences of mean)

Examining Unendowed Group vs Limited-Feature Freemium Endowed Group

Group Statistics

Grouping		N	Mean	Std. Deviation	Std. Error Mean
Game_Response	1 Unendowed	120	0.26	0.440	0.040
	3 Freemium_Endowed	132	0.45	0.500	0.044
Media_Response	1 Unendowed	120	0.32	0.467	0.043
	3 Freemium_Endowed	132	0.54	0.500	0.044
Productivity_Response	1 Unendowed	120	0.30	0.460	0.042
	3 Freemium_Endowed	132	0.52	0.502	0.044

Independent Samples Test

	t-test for Equality of Means						
	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
Game_Response	-3.295	250	0.001	-0.196	0.060	-0.313	-0.079
	-3.315	249.733	0.001	-0.196	0.059	-0.313	-0.080
Media_Response	-3.617	250	0.000	-0.221	0.061	-0.342	-0.101
	-3.629	249.821	0.000	-0.221	0.061	-0.341	-0.101
Productivity_Response	-3.536	250	0.000	-0.215	0.061	-0.335	-0.095
	-3.551	249.978	0.000	-0.215	0.061	-0.334	-0.096

Examining Unendowed Group vs Full-Feature Free-Trial Endowed Group

Grouping		N	Mean	Std. Deviation	Std. Error Mean
Game_Response	1 Unendowed	120	0.26	0.440	0.040
	2 FreeTrial_Endowed	129	0.50	0.502	0.044
Media_Response	1 Unendowed	120	0.32	0.467	0.043
	2 FreeTrial_Endowed	129	0.57	0.496	0.044
Productivity_Response	1 Unendowed	120	0.30	0.460	0.042
	2 FreeTrial_Endowed	129	0.65	0.478	0.042

Independent Samples Test

	t-test for Equality of Means						
	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
Game_Response	-3.965	247	0.000	-0.238	0.060	-0.356	-0.120
				-0.238	0.060	-0.355	-0.120
Media_Response	-4.199	247	0.000	-0.257	0.061	-0.378	-0.136
	-4.208	246.966	0.000	-0.257	0.061	-0.377	-0.137
Productivity_Response	-5.894	247	0.000	-0.351	0.060	-0.469	-0.234
	-5.903	246.720	0.000	-0.351	0.059	-0.468	-0.234

4.5.10. Results Table 1J – Hypothesis 6

Choice Perspective

Examining choices between Unendowed Group vs Freemium Endowed Group vs Free-Trial Endowed Group

Descriptives

		N	Mean	Std. Deviation	Std. Error
Game_Response	1 Unendowed	120	0.26	0.440	0.040
	2 FreeTrial_Endowed	129	0.50	0.502	0.044
	3 Freemium_Endowed	132	0.45	0.500	0.044
	Total	381	0.41	0.492	0.025
Media_Response	1 Unendowed	120	0.32	0.467	0.043
	2 FreeTrial_Endowed	129	0.57	0.496	0.044
	3 Freemium_Endowed	132	0.54	0.500	0.044
	Total	381	0.48	0.500	0.026
Productivity_ Response	1 Unendowed	120	0.30	0.460	0.042
	2 FreeTrial_Endowed	129	0.65	0.478	0.042
	3 Freemium_Endowed	132	0.52	0.502	0.044
	Total	381	0.49	0.501	0.026

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Game_Response	Between Groups	3.975	2	1.988	8.541	0.000
	Within Groups	87.967	378	0.233		
	Total	91.942	380			
Media_Response	Between Groups	4.775	2	2.387	9.991	0.000
	Within Groups	90.328	378	0.239		
	Total	95.102	380			
Productivity_Response	Between Groups	7.762	2	3.881	16.770	0.000
	Within Groups	87.472	378	0.231		
	Total	95.234	380			

Multiple Comparisons

Tukey HSD

Dependent Variable			Mean Difference (I-J)	Std. Error	Sig.
Game	1 Unendowed	2 FreeTrial_Endowed	-.238*	0.061	0.000
		3 Freemium_Endowed	-.196*	0.061	0.004
	2 FreeTrial_Endowed	1 Unendowed	.238*	0.061	0.000
		3 Freemium_Endowed	0.042	0.060	0.766
	3 Freemium_Endowed	1 Unendowed	.196*	0.061	0.004
		2 FreeTrial_Endowed	-0.042	0.060	0.766
Media	1 Unendowed	2 FreeTrial_Endowed	-.257*	0.062	0.000
		3 Freemium_Endowed	-.221*	0.062	0.001
	2 FreeTrial_Endowed	1 Unendowed	.257*	0.062	0.000
		3 Freemium_Endowed	0.036	0.061	0.825
	3 Freemium_Endowed	1 Unendowed	.221*	0.062	0.001
		2 FreeTrial_Endowed	-0.036	0.061	0.825
Productivity	1 Unendowed	2 FreeTrial_Endowed	-.351*	0.061	0.000
		3 Freemium_Endowed	-.215*	0.061	0.001
	2 FreeTrial_Endowed	1 Unendowed	.351*	0.061	0.000
		3 Freemium_Endowed	0.136	0.060	0.059
	3 Freemium_Endowed	1 Unendowed	.215*	0.061	0.001
		2 FreeTrial_Endowed	-0.136	0.060	0.059

*The mean difference is significant at the 0.05 level.

4.5.11. Results Table 1K – Hypothesis 6

NPS/Affect Perspective

Examining choices between Unendowed Group vs Freemium Endowed Group vs Free-Trial Endowed Group

Category: Games

Games_NPS

	N	Mean	Std. Deviation	Std. Error
1 Unendowed	31	5.48	3.182	0.571
2 FreeTrial_Endowed	64	5.91	2.245	0.281
3 Freemium_Endowed	60	6.47	1.987	0.257
Total	155	6.04	2.385	0.192

ANOVA

Games_NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	21.655	2	10.827	1.927	0.149
Within Groups	854.113	152	5.619		
Total	875.768	154			

Multiple Comparisons

Dependent Variable: Games_NPS

Tukey HSD

(I) Groupings_Games		Mean Difference (I-J)	Std. Error	Sig.
1 Unendowed	2 FreeTrial_Endowed	-0.422	0.519	0.695
	3 Freemium_Endowed	-0.983	0.524	0.150
2 FreeTrial_Endowed	1 Unendowed	0.422	0.519	0.695
	3 Freemium_Endowed	-0.560	0.426	0.389
3 Freemium_Endowed	1 Unendowed	0.983	0.524	0.150
	2 FreeTrial_Endowed	0.560	0.426	0.389

*The mean difference is significant at the 0.05 level.

4.5.12. Results Table 1L – Hypothesis 6

NPS/Affect Perspective

Examining choices between Unendowed Group vs Freemium Endowed Group vs Free-Trial Endowed Group

Category: Media

Media_NPS

	N	Mean	Std. Deviation	Std. Error
1 Unendowed	31	5.45	3.031	0.544
2 FreeTrial_Endowed	64	6.67	1.919	0.240
3 Freemium_Endowed	60	5.70	2.367	0.306
Total	155	6.05	2.393	0.192

ANOVA

Media_NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	43.200	2	21.600	3.916	0.022
Within Groups	838.387	152	5.516		
Total	881.587	154			

Multiple Comparisons

Dependent Variable: Media_NPS

Tukey HSD

(I) Groupings_Games		Mean Difference (I-J)	Std. Error	Sig.
				0.695
1 Unendowed	2 FreeTrial_Endowed	-1.220*	0.514	0.049
	3 Freemium_Endowed	-0.248	0.519	0.882
2 FreeTrial_Endowed	1 Unendowed	1.220*	0.514	0.049
	3 Freemium_Endowed	0.972	0.422	0.058
3 Freemium_Endowed	1 Unendowed	0.248	0.519	0.882

*The mean difference is significant at the 0.05 level.

4.5.13. Results Table 1M – Hypothesis 6

NPS/Affect Perspective

Examining choices between Unendowed Group vs Freemium Endowed Group vs Free-Trial Endowed Group

Category: Productivity

Productivity_NPS

	N	Mean	Std. Deviation	Std. Error
1 Unendowed	31	5.19	3.103	0.557
2 FreeTrial_Endowed	64	7.22	1.786	0.223
3 Freemium_Endowed	60	5.98	2.236	0.289
Total	155	6.34	2.394	0.192

ANOVA

Productivity_NPS

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	97.795	2	48.898	9.471	0.000
Within Groups	784.760	152	5.163		
Total	882.555	154			

Multiple Comparisons

Dependent Variable: Productivity_NPS

Tukey HSD

(I) Groupings_Games		Mean Difference (I-J)	Std. Error	Sig.
				0.695
1 Unendowed	2 FreeTrial_Endowed	-2.025*	0.497	0.000
	3 Freemium_Endowed	-0.790	0.503	0.261
2 FreeTrial_Endowed	1 Unendowed	2.025*	0.497	0.000
	3 Freemium_Endowed	1.235*	0.408	0.008
3 Freemium_Endowed	1 Unendowed	0.790	0.503	0.261

*The mean difference is significant at the 0.05 level.

4.6. Discussion

The results from the two-stage experiment have yielded important insights. First and foremost, the analysis extends prior research and findings from Shampanier et al.'s (2007) well-known experiments as well as reaffirming some of Huttel et al.'s (2018) findings. The results from the examination of the first hypothesis (*The zero-price effect (ZPE) generalizes to the digital context, and is observed for digital offerings across all three categories, namely games, productivity and media-streaming mobile applications*) suggest that the ZPE truly extends beyond its impact on tangible products, concurring with Huttel et al.'s (2018) findings. Furthermore, the results also indicate that the three mobile software application categories – games, media-streaming and productivity – exhibit similar characteristics, beyond just the media-streaming application category demonstrated by Huttel et al. (2018). The proportion of respondents choosing the basic offers in the zero-price group was shown to be significantly different from the proportion of respondents choosing the basic offers in the bargain-price group. Correspondingly, the proportion of respondents for the premium offers in the zero-price group was shown to be significantly different from the proportion of respondents for the premium offers in the bargain-price group. It is also evident from the bar charts presented in the previous section that when juxtaposed only with the bargain-priced option of S$1.48, a larger proportion of respondents chose the premium option, lending credence to Tversky and Kahneman's (1981) notable framing effect and its influence on consumer decisions.

The results from the testing of the second hypothesis (*The zero-price effect (ZPE) varies across different digital application categories*) shed additional insights. These results showed that even though the zero-price/free offering does influence choice, and nudges consumers towards a desired action (i.e. to download the application at this awareness stage) this effect varied according to category. From a choice perspective, results suggest that a free offering tends to nudge consumers to try out applications from the games category more than those from the media-streaming or productivity categories. In fact, a larger proportion of respondents chose the premium offers for the media-streaming and productivity categories relative to the games category. A possible explanation for this phenomenon is that consumers have a relatively deeper understanding of what a “media-streaming” or “productivity” application will and can accomplish, whereas for the games applications this might be less true. Thus the free offering makes the mental hurdle for the games category easier to overcome, leading consumers to proceed with downloading the application to try it out. For applications in the media-streaming or productivity category, consumers may be able to discern the key differences between a limited-feature basic offer as opposed to the full-feature premium offer, and thus have no need to defer their decision-making as to whether they will make the leap to choosing a premium offer or not. This also may relate to the possibility that consumers may already have preconceived notions and cost-benefit expectations of applications from specific categories prior to making any decisions. The “reference point” for either a productivity application category or a media-streaming application category is thus more codified than for the games category, which in turn may potentially “nudge” a digital consumer more (i.e. have a stronger ZPE) to download an app with a free offering. As such, it is conceivable that categories truly moderate the cognitive processes that influence consumers’ *choices*, particularly at the price of zero/free.

From the affect perspective, which I used the Net Promoter Score (NPS) to empirically examine, the results generate similar observations. Focusing on data collected only from the ZP group, the mean NPS captured for the productivity category was higher than the mean

NPS from the games and media categories. This suggests that consumers do feel differently towards applications from different categories. The level of affect and NPS measured differed significantly between the gaming applications and the productivity applications. Media-streaming applications seem to reside within the spectrum marked by the games and productivity categories, although the results do not suggest a meaningful difference in the mean NPS between the media-streaming category and the other two categories at the 5% significance level. In other words, the results seem to suggest that, at the price of zero/free, consumers do feel significantly different towards apps from both the games and productivity category. It would seem that if a mobile application's key purpose is more *embedded* in the user's daily routine or workflow, the ZPE will be stronger, eliciting a higher level of positive affect.

The same cannot be said as we examine the empirical results collected from the BP group for testing the third hypothesis (*At the bargain/nominal price, the choice proportions and the level of affect vary across different digital application categories*). While there was a difference between the proportions of respondents who chose both the basic and premium offers for the three categories, the mean NPS did not differ significantly among the three categories. This suggests that the moderating effect posed by the categories towards the level of affect does not seem to affect consumer choices for the BP group (i.e. consumers who are offered choices priced at S$1.48 vs the premium offers). Therefore, there is insufficient data to suggest that the moderating effect by categories extends to digital offerings priced beyond zero, even at a deemed bargain/nominal price.

The results for the testing of the fourth hypothesis (*Digital consumers prefer to download the full-feature free-trial option for evaluation at this stage as opposed to the* *limited-feature freemium version for all three digital application categories*) are potentially instructive as well. From a choice perspective, when surfaced with a limited freemium version as opposed to a full-feature free-trial version, there was a clear difference between categories in which version consumers preferred. The results showed that for games, consumers do prefer the freemium version, whereas for media-streaming and productivity apps which are more *embedded* into a user's daily routine or lifestyle, more consumers prefer the full-feature free-trial version; and within the latter two categories, a larger proportion of the respondents chose the free-trial version for productivity apps than the free-trial version for media-streaming apps. It would seem that for the productivity app, being substantially more *embedded* into people's daily routine or lifestyle than the other two categories, the free-trial approach may be preferred. However, it should be noted that potentially deceptive or predatory actions involving "tricking" users into continuing subscriptions post a "free-trial" period are frowned upon by the larger app-using community, as detailed by Perez (2018), and that Apple's App Store and Google's Play Store have made big strides in making refunds of such unintended subscriptions easier, through a fairly straightforward refund process. One way to adopt insights from this finding is for digital practitioners to be selective when it comes to using free-trial as a strategy. If the app is deemed to be embedded into consumers' daily routine or lifestyle, particularly in the context of a productivity app, then perhaps a free-trial strategy is useful, because the cost of cancelling it vis-à-vis the level of comfort the user enjoys from having ready access to the tool required to perform a routine task is higher. In addition, other behavioral concepts, such as present bias or hyperbolic discounting, may potentially reinforce such inherent biases, and allow digital practitioners to benefit from this insight. Notwithstanding, for more trivial categories such as games, since they are less likely to be embedded into the daily routine or lifestyle, a free-trial approach may backfire, as it may lead to users not downloading the app at all at the first awareness stage when given the choice, as shown by the quantitative research results presented here, or even deleting it promptly after downloading so as not to fall for the deceptive or predatory subscriptions that such strategies are associated with, thereby preventing the endowment effect from working its magic in the second, conversion stage.

When we further examine the population that chose the freemium option, in order to evaluate their mean NPS as a measure of affect in this awareness stage, it is also clear that there was a significant difference between the means for the three categories. Post-hoc multiple comparison analysis indicated that the games differed from both the productivity and media-streaming categories, but between media-streaming and productivity categories, there was not enough evidence to suggest there a significant difference. The mean NPS for the games category was clearly higher for the respondents who chose the freemium version compared to those who chose the free-trial version, suggesting that consumers may feel more comfortable choosing a limited-feature freemium version of games relative to the other option.

The same examination was undertaken for the population that chose the free-trial option, and the mean NPS for these groups also showed a significant difference from each other. However, in the free-trial population, post-hoc multiple comparison analysis indicated that all three categories demonstrated a significant difference in mean NPS. This suggests that consumers may feel better or more comfortable choosing the free-trial version if the app belongs to the productivity or media-streaming category. This result complements the findings related to the choice proportions, discussed above.

Coupled with the insights derived from the choice proportions perspective, this finding may suggest that for the category of games, practitioners may be better off using the limited-feature freemium strategy, whereas for the categories of media-streaming, and productivity, practitioners may wish to consider the full-feature free-trial strategy instead. A possible explanation outlined next extends the above elaboration of how a consumer perceives a digital offering based on its category. For a gaming app, particularly in this awareness stage, where the consumer's decision is whether to download or not, the consumer may wish to retain a sampling experience of the digital offering for as long as they wish, even if the sampling experience only consists of limited features from which the full experience can be extrapolated relatively easily. However, when it comes to a media-streaming app or a productivity app, the consumer may wish to sample the full extent of the full-featured offering in order to serve a special or specific need. The consumer may already have a much better idea of what the difference between the basic (limited-feature) and premium (full-feature) offers are, given that the application's purpose is more embedded with the user's daily routine and lifestyle. This greater knowledge means that there is no need for an additional period of evaluation and extrapolation, or it may help the consumer understand that their objective in using the app will not be met by a limited-feature option. Therefore, we may infer that for apps which serve certain functions that are well established or for those that are very much embedded in the daily lifestyles of consumers – such as media-streaming apps like Netflix or Spotify or productivity apps like Dropbox or a profession-specific calculator – a limited-feature freemium offering will serve a less useful role at this awareness stage in getting the user to download the app.

Moving to the second, conversion stage of the scenario-based experiment, results for the testing of the fifth hypothesis (*An endowment effect exists for consumers who are being endowed with a limited-feature freemium basic offer or with a full-feature free-trial period basic offer*) extend the findings of the endowment effect introduced by Kahneman et al. (1990, 1991). However, given that prior research on the endowment effect has focused on tangible products, I am confident that the findings from this study will be able to usefully inform practitioners in the digital context. From a choice perspective, the results clearly show that, relative to the unendowed group, there was a significant difference in the proportions of respondents who chose to upgrade to the premium option for both the group endowed with the limited-feature freemium version as well as the group endowed with the full-feature free-trial version. This underscores the observation that the endowment effect extends to the digital context across all three mobile software application categories.

It is also evident from the results of testing the final and sixth hypothesis (*Consumers who are endowed with the full-feature free-trial period basic offer are more likely to pay for the premium offer than consumers who are endowed with the limited-feature freemium basic offer after a predetermined period of time for all three digital application categories*) that the proportions of respondents who chose to upgrade to the premium offer significantly varied across the three different categories, whether they were endowed with the free-trial or freemium version. However, if we drill deeper into the post-hoc multiple comparison analysis, we can derive deeper insights. Compared to the unendowed group, it is evident that both the freemium or free-trial endowed group had a significantly different (larger) proportion of respondents who chose to upgrade, reinforcing the results demonstrated for the previous, fifth hypothesis that the endowment effect exists for digital offerings across the three categories. However, between the free-trial endowed group and the freemium endowed group, the proportions of respondents who upgraded did not differ significantly. Similar results were observed across all three categories. From an affect/NPS perspective, we can see that there was no significant difference in the mean NPS observed between the unendowed group and the two endowed groups in the games category. However, there was an observable difference in the mean NPS between the group endowed with the full-feature free-trial version that chose to upgrade to the premium version vs the unendowed group for both the media and productivity categories. In the productivity category, the mean NPS differed significantly to a larger extent as well, and a significant difference in NPS was also observed between the freemium endowed and the free-trial endowed group.

A possible explanation for this phenomenon is that the endowment effect is moderated by the "category", with an app eliciting a stronger positive affect/influence if (as appropriately categorized) it is deemed to be embedded in the consumer's workflow or lifestyle. As such, the full-feature free-trial version will trigger a more positive affect (as measured by the higher mean NPS shown in the productivity category, compared to the media-streaming category which, in turn, was higher than the games category). It is noteworthy that the mean NPS of those endowed with the limited-feature freemium offer did not differ significantly from the unendowed group for either the media-streaming or productivity categories. For games – which could be potentially perceived to be trivial and to be less embedded into the consumer's daily lifestyle or having any relevance to a consumer's workflow – there is no preference for either strategy, whether limited-feature freemium or full-feature free-trial, given that the findings are non-conclusive. Therefore, from the practitioner's perspective, such findings should be instructive in deciding on a strategy for increasing the conversion of newly acquired users who download apps for free from app stores.

4.7. Limitations

As with most research studying a narrow phenomenon, this study certainly involves some limitations. First and foremost, the sample population used was between 18 and 65 years old, involving participants from different generations: Generation Z (individuals born from 1994 to 2005); Generation Y, otherwise known as millennials (individuals born between 1977 and 1993); Generation X (individuals born between 1965 and 1976); and baby boomers (individuals born between 1946 and 1964), as broadly defined by Turner (2015). Therefore, it is conceivable that respondents had different levels of understanding of mobile technology and, thus, different levels of sophistication in the adoption of mobile software applications from the three focus categories of games, media-streaming and productivity. Notwithstanding this, as Tversky and Kahneman (1979) and Shampanier et al. (2007) also noted, studies in behavioral economics and studies of various behavioral effects, including the zero-price effect, involve the study of phenomena that generalize to the larger human condition. As such, factors like ethnicity, race, gender and age were not taken into consideration when the pioneering behavioral scientists designed most of their experiments, which were mostly held within physical confines, such as the canteens of their respective universities. The target audience group for my experiment is considered, within the Singapore context, to fall within the definition of the working-age population, and respondents would at least have been aware of what the three stated categories were when embarking on the quantitative survey. In Singapore, as has been evident in the COVID-19 pandemic period during which my research was conducted, the entire Singaporean population needs to have a functional understanding of the mobile app TraceTogether SG, used for nationwide contact-tracing, in order to even purchase basic groceries from local stores or supermarkets. This context helped to mitigate the mobile app/technology awareness hurdle as the quantitative survey was conducted.

Secondly, while I did collect a sizeable number of online responses – 381 complete and valid responses out of a total of 477 collected – I was unable to break down the data further to see whether the age/generational gap would generate further insights, given that if I wished to apply the central limit theorem for the assumption of normality, as Edwards (1962) suggests, each of the sample population sizes must be at least 30. The majority of the respondents were aged 45 and below. Therefore, with such small groups split even further into the zero-price (ZP) and bargain-price (BP) groups, suitable comparisons between the baby boomers and Generation X, or the younger millennials (Generation Y) and Generation Z, could not be examined further if statistical inferences were to be applied. However, this limitation provides an opportunity for further research by other behavioral economists.

Thirdly, for the second stage of the experiment, examining the endowment effect, there are conceivably many reasons why a consumer might "choose" to pay to upgrade to the premium options via various strategies. One such reason is when digital app companies, by design, require consumers to provided credit card payment details and adopt an opt-out approach, such that the consumer has to make a special effort to remember the period of the free-trial evaluation before deciding whether to renew the subscription for the premium offering. Therefore, if the consumer forgets to cancel the subscription, the consumer is, by default, charged for continuing the subscription. While this is technically considered a digital nudge (i.e. a software or process designed to direct consumers towards a particular outcome), as a mitigating approach I created the quantitative survey using an imaginative scenario to measure the specific choice made and level of affect or NPS registered by the respondent. Furthermore, it is notable that such digital nudge, known as "default", which was also detailed in the literature review section of this dissertation, and designed to "trick" customers into paying for subscriptions they do not want, is not a sustainable approach and may lead to an inordinate amount of unexpected cost in the form of customer relationship management and brand reputation. What my research was keen to examine was the impact of such a strategy (free-trial or freemium) on choice and affect for different categories of apps. Therefore, the digital nudge to "trick" consumers into a payment for a premium digital offering lies outside the purview of this research, and may be an interesting focus for future research, including on its actual efficacy for practitioners. Another key limitation of this study was that the free-trial period for the scenario posed in the quantitative survey was set at one week for all three categories. It may be worthwhile for future researchers to examine whether the length of the free-trial period impacts the endowment effect or not.

Finally, it is abundantly clear that apps today are very sophisticated, and digital entrepreneurs adopt various strategies based on the various behavioral heuristics and the effects or variables that may have a confounding effect on the phenomena of the zero-price effect and endowment effect examined in this quantitative study. For example, Chou and Wang (2016) already highlighted how advertisements, which typically complements the freemium model, may have nuanced effects on young adults, such that advertisements embedded in calm-happiness (as opposed to excited-happiness) contexts generate better advertising effects and that red backgrounds (relative to gray and blue ones) along with promotional incentives having better advertising effects. Shen (2015) also shared how different sort of message framing moderates the perceived usefulness of the app prior to the downloading process. Therefore, all these examples provide fertile ground for future research to examine what other such variables could be and empirically determine their impact on shaping a consumer's decision at both the awareness and conversion stages. Furthermore, in order to study the stated narrow phenomena, I attempted to focus more deeply on the three main app categories of games, media-streaming and productivity, given that it is not feasible to evaluate all 24 different app categories available on the Apple App Store and the 33 different categories on the Google Play Store (and noting that many of these categories are considered sub-categories of the three key categories I used). Future research could examine if such sub-categories would further moderate the positive affect experienced by consumers in their respective choice and purchasing decisions. Furthermore, as Purohit et al. (2020) highlighted, insights derived from the above-mentioned research can truly shape new designs aiding in digital detoxing for the consumers of the 21st century, given that social media addiction concerns have escalated in recent years. Furthermore, new studies on how the ZPE and endowment effect can complement other kind of interventions to constitute even more effective digital nudges can also be explored for influencing consumer or user behavior in the digital context.

Aside from that, it should be noted that there is a number of policy implications associated with digital nudging particularly surrounding the key issues of privacy and the potential for abuse by digital practitioners. Areas surrounding such ethical concerns and transparency also provide fertile ground for further research as well. My research focuses a lot on how zero-price and the endowment effect nudges towards consumer adoption in a non-intrusive way, but this strategy when pushed to the extreme by incumbents, can contribute greatly to market concentration with result in potential monopolistic behavior where value is extracted from digital consumers, crowding out innovation for other startups and smaller businesses.

Chapter 5: Managerial Implications

This chapter of the thesis focuses predominantly on how digital practitioners can design the suitable "nudges" in their products and services based on the findings of the research, and how an understanding of the various nuanced reference points in the digital consumer' minds can help shape suitable strategies for effective conversion into actual paying customers. In this chapter, I will also be introducing the cognitive bias codex along with its key classification criteria for the different categories of biases and effects. Furthermore, I have also formally proposed that the zero-price effect to be included in the codex with a suitable corresponding category in the final section of this chapter.

5.1. General Discussion

As my supervisor, Dr Craig Applegate, often proclaims, "Everything is economics". Since Tversky and Kahneman's (1979) prospect theory, which essentially suggests that human beings do not evaluate things in absolute terms but in "relative" terms, behavioral economics has moved into the mainstream and developed into an accepted subset of the realm of economics, recognizing that the "relative" reference point is a key determinant of how an outcome is generally perceived by a person. Understanding the different and nuanced reference points surrounding zero-price/free offerings, particularly in the digital context, was the object of my research, as such an understanding will help shape business strategies going forward. One potential benefit of digital nudges is that they can be implemented at low or even zero cost and with minimal disruption. Simply changing the default options or the way information is presented to users, can be useful especially in the early days of gaining traction. In this case, presenting digital products or offerings utilizing a specific form of free strategy, whether is it freemium for leisure or more trivial gaming category of applications, or free-trial for productivity/more embedded category of applications, can be seriously considered for digital practitioners seeking to influence consumer behavior.

The quantitative study described in the previous chapter provides evidence that consumers perceive “free” differently for different digital offerings. Given that this study has established that the zero-price effect (ZPE) extends to the digital context, pricing an offering for free certainly helps to lower the digital consumer’s awareness hurdle. Notwithstanding this, in order to ensure the sustainability of a startup’s financial viability, the digital practitioner needs to be discerning. When it comes to the first awareness stage – both in nudging consumers to download and from an affect/NPS perspective – results do indicate that for the games category, digital practitioners are better off choosing the freemium strategy, whereas for the media-streaming and productivity categories, they are better off choosing the free-trial strategy. However, when it comes to whether this will lead to a stronger endowment effect, results suggest that for the games category, there is no greater benefit in adopting the freemium over the free-trial strategy, or vice versa. The level of affect/satisfaction, as measured by the NPS, did not necessary imply a higher level of satisfaction with the freemium compared to the free-trial endowed strategy, and digital entrepreneurs could use other strategies, such as in-game purchases, or take advantage of other effects, such as the empathy (cold-hot) gap effects detailed in the literature review section, for more effective conversion. For the media-streaming and productivity category, a free-trial strategy may be preferred, as the endowment effect seemed to elicit a higher level of satisfaction, as measured by the mean NPS, relative to the unendowed or freemium endowed groups. Digital entrepreneurs offering apps or digital services in these two categories could seek to identify the appropriate period for a free trial, while ensuring that the entire suite of features is made available to customers, in order to ease users into their transition into paying customers. The relevance and validity of this research is thus established especially when digital practitioners can now determine that it is better to use a particular kind of free-related strategy (i.e. whether freemium or free-trial) given the category of the application they are developing and promoting and whether their application is embedded or not into the daily workflow of the digital consumer. This can prove to be lucrative and profitable as startup entrepreneurs often have to make such important decisions to ensure they have the cashflows to tide through the difficult early user traction and adoption phase of their digital product offerings.

My research also seeks to contribute to the digital nudging literature, and I suggest that pricing an app for free with the appropriate free-related strategy is just one of multiple reasons that a digital startup may be able to overcome the awareness hurdle faced by many new businesses and grow rapidly, particularly in its early stages. To sustain a startup's financial viability and growth profile, I do recognize that such digital nudges, in the form of the zero-price and freemium/free-trial strategy, need to tie in with other strategies to achieve fast growth in user traction which will contribute to actual practical usage and help in bridging the academic-practitioner divide as Shepherd and Gruber (2021) described. Introduction to the Cognitive Bias Codex

As discussed in Section 2.3 of the literature review, which frames the research question for this dissertation, behavioral economics has come a long way. Beyond the key ones listed in Section 2.3, Ellis (2018) listed a total of around 188 effects and biases. These are summarized in Figure 13 below, divided into four main quadrants. However, they are also summarized aptly by Nortjie (2021) as follows:

A. Too much information
    - reflecting biases that affect how we perceive events and people.

B. Not enough meaning
    - involving biases that we use when we have too little information, and thus need to fill in the gaps to form a comprehensive narrative/story.

C. Need to act fast
    - including biases that affect how we make decisions quickly.

D. What should we remember?
    - including biases that affect our memory for people, events and information.

A major issue with this large codex of all the biases studied by researchers over several decades, is that, beyond serving as a reference, it has limited application for practitioners. Practitioners tend to explain their executed business strategies by post-hoc references to this codex of biases and heuristics rather than using this codex effectively in developing useful "nudges" (i.e. choice architectures referenced by Thaler and Sunstein [2008], and in the digital context, "digital nudges"). It is thus the objective of the subsequent subsections to illustrate some of the applications of the behavioral effects documented within this codex in a real-world context, and finally, in Chapter 6.3, to tie this up in a purpose-driven framework, marrying this useful codex with other useful digital marketing frameworks so that practitioners can deploy it effectively, particularly in the early stages of a digital startup's efforts to achieve traction.

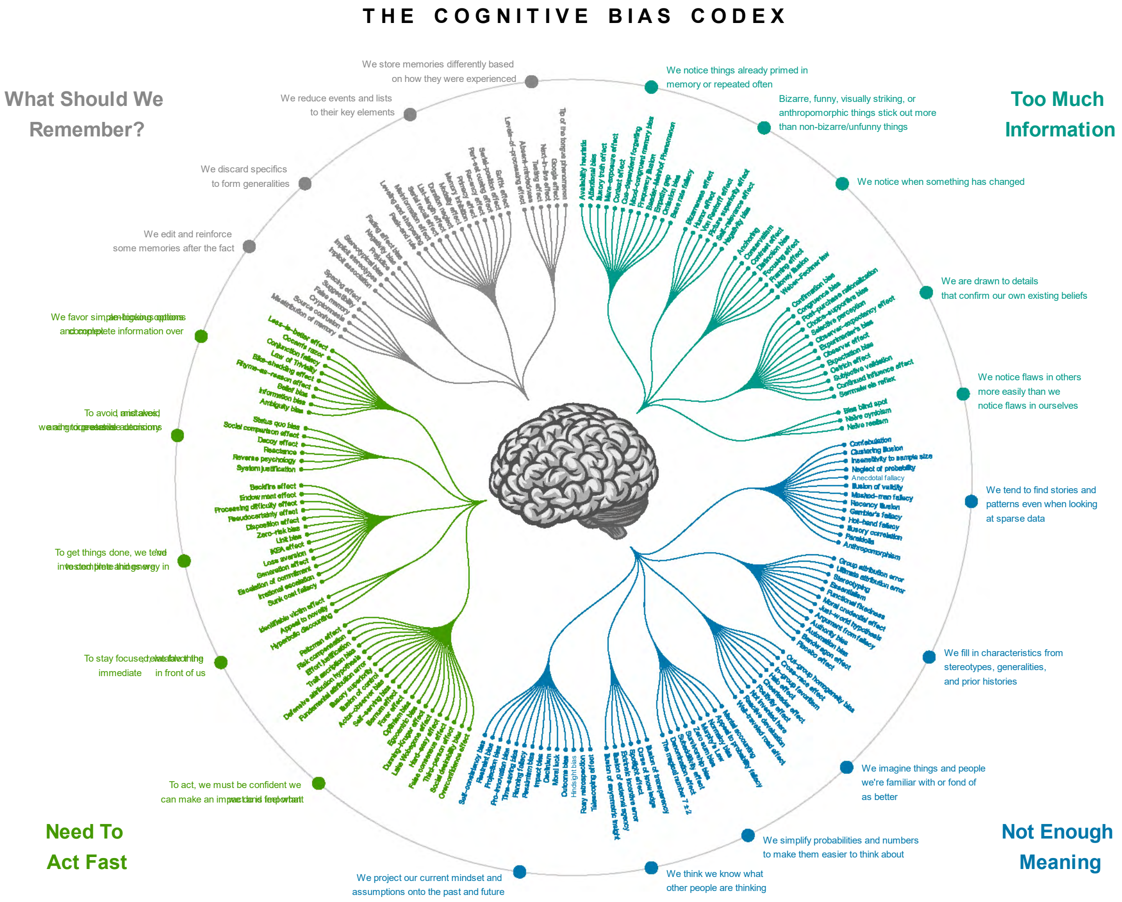


Figure 13: Benson and Manoogian's (2018) Cognitive Bias Codex Extracted From Wikimedia[12]

As shown in Figure 13, the four main areas of "why" a bias occurs, as Ellis (2018) discussed, are further subdivided into 20 bulleted categories listing "how" humans cope with the corresponding "reason why" quadrants; this is reflected in the following Table 2. The respective cognitive biases and heuristics within each category are all captured in Table 8, in Appendix 3, given the restricted font sizes for the individual biases/heuristics in Figure 13.

[12] https://commons.wikimedia.org/wiki/File:Cognitive_bias_codex_en.svg presented in Table 8 of Appendix 3.

Table 2: Twenty Key Categories of "How" Humans Cope With the Four Key "Whys"

A. Too Much Information 1. We notice things already primed in memory or repeated often 2. Bizarre/funny/visually striking/ anthropomorphic things that stick out more than mediocre stuff 3. We notice when something has changed 4. We are drawn to details that confirm our own existing beliefs 5. We notice flaws in others more easily than flaws in ourselves	**B. Not Enough Meaning** 1. We find stories and patterns even in sparse data 2. We fill in characteristics from stereotypes, generalities and prior histories 3. We imagine things and people we're familiar with or fond of as "better" 4. We simplify probabilities and numbers to make them easier to think about 5. We think we know what other people are thinking 6. We project our current mindset and assumptions onto the past and future
C. Need to Act Fast 1. To act, we must be confident we can make an impact and feel what we do is important 2. To stay focused, we favor the immediate, relatable thing in front of us 3. To get things done, we tend to complete things we've invested time and energy in 4. To avoid mistakes, we're motivated to preserve our autonomy and status in a group and to avoid irreversible decisions 5. We favor simple-looking options and complete information over complex, ambiguous options	**D. What Should We Remember?** 1. We edit and reinforce some memories after the fact 2. We discard specifics to form generalities 3. We reduce events and lists to their key elements 4. We store memories differently based on how they were experienced

* Table adapted from Benson and Manoogian's (2018) Cognitive Bias (Figure 13)

5.2. Proposed Inclusion of the Zero-Price Effect into the Cognitive Bias Codex

The elephant in the room when we examine Benson and Manoogian's (2018) codex, given my research and the focus of this dissertation, is the notable absence of ZPE. I wish to highlight that the endowment effect and the loss aversion phenomenon, also examined in my research and explored in this dissertation, are already classified under a separate category within the same quadrant C, number 3 (C3) point: "to get things done, we tend to complete things we've invested time and energy in". One reason for the omission of ZPE is probably because many people tend to associate ZPE with the endowment and loss aversion effect, which is already covered in C3. However, as my research, along with much freemium-related research in the information systems literature suggests, the zero-price or free offering, particularly in the digital context, seems to serve as another main rationale in the consumer decision-making process; that is, to nudge digital consumers to become aware of the product first, before adoption.

As shown in my conceptual framework in Figure 5 in Section 2.6, an awareness Stage 1 before the conversion Stage 2 exists in the digital context. Therefore, since the rationale and motivation for zero-price or free offerings does not technically fit the definition of "completing things we've invested time and energy in", since an individual cannot possibly have invested time and energy in something if they are not even aware of it or have not yet downloaded it to try it out, it may be more appropriate to classify this under C5: "we favor simple-looking options and complete information over complex, ambiguous options". A free offering is deemed to be an effective digital nudge, packaged as a complete simple offering with minimal "costs" to the consumer for faster decision-making (quadrant C's main rationale). Furthermore, given its dominance and increasing adoption in the digital context for the purpose of early-stage user adoption, the effect deserves a formal induction into this comprehensive codex. As such, I would also formally propose the inclusion of ZPE into the codex, to be categorized under C5. This ZPE cognitive bias addresses the key "why" of the "need to act fast". The addition is reflected in bold and highlighted in yellow within Table 8 of Appendix 3.

Suffice to say from the discussion above, I agree with Ellis (2018) that, despite the codification of so many different biases, how humans make decisions is still largely a mystery, and as the context changes, the complexity only increases. The digital context which my research is situated within is indeed fertile ground for such research.

Notwithstanding this, and in the spirit of pragmatism and through a descriptive literature review, I will attempt to lay out a purpose-driven approach, using Table 2 to help identify the particular kind of biases shown in the cognitive bias codex shown in Figure 13 (a more granular list is also provided in Table 8 of Appendix 3) and recommending suitable digital nudges based on those biases, to emulate such strategies for the digital age. However, before developing this useful and purpose-driven framework, I think it is worthwhile to explain some other notable frameworks from other bodies of management literature, such as those concerned with growth hacking, word of mouth (WOM) and virality, as well as technology diffusion, and examine practical applications of these frameworks in the real world through an anthological compilation (presented in the next chapter). This will help to systematically embed the behavioral insights from the current study, for better efficacy in the digital context.

Chapter 6: A Purpose-Driven Framework for the Digital Context

The focus of this chapter is to elide the insights and managerial implications derived from the preceding chapter with the nascent body of growth hacking literature since the mid-2000s, to propose a purpose-driven framework that will be useful for the digital practitioners. In this chapter, I have conducted a descriptive review of the growth hacking literature as well as included an anthology of contemporary business growth hacking examples that have made use of various behavioral effects including those of zero-price effect and endowment effect which form my research focus in the main quantitative study in Chapter 3. I have also conducted a comprehensive review of the existing word-of-mouth (WOM) literature and attempted to link the respective cognitive biases and heuristics found in the cognitive biases codex with the relevant principles employed in some of the prevailing WOM literature, in order to provide a guiding framework for digital practitioners to go about thinking how to design suitable strategies or to employ suitable nudges in their product or services design.

6.1. Introduction to Growth Hacking

As we approach the first quartile of the 21st century, we must recognize that the digital revolution has already led to much change in our social habits, including even our prevailing cognitive biases. Sparrow et al. (2011) have identified the internet as a primary form of "transactive memory", where information which can be readily accessed via Google is stored externally. Sparrow et al. (2011), together with WTOP (2015) coined this particular "Google effect" as a new cognitive bias known as "digital amnesia"; specifically, "the experience of forgetting information that you trust a digital device to store and remember for you". Such a cognitive bias has already been witnessed in various aspects of our lives, including tourism (Greenwood & Quinn, 2017) and the learning community (Mason, 2015). This dissertation has focused on the narrow phenomena of the zero-price effect (ZPE) and the endowment effect within the digital context, but there are certainly many other cognitive biases and heuristics that we can tap into to craft innovative and viral strategies for achieving good traction.

The following sections will detail several examples of how modern business leaders champion new ways, utilizing various well-known cognitive biases to drive new product development as well as achieving stellar traction and adoption among early users. In this section, I will also attempt to marry such insights with another growing body of business strategy literature known as growth hacking, in order to provide guidance and insights for practitioners to develop their strategies or tactics accordingly. I will also look at several contemporary digital success stories, including how they have deployed various aspects of behavioral economics, such as digital nudging tools, heuristics and other cognitive biases, in their growth hacking strategies. While many prefer to attribute startup success to mostly luck, I agree with Ries (2011) that "startup success is not a consequence of good genes or being in the right place at the right time. Startup success can be engineered by following the right process, which means it can be learned, which means it can be taught" (pp. 2–3). Ries (2011) further introduced a five-phase marketing lifecycle for a typical digital product, with the phases of acquisition, activation, retention, revenue and referral. This lifecycle serves as the basis for relevant user data to be collected, measured and analyzed for effective scaling.

Ellis (2010, July 26) coined the term "growth hacker", stating that a growth hacker is someone whose north star is "growth". Sineni (2014) also quoted Sean Ellis, stating that "growth hacking focuses on qualitative marketing with product-market fit at its core. It is where statistics, computer science and marketing intersect" (p. 6). Holiday (2014) provided a succinct definition in a glossary section, describing growth hacking as a "business strategy that throws out the playbook of traditional marketing and replaces it with customer acquisition techniques that are testable, trackable, and scalable" (p. 132). However, academic literature surrounding this topic remains limited despite more than a decade since its introduction. Saleem (2014) also highlighted that growth hacking is often confused with online marketing tactics such as search engine optimization and social media platform marketing, which are nothing new. Herttua et al. (2016) also agreed with this position, noting that despite the plethora of definitions provided by various online blogs and articles, there appears to be no scientific definition recognized by the academic community. Therefore, they conducted a multi-method research project with grass-roots industry practitioners to identify the appropriate definition, further describing the entire growth hacking process and summarizing it. This summary is reproduced in Figure 13 below.

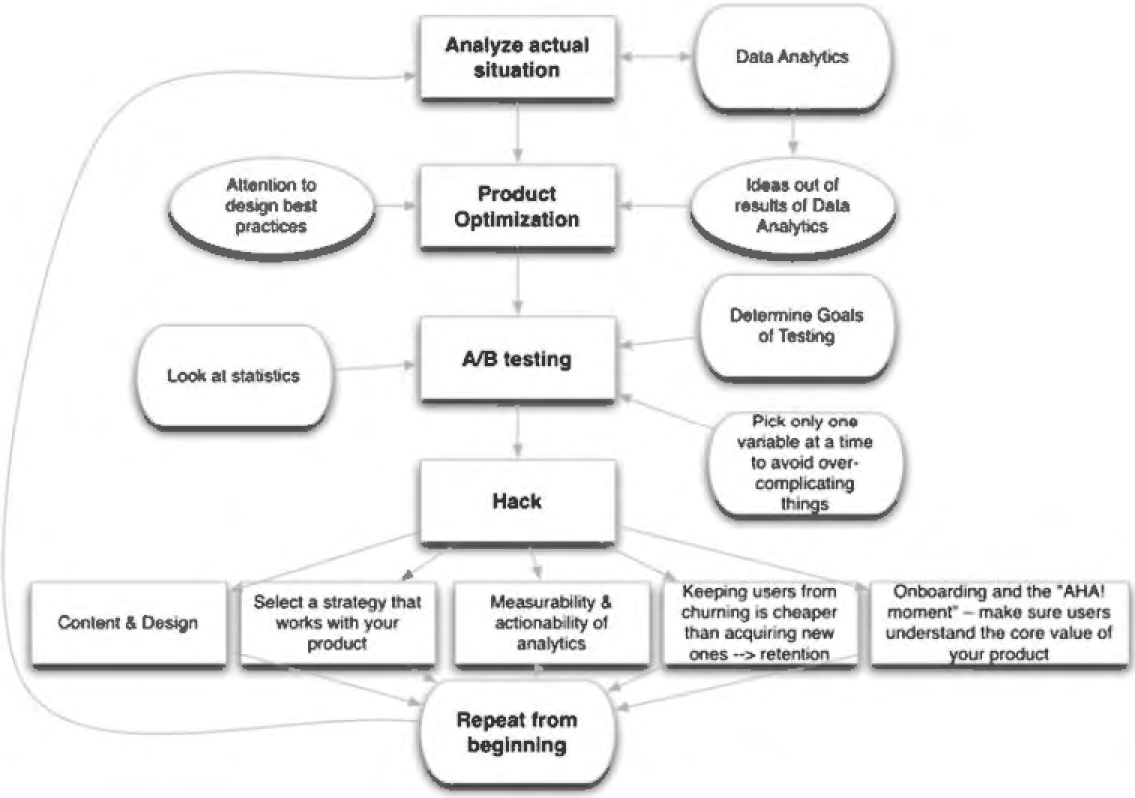


Figure 14: Growth Hacking Process Diagram (Herttua et al., 2018, p. 159)

This perpetually iterative process, as illustrated in Figure 14, concurs with Pizza's (2016) position that growth hacking is a new marketing mindset, involving a continuously evolving digital product or service offering, which differs from the traditional marketing of an existing predetermined, already-made product or service. He echoes Holiday's (2014) assertion that it is not in traditional marketing's DNA to be integrated with the product development team, an element which is critical to the growth hacking process. Pizza (2016) also highlights that for digital product offerings, it is important to get the attention of users first with a minimum viable product (MVP) and subsequently understand their needs further to seek their conversion into a paid customer. This is in line with the focus of this dissertation, given that I also adopted a two-stage model, reflected in the conceptual framework, to examine first the willingness to download (coinciding with the acquisition strategy) and subsequently the user's willingness to pay (coinciding with the conversion strategy).

It is also apparent that growth hacking as a strategy has taken off in several countries. Some examples of research reflecting this include Lin and Chen's (2018) work, involving a case study of an electronics store based in Taipei, Taiwan transiting from offline to online. Geruet al. (2014) also examined the motivations and impact of growth hacking strategies on another startup case study based in Romania, while Vunk (2017) explored the application of such strategies in Estonian digital startups. Elezovic (2017) looked at growth hacking's applications within the context of a real estate developer based in Belgrade, Serbia and Roschier (2018) identified growth hacking strategies typically used in startups to be applied to large Finnish companies. In the next section, I attempt to list out in a table (Table 3) the examples of how growth hacks have been used by companies globally and to identify the main cognitive biases, heuristics and corresponding nudges employed. Most of the case studies and examples are derived from Ries (2011), Holiday (2014), Peters (2014) and growthhackers.com, a site co-founded by Sean Ellis who, as noted earlier, coined the *term* "growth hacking".

6.2. An Anthology of Contemporary Growth-Hacking Examples

Table 3: List of Growth hacking Examples in the Digital Context With Corresponding Identifiable Cognitive Biases/Heuristics and Nudges

Company /Project	**Case Study Summary and Description**	**Identified Cognitive Biases, Heuristics/Nudges**
Hotmail	Perhaps one of the earliest examples of a growth hack, Holiday (2014) described famed venture capitalist and Hotmail's former board member Tim Draper's recommendation of "core product-modification" to the nascent email service provider, adding the line "PS: I love you. Get your <u>free</u> e-mail at Hotmail" at the end of all emails sent out by the existing user base instead of spending precious marketing dollars on billboards, or spamming everyone. Hotmail achieved one million new users in six months between mid-1996 and early 1997. This example has often been juxtaposed against the US$1.2m spent by Pets.com on a Super Bowl commercial to emphasize the effectiveness of this early form of growth hacking. It is apparent that the free offering was one of the crucial factors that facilitated Hotmail's rapid early user base growth. While free pricing to achieve user base traction may seem like a given today, back in the 1990s, following the	Zero-price effect, FOMO effect, underpinned by loss aversion bias, and social proof effect via a default nudge tool.

	introduction of the World Wide Web in 1991 by Tim Berners-Lee, many telecommunications companies were still toying with different revenue models for the revolutionary communication system of email, sometimes referred to as the killer application of the internet era. It was Hotmail's strategic imperative to achieve rapid user growth that prompted the use of free/zero-pricing, laying the foundation for utilizing humans' inherent bias towards free pricing as a primary growth hacking tool in the online world. In this particular example, Hotmail also deployed the social proof effect in their *default* nudge tool with the additional line suggested by Draper, subtly hinting to new recipients of such mail who might be using other email platforms that the sender was endorsing Hotmail by being an existing user.	
Hamilton - The Musical	Lin-Manuel Miranda, an American composer, producer and playwright, first conceptualized this popular Broadway musical as a concept album called "The Hamilton Mixtape", which was essentially his minimum viable product (MVP), in May 2009. Using the hit song album, he tested the concept out with a political history-savvy audience at the United States White House under President Obama's administration in November 2009, an event which was widely acclaimed and	Zero-price effect, authority bias, FOMO and social proof effect.

	was captured on YouTube.[13] The performance was released by the official White House channel for free, and the popular ratings and positive reviews online supported him to further develop the concept into a full-blown musical, which won seven Olivier Awards in 2018, including Best New Musical (Brown, 2018). Lin-Manuel also experimented with pre-opening shows to test reactions, and inaugurated the first official #Ham4Ham movement to get fans to record their own videos, shareable on various social media platforms, essentially creating free peripheral digital products through fans, and thus achieving a tremendous viral diffusion and awareness effect. In essence, Lin-Manuel Miranda was also riding on the free/zero-priced offering of the YouTube video sharing platform in its early days, enabling Miranda to reach out to many viewers in exchange for their validation and feedback. (Please note that this was even prior to YouTube, or it parent company Alphabet, introducing its in-video advertisement strategy.) That traction, registered in the forms of	

[13] https://www.youtube.com/watch?v=WNFf7nMIGnE.

	the "thumbs-up" button and valuable comments and feedback, gave him confidence and allowed him to secure further funding for development of the concept. Hamilton is widely used as a great example of the lean startup framework as well as an iterative design-thinking strategy, which limits overspending for early-stage entrepreneurs before they get appropriate feedback for further product development and market scaling.	
Evernote	Another great example is Evernote, a mobile application platform designed for note-taking, organizing, task management and archiving. It is delivered as a software-as-a-service or "SAAS" with a freemium strategy. According to Brown (n.d.), it took Evernote around 446 days to gain it first million users in 2008–09, but only 222 days to get the next million, almost halving the number of days to achieve each of the next few million. According to Shah (2018), Evernote has achieved 225 million users worldwide. It mainly focuses on offering its basic features for free, and has achieved great word-of-mouth campaigns through the "shareability" features on its app, integrating with all major social media platforms. It also employs a referral program, where a referring member earns points to redeem as gift cards or through more storage capacity. However,	Zero-price effect, affect (positive) and availability heuristic, instant gratification effect underpinned by present bias.

	despite the positive affect observed among its large group of early adopters, the company also recognized that it had to earn revenue from upselling some other features. Initially, it did not pay attention to its users, and rolled out peripheral services, such as offering free users the paid choice of leather-bound notebooks and offline printing services by partnering with Moleskine, a strategy which flopped. The company eventually focused carefully on studying its existing free user base's usage patterns, such as team-sharing features and integration with Google Drive and similar apps, for upselling purposes, focusing predominantly on ensuring convenience and being available and readily accessible. Evernote evolved as a positive example of the freemium strategy only in recent years, after its realigned focus on finetuning product offerings after studying users' usage patterns, typifying growth hacking instead of the more traditional marketing approach of pushing out an already-made product. Evernote is one of those early examples that indicates how a freemium strategy can truly help to achieve rapid user base traction riding on the zero-price effect (ZPE). However, without a clear plan to convert these users, such a strategy often spells trouble for a startup enterprise. In this example,	

	the peripheral upselling of a physical notebook did not work, and, as my research results have shown, given that Evernote is considered a productivity tool, a free-trial strategy at the beginning might have potentially curbed the escalating expenses from a large user base who were not converted into paying customers. While it should be noted that there is still a free version of Evernote today, the revenue generated by the premium-paying customers has more than covered the expenses incurred from the entire user base.	
LinkedIn	LinkedIn is a social networking site mainly for recruiters and business professionals. According to Lin (2020), it boasts a total of 660 million users across more than 200 countries. In 2008, LinkedIn only had 13 million users, but the company hired Elliot Shmukler, who made product enhancements that caused its user base to explode to more than 250 million users in five years (Peters, 2014). Besides providing a free online platform on which a user could organize their curriculum vitae, Elliot introduced plugins to the email clients of LinkedIn's existing user base, which automatically sent out invitation requests *by default* to the users' contacts and promoted the "discovery" of other users whom the new user would know, based on the address book of the said user. This worked	Zero-price effect, default nudge tool underpinned by status quo bias. Endowment effect, FOMO, social proof effect, reciprocity bias.

	tremendously well, although the campaign was brought to a halt when customers filed a lawsuit against LinkedIn in September 2013 for compromising their personal contact lists, but this was eventually resolved after a US$13m settlement in 2015 (Roberts, 2015). Elliot also created features that allow for mutual endorsements of each user's skills and contributions especially between colleagues and former colleagues, and with every endorsement and efforts to update users' personal particulars, the endowment effect kicks in and increases any potential switching costs to other competing platforms. The company's early start in growth hacking had enabled it to achieve critical mass even before the lawsuit of 2013 was filed. Today, it still sends out invitation requests, but this has evolved to require the user to execute a simple one-click process, thus ensuring LinkedIn adheres to the Personal Data Protection Act (PDPA) or local legislation, still allowing it to achieve the stellar user base growth that is now well known, and which has led to it becoming an indispensable tool for recruiters and job-hunters everywhere.	
Airbnb	Founded in August 2008, Airbnb's early days provide an excellent case study for learning the intricacies of growth hacking. Given that its birth was just prior to the great financial crisis of 2008,	Zero-price effect, availability, salient

	the founders, Brian Chesky and Joe Gebbia, who are designers by training, hustled their way forward by selling special-edition election-themed cereal boxes, known as Obama O's and Cap'n McCain's, to raise funds. They were initially rejected by several top-tier venture capitalists but graduating from Y-Combinator[14] enabled them to scale up rapidly. While many investors dismissed them as mere designers making listing pages pretty, their early growth hack was their creation of a bot that automatically posted their user's listings to Craigslist with one simple click on an email notification, despite the fact that a public application programming interface (API) from Craigslist was not available at that time. Naturally, as they were operating outside of the terms of service, this reverse-engineering of stealth integration was eventually discovered and Airbnb was removed from Craigslist, but not before they already achieved critical mass and awareness. Besides this ingenious move, Garcia (2017) also highlighted that Paul Graham, co-founder of Y-Combinator and	heuristics, priming (images) nudge tool, social proof effect.

[14] Y Combinator is an American technology startup accelerator which started since 2005 and has since launched many successful companies including Stripe and Airbnb.

	mentor to the founders, devised a plan to ensure that Airbnb's representatives traveled to the listings in New York City with professional photography equipment to take better pictures of the properties for free. This was scaled up further via an "Airbnb Photography Program" in 2010 for other cities' listings, with pictures taken and labelled as "Airbnb Verified Images". Eventually, the Airbnb's salient, simple, picture-oriented, attractive and free listings, relative to the mostly text-based, web 1.0 forum design of Craigslist, won most users over, and the company expanded globally to become one of the tech titans of today, worth approximately US$26bn (Sonnemaker, 2020).	
Spotify	Spotify, a music streaming platform company, that is worth more than US$20bn of market capitalization is another tech titan of today which has redefined the music industry. Brown (n.d.) quoted then LinkedIn's public relations director Mario Sundar as saying: "Spotify is to Apple iTunes as Google is to newspapers". It is a truly disruptive product; its focus on returning "control" to the users shows Spotify's special focus on user experience, given that its initial competitors, like Pandora or Last.fm, did not allow users to select specific songs or create own playlists. Spotify	Positive affect, FOMO, zero-price effect, availability heuristics, priming (select audio, and artists' branding), instant gratification effect

	became the first streaming platform that allowed users to have better selection and control over legal streaming of its entire portfolio of music. Furthermore, its recommendation engine, which underpins its "Discover" feature, made use of state-of-the-art machine learning algorithms at that time to understand the user's preferences and recommend music or tunes. This has reinforced the platform's sustainable stickiness, i.e. the tendency for users to continue using the platform. Netflix, another popular movie-streaming platform also used similar machine learning algorithms to recommend suitable movies and shows to its users. Spotify's freemium strategy was also beautifully executed, with ad-supported, skip-restricted shuffling and ready-made playlists available on mobile devices and the ability to select any song anytime on personal or tablet computers. This freemium strategy also reinforces Spotify's growth momentum, given that it acts as a bridge for the prevalently pirated music industry's addressable market to transit to the legally paid streaming population at a bargain subscription price, with correspondingly deep perceived value gap. The inconvenience and security risk associated with the BitTorrent P2P sharing platforms	underpinned by present bias and temporal discounting bias,

	associated with music piracy also constitute various forms of attentional and opportunity costs for the users.	
Eventbrite	Eventbrite was founded in 2006 as an online ticketing service. It has evolved to be a platform of choice for organizing events (Peters, 2014). It offers a free service for free tickets for all events organized, but charges a range of 1–2.5% plus a nominal fee of up to US$0.99 per ticket for each paid event. One of its earliest growth hacks involved standing on the shoulder of giants, which in this case was the popular social networking site, Facebook. Peters (2014) highlighted that the management of Eventbrite was laser focused on integrating with networking sites, including LinkedIn and Twitter, to facilitate "social commerce" that requires face-to-face meetups, where their platform comes in handy. It was also opportune that Facebook Connect – a novel service introduced by Facebook for unique digital identity login – came along in the late 2000s, and made the integration seamless. Eventbrite was determined to make its event registration process seamless, and to make event awareness blurbs or digital posters as "shareable" as possible on various social networking platforms, because of the company's firm belief in the social norm bias,	Zero-price effect, social norm bias, social proof, reciprocity, availability heuristics,

	and the principle that "people act in relation to what their friends are doing" (Peters, 2014, p. 95). Event-sharing and registration became a "one-click" process, which has propelled Eventbrite to its global presence today, handling up to 265 million tickets, corresponding to nearly US$292m revenue in 2018 (Smith, 2020).	
Uber	Any list of mobile age tech titans would not be complete without mentioning Uber, a company which has revolutionized urban transportation. Despite its controversial and flamboyant founder and ex-CEO, this dissertation seeks to explore how the company achieved such a stellar user base growth during its early stages by employing ingenious growth hacks. Garcia (2017) described Uber's key challenge of creating awareness for its novel product in its early days. The company leveraged off the South by Southwest (SXSW) media festival by providing free rides for festival goers and facilitating food delivery services during the event. This solicited great feedback from this core group of users and built traction for the app. Given that many attendees of the SXSW festival are social influencers, their early adoption also helped generate much buzz around the Uber brand and mobile application. The company pays particular attention to addressing the impatience and need	Zero-price effect, authority bias (social influencers), social proof, salience bias, instant gratification and availability bias.

	for instant gratification for both drivers and the riders, as Brown (n.d.) has described. Peters (2014) also highlighted that the fanatical focus on ensuring ease of use and high satisfaction among early adopters contributed much to the company's success. In addition, each new user was given a referral code, through which both the new user and referred contact received a $10 discount towards their next ride, effectively transforming Uber's early base of adopters into a potent force of ground marketers, further increasing its fast adoption. With subsequent substantial venture capital funding, Uber has aggressively rolled out sponsorship of tech events, even providing free rides to deliberately juxtapose Uber's quality of cars and drivers against prevailing standards of taxi companies in various cities. Uber eventually achieved a market value of more than US$70 billion during its initial public offering in mid-2019.	
GitHub	Warren (2018) reported that Microsoft completed a major acquisition of GitHub in 2018 for a huge US$7.5 billion. For a company founded only 10 years before, this was a stellar accomplishment. GitHub is a platform that facilitates collaborative coding and software development. It improved upon Linus Torvalds' 2005 innovation that facilitated open-source collaboration for Linux Kernel	Zero-price effect, social proof, reciprocity bias, status quo bias, default nudge tool.

	development. GitHub allows for “forking” or copying of any code repository which has been made public, for modification within the user’s own account. Again, as with many of the prior examples, GitHub provides *free* access for all customers, although users can pay to subscribe to a private account. Brown (n.d.) explains that the company’s business model is highly scalable, given that it is driven substantially by network effects, as code-repository forking facilitates more collaboration, which inherently attracts more developers to come on board to use the platform. This enhances the “stickiness” and user loyalty even further. Almost all computer science students recommend the freemium service of GitHub’s platform to each other for their school projects. When they graduate, they are so used to the development environment that they seldom change platforms. GitHub championed a new concept of social coding which became a powerful growth engine, and defined several de-facto standards for software developers and processes all over the world. In fact, hiring decisions for software developers are sometimes contingent on the respective contributions and accolades shown on the candidates’ user profiles on GitHub. Employers also prefer this platform, as the code repositories of new hires can easily be “forked” and utilized for	

	their own purposes. Peters (2014) also highlighted that the company's development environment has been made so user-friendly and efficient that file sharing, co-authoring of projects and even the design of circuit-board schematics by electrical and electronics engineers are also done on such a platform.	
Candy Crush Saga	I have reserved the final example for a unique social mobile app game developed and published by King Digital Entertainment, a cross-platform video game developer based in Malta. It is a game that deploys many of the digital nudges and concepts expounded by Eyal (2014), pertaining to the variable psychological reward cycle of the "hooked" model. This variable psychological reward cycle is also known as the compulsion loop or core loop, as Kim (2014, March 2014) explained, which refers to a "habitual, designed chain of activities that will be repeated to gain a neurochemical reward: a feeling of pleasure and/or a relief from pain". This neurochemical reward is commonly known as dopamine, which induces further reinforcement the more one engages in the activity. Eyal (2014) explained that the more users have invested their time, money or effort into the product, the more likely the habit will entrench. Candy Crush Saga's users certainly manifest that	Zero-price effect, social proof, reciprocity bias, IKEA effect, loss aversion, FOMO effect, instant gratification effect underpinned by present bias.

	tendency, as they build up their level progress, akin to the “IKEA effect” which Norton, Mochon and Ariely (2012) described as a behavioral bias in which people tend to value an object more if they are the ones developing, making or assembling them. Sineni (2014) also underscored the app’s special feature of utilizing Facebook’s open graph (OG) features to allow its users to view their friends’ progress and provide “reinforcement” or “assistive” remedies, such as sending “extra lives or tickets”. King Digital Entertainment developers’ special focus on optimization and best user experience, which epitomizes the essence of growth hacking including the key steps of rapid testing and iteration, has been noticeable since its early days of 2012–13. According to Sineni (2014), the constant upgrades to the app stores’ versions reflect consistent modification after tracking demographics and usage patterns of gamers. The game’s freemium version encourages rapid growth in the user base, and encourages microtransactions within the game, riding a lot on the impatience factor and instant gratification of the gamers.	

6.3. A Purpose-Driven Framework to Growth Hack

A digital startup is, at the end of the day, a business. And in the Chinese language, business is normally translated as “生意”, but the two characters “生” and “意” literally translate to “deriving meaning or purpose”. There is profound wisdom in this term, as it indicates that the raison d’être of a business needs to be first established before the company can focus the energies of its employees and stakeholders accordingly towards achieving their collective goals. This is especially crucial in the digital context, with the prevalence of accelerators and startup incubators globally that are promoting the lean startup methodology championed by Ries (2011) and Blank (2013). This hypothesis-driven and problem-solving approach towards entrepreneurship has been greatly welcomed, especially in emerging Asia where a substantial part of the “old-world” wealth of the past century has been amassed largely via a trading mindset, as detailed by Haynes (2018), through profiteering by arbitraging between the exploitation of low-cost labor or natural resources in the region and the customers’ access to pricing information or the lack thereof. Notwithstanding this, the digital context brought about by the internet and smartphone revolutions over the last three decades has laid a fertile foundation for a return to the purpose-driven approach towards entrepreneurship, which focuses on problem-solving and delivering genuine value creation for the specific target market audience through an iterative process expounded in Section 6.1.

In the same spirit, I propose a purpose-driven framework for growth hacking for early-stage digital entrepreneurs, eliding insights and useful frameworks from the large body of marketing literature with behavioral economics literature, focusing primarily on the early stages of a digital startup, where the target is to build traction and establish a community of loyal users and customers. The next subsections involve a descriptive review of the word-of-mouth literature. I have adopted two popular frameworks developed by Professor Jonah Berger from the Wharton Business School – summarized by the acronyms STEPPS and REDUCE – and tied them in with my dissertation's two-stage conceptual framework illustrated in Figure 5 in Section 2.6 ("Framing the Research Objectives and Questions") to form a more holistic framework suitable for the digital context.

6.3.1. A Brief Descriptive Review of Word-of-Mouth Literature

As proposed in Section 2.6, the decision-making process for a customer in the digital context is split into two stages: the awareness stage and the conversion stage. While it is not the focus of this dissertation to review all of the marketing literature, I have paid particular attention to identifying relevant research that may play a crucial role in this awareness stage because, as Dawkins (1989) underscored, even ideas, like genes, struggle to survive. Dawkins (1976) coined the term "memes", from the Greek word "mimeisthai", which translates to "imitate", and suggested that memes should be regarded as living structures that can literally be "planted" in the minds of individuals and spread from one person to another. His seminal work also set the stage for a large body of literature around the word-of-mouth (WOM) effect. Notable examples include the research by Berger and Schwartz (2011), which showed that even mundane products can generate substantial WOM by ensuring they are publicly visible and cued frequently by the environmental context. Berger and Milkman (2012) also studied what makes some online content more viral than others. They concluded that positive content, as opposed to negative content, is more viral, and they empirically demonstrated that this virality is driven by physiological arousal from content that evokes high-arousal emotions, whether positive (awe) or negative (anger or anxiety), reinforcing Berger's (2011) findings about arousal's efficacy for the social transmission of information. Professor Jonah Berger and his collaborators' research laid the foundation for the STEPPS framework introduced in Berger's (2013) book *Contagious: Why things catch on*, and which has been instructive for many digital entrepreneurs in the past decade.

Indicating that the WOM effect explains 20 to 50 percent of all consumer purchasing decisions, Berger (2013) proclaimed that it is critical for all business managers to understand the main reasons why WOM drives effective marketing campaigns. I would also argue that this is more relevant than ever, given that 70% of value in the technology sector in the public markets is driven by network effects, as highlighted by Currier (2018, 2021), and we simply cannot have network effects if there is no community of customers or users in the first place. Beller (n.d.) also accentuated the importance of communities for businesses in the digital context, and how the size and talent of core contributors will prove invaluable for community-building efforts to achieve "escape-velocity". It is thus worthwhile to explore more deeply the STEPPS framework proposed by Berger (2013).

The STEPPS framework is designed to help managers get their ideas, products and service offerings to spread, and involves six main principles: (1) social currency, (2) triggers, (3) emotion, (4) public, (5) practical value and (6) stories. Managers are encouraged to consider all these principles when crafting content to generate virality, critical for building awareness. Table 4 provides a brief summary of the six principles.

Table 4: A Brief Summary of the Six Principles Underpinning the STEPP Framework

	STEPPS – The Principles and Their Description
S	**Social currency** In essence, social currency is all about making the users, customers or other relevant stakeholders look good and feel better about themselves. There are multiple approaches, and Berger (2013) essentially suggested three key areas to focus on to achieve this objective. Firstly, managers should generate content that is simply remarkable. He proceeded to define remarkability as unusual, extraordinary or worthy of notice or attention, but most importantly, worthy of "remark". Within the digital context which is the focus of this dissertation, identifying what is remarkable about the digital product offering would be paramount. Berger (2013) also stated that if the product can help the target audience locate their own inner remarkability, this will accentuate the WOM effect and the virality of the digital offerings. Facebook, YouTube, Snapchat and Instagram are well-known platforms that assist their users to identify and propagate their inner remarkability. Secondly, game mechanics, or what many people refer to as gamification, should be embedded in the product design. This suggestion is also substantiated by Hofacker et al.'s (2016) research, which indicated that gamification was not a fad but a useful way to propagate diffusion and virality. Both Eyal (2014) and Berger (2013) suggested that good game mechanics, such as a score chart, will keep users engaged and motivated.

	Once such habits are formed, the digital product can even be addictive, likely to leave users wanting for more. Thirdly, Berger (2013) talked about making people feel like exclusive insiders. This has a lot to do with the community building that Beller (n.d.) highlighted. He suggested that managers should consider scarcity and exclusivity to help products catch on. This is also evident in the rapid user adoption of Clubhouse, an audio-based social media network, as described by Hutchinson (2021), with users increasing from 2 million in January 2021 to more than 10 million by May 2021. The company focuses greatly on exclusivity and scarcity, giving only two invites to every new person who joins the network. This strategy makes people feel special and unique, because it suddenly makes those who managed to join the network earlier particularly desirable, as their respective friends and contacts might court them to get that precious invitation.
T	**Triggers** This principle is based primarily on the findings of Berger and Schwartz (2011), and indicates that if the product or content is often triggered by the context or environment, there will be a higher probability of faster and more effective propagation. In essence, as Berger (2013) summarized, content that is "top of mind leads to tip of tongue" (p. 4). It is noteworthy that he also underscored the difference between *immediate* and *ongoing* WOM, and that ongoing WOM is the preferred approach to generate effective virality for managers. This is also supported by Currier (2018), who indicated that memes or movements with immediate WOM tend to be just fads, whereas a sustainable viral effect requires special attention towards

	generating content that is worth discussing over time. As Eyal (2014) described, habits that are formed and entrenched can be powerfully addictive, and Berger (2013) saliently described the strong product trigger between peanut butter and jelly, and how Kit-Kat proactively engineered the strong trigger between its products and a coffee break. This principle is instructive for entrepreneurs, who should consider what kind of triggers in the digital context they should associate their digital offerings with. As more and more digital consumers frequent standard platforms such as YouTube, Facebook or TikTok, in this winner-take-most digital context it is potentially useful for digital startups to consider what kind of triggers or digital nudges they can engineer with known online behaviors.
E	**Emotion** As Harari (2014), as well as Whyte and Marshall (1970), stated, humans are social animals, powered by a myriad of emotions studied extensively by researchers as “affect”. As social animals, people like to share all sorts of information, and this can even be considered as gossip, either good or bad. Berger (2013) suggested that the internet and, arguably, the smartphone revolution have accentuated these proclivities. The quantification of views and “likes” in apps and websites invokes various behavioral biases that seek to reinforce such emotions in human beings and which perpetuate the virality of such digital content or products.

	This principle stems mostly from Berger and Milkman's (2012) work, which identified that high-arousal emotions, whether positive ones like "awe" or negative ones like "anger" or "anxiety", tend to propagate sharing, whereas low arousal emotions, whether positive ones like "contentment" or negative ones like "sadness", will decrease sharing. It is therefore not unfair to suggest that the object of generating great virality is to nudge people towards "emotional extremes", although I would caution managers against fabricating untruths to achieve that objective, as that would breach both ethical boundaries as well as potential legal responsibilities.
P	**Public** The essence of this principle is about making the product more observable and, for lack of a better word, "public". Berger (2013) identified several examples, including the large logos on the physical products of Ralph Lauren and Lacoste as well as the uniquely simple and blatantly white design of Apple's headphones and AirPods to clearly display these companies' tangible physical products. Berger (2013) also highlighted the concept of "behavioral residue", which generates social proof that lingers around even after a particular touchpoint with a customer has been completed. An example would be a call to action such as the "PS: I love you. Get your free e-mail at Hotmail" line, also described in Section 6.2 as one of the original growth hacking strategies adopted by early internet-era entrepreneurs; another example is certain information in digital receipts or invoices generated by digital entrepreneurs.

	While arguably, Berger's (2013) examples are predominantly focused on tangible physical products, there are also other good examples in the digital context. Paavilainen et al. (2017) and Henthorn et al. (2019) have researched the Pokémon GO phenomenon extensively, showing that game designers have deployed augmented reality technologies effectively to saliently showcase the game and to promote substantial virality in the early stages of its adoption.
P	**Practical Value** Practical value as a principle refers to the need to trumpet the "value" the company/brand is offering to its users or customers. This relates closely to the framing effect elucidated in Section 2.3.1. In fact, Berger (2013) also paid tribute to Tversky and Kahneman for their pioneering research in prospect theory. He also introduced the "Rule of 100", suggesting that percentage discounts will seem larger if a product or service offering is priced at less than \$100, but for prices above the \$100 mark, an absolute numerical discount strategy may be more viable. This is a nod to the diminishing sensitivity effect also expounded by Tversky and Kahneman (1981). Berger (2013) also noted that useful information, pertinent to the product/brand's core offering, is also particularly useful. He used examples like Michelin Tire co-founders Andre and Edouard Michelin initiation of the Michelin Star Restaurant and Food Guide as valuable practical information to share. Even though restaurants are not what the tire company sells, in the historical context, where there were only 350 cars on the road in France in the late 19th century, such a guide promoted greater automobile traveling and thus the need for more tires. This is particularly instructive

	for digital age entrepreneurs as well. For example, an electric vehicle (EV) company like Tesla may provide practical valuable information, such as updated maps of EV charging stations in a city, state or country, in order to promote virality of relevant content and generate positive brand awareness. Another contemporary example in the digital context shared by Berger (2021a) is CBInsights, a data-driven B2B business insights platform. CBInsights shared a free newsletter to information workers globally, growing from only about 14,000 subscribers in 2013 to around one million in 2021. Adopting brevity, humor and arousal effectively in their email campaigns, the company has been able to successfully create top-of-mind brand positioning for thought leadership in the digital context.
S	**Stories** As Loewenstein (1994) highlighted, curiosity acts as a form of cognitively induced deprivation that arises from a perceived gap in understanding or knowledge, and subsequently drives us to close the gap. This human tendency is primal, just as when Bodhi (2005) quoted the Buddha likening the mind to a monkey, constantly seeking for a new branch to grasp. Harari (2014) also suggested that humanity's desire for a logical and believable narrative is so entrenched and its effects so nuanced that we need to pay special attention to recognize them. Berger (2013) underscored that stories are the easiest way to talk about products and ideas, and which can subsequently promote their virality. Instead of focusing on the features of a product, companies should focus on the stories and the why. This echoes

	the central thesis of Sinek's (2009) masterpiece, highlighting that the "why" is what galvanize the energies of the stakeholders towards a particular goal or objective, and this includes getting the customer to take a particular course of action. Berger (2013) thus suggested that managers should develop "Trojan horses" – stories that get other people to start sharing and talking. An example Berger (2021b) used for such a Trojan horse strategy was that of Caterpillar, an American Fortune 100 manufacturer of construction equipment. Instead of trumpeting the "features" of its products vis-à-vis its competitors, it showcased in an advertisement its dogmatic focus on precision by featuring a Caterpillar mini-excavator in a china shop[15] completing a wineglass tower maneuver. This embedded high-emotion cues like anxiety into this Trojan horse, which achieved tremendous virality and engagement effects after the advertising campaign. Notwithstanding these insights, recognizing that early-stage digital entrepreneurs will often face resource constraints in budgeting for such advertisements, Berger (2013) suggested that entrepreneurs should try to crowdsource such stories from early adopters or community users. Berger (2021b) also shared an example where Subaru used the myriad of video stories posted by its community of users that successfully showcased its dogmatic commitment to safety without needing to trumpet this from its own marketing or public relations department. Collins (2021) also used the movie *Straight Outta Compton*, produced by Ice Cube and Dr Dre, two famous American

[15] Original YouTube URL of the Caterpillar "China-shop" advertisement: https://youtu.be/K3sdMEgor7E.

	rappers, as an example for how virality can be achieved by engaging the community of global fans to create their own memes (in this case, with "Straight Outta 'your city'"), to generate effective buzz and achieve the virality effects. The campaign turned out to be a phenomenal success, with fans globally building their own memes such as "Straight Outta London" or "Straight Outta Tokyo" and spreading these via social media. Even celebrities like Sir Richard Starkey, otherwise known as Ringo Starr of The Beatles fame, created the meme of "Straight Outta Liverpool". Within 24 hours, it became the top-trending meme in different social media platforms such as Twitter, Instagram and Facebook.

Berger (2014) also argued that WOM through interpersonal communications is goal-driven and serves five main functions, namely:

- impression management
- emotion regulation
- information acquisition
- social bonding
- persuasion.

The main effects of Berger's (2014) research, stemming from the respective components of the five abovementioned functions of WOM, are summarized in Figure 15.

Function	Components	Effects On Sharing
Impression-Management	Self-Enhancement Identity-Signaling Filling Conversational Space	+ Entertaining content + Useful information + Self-Concept relevant things + High status things + Unique and special things + Common ground + Accessible things + When aroused Shapes content valence
Emotion Regulation	Generating Social Support Venting Facilitating Sense Making Reducing Dissonance Taking Vengeance Encouraging Rehearsal	+ Emotional Content + Arousing Content Shapes content valence
Information Acquisition	Seeking Advice Resolving Problems	+ Sharing when decisions are important or uncertain +Sharing when alternative info is unavailable or untrustworthy
Social Bonding	Reinforcing Shared Views Reducing Loneliness and Social Exclusion	+ Common Ground Content + Emotional Content
Persuasion	Persuading Others	+ Polarized Content + Arousing Content

Figure 15: Five Functions of Word of Mouth and Their Effects as Described by Berger (2014)

6.3.2. Awareness Stage 1 – Linking Cognitive Biases to the STEPPS Principles

Using my dissertation's conceptual framework, shown in Figure 5 in Section 2.6 ("Framing the Research Objectives and Questions"), the awareness Stage 1 of the digital consumer's decision-making process is where digital practitioners (entrepreneurs or markets) need to consider how to make their product or services known to users and preferably viral. As an example, my research findings, showing that the ZPE extends to the digital context and how categories of software applications (games, media or productivity) affect the choice of the consumers to download, will be instructive for digital practitioners, helping them to achieve more effective user traction and assisting in overcoming the awareness hurdle commonly faced by early-stage digital startups.

Furthermore, and as is evident from the descriptive review in Section 6.3.1, Berger's (2013) STEPPS principles also include many behavioral elements and I will attempt to relate these principles to the key relevant behavioral biases/heuristics from the cognitive bias codex shown in Figure 13. Referencing Table 1, the literature review of various major heuristics and cognitive biases observed in the digital context from Section 2.3.1, and Table 2, the 20 key categories of how humans cope with the four key "whys" are reproduced again in this subsection as follows:

Table 2: Twenty Key Categories of "How" Humans Cope with the Four Key "Whys" of Biases

A. Too Much Information	**B. Not Enough Meaning**
1. We notice things already primed in memory or repeated often	**1.** We find stories and patterns even in sparse data

2. Bizarre/funny/visually-striking/ anthropomorphic things that stick out more than mediocre stuff **3.** We notice when something has changed **4.** We are drawn to details that confirm our own existing beliefs **5.** We notice flaws in others more easily than flaws in ourselves	**2.** We fill in characteristics from stereotypes, generalities and prior histories **3.** We imagine things and people we're familiar with or fond of as "better" **4.** We simplify probabilities and numbers make them easier to think about **5.** We think we know what other people are thinking **6.** We project our current mindset and assumptions onto the past and future
C. Need to Act Fast **1.** To act, we must be confident we can make an impact and feel what we do is important **2.** To stay focused, we favor the immediate, relatable thing in front of us **3.** To get things done, we tend to complete things we've invested time and energy in **4.** To avoid mistakes, we're motivated to preserve our autonomy and status in a group and to avoid irreversible decisions **5.** We favor simple-looking options and complete information over complex, ambiguous options	**D. What Should We Remember?** **1.** We edit and reinforce some memories after the fact **2.** We discard specifics to form generalities **3.** We reduce events and lists to their key elements **4.** We store memories differently based on how they were experienced

Practitioners in the digital context can then refer with ease on how to systematically apply insights from the research in various behavioral economics research to the STEPPS framework in the following Table 5 for purpose of designing more effective digital nudges and marketing WOM campaigns. This table will also be instructive for future researchers in applied behavioral economics to identify.

Table 5: Berger's (2013) STEPPS Principles and Relevant Cognitive Biases

	STEPPS Principle	**Relevant and Identifiable Cognitive Biases/Heuristics**
S	Social Currency	This principle could potentially employ several biases and heuristics from the cognitive bias codex shown in Figure 13. However, the key ones can be found in quadrants B and C. This is because, the social currency principle is primarily about making relevant stakeholders look good. The gap in "meaning" within the digital context constitutes opportunities for digital entrepreneurs and managers to exploit. Furthermore, as the digital context also accentuates the need to act fast, corresponding effects can be examined further to derive effective strategies and potentially guide digital nudges in the product design. The social proof effect and the reciprocity biases stem mostly from item B3 in Table 2 (i.e. "We imagine things and people we're familiar with or fond of as 'better'"). As such, biases such as the in-group effect, halo effect, positivity effect and cheerleader effect are also potentially relevant. Digital

		entrepreneurs and managers can design digital nudges based on insights from research into these effects. Furthermore, B2 (i.e. "We fill in characteristics from stereotypes, generalities and prior histories") can be instructive as well for this principle. Bandwagon effects and authority bias could be useful for digital entrepreneurs and managers to incorporate into the gamification of digital offerings, such as score chart, to facilitate deeper engagement with the community. The self-serving bias, egocentric bias and overconfidence effect categorized under C1 (i.e. "To act, we must be confident we can make an impact and feel what we do is important") is also useful for managers to develop strategies around this principle. The various biases, such as loss aversion effect, endowment effect and sunk cost fallacy, which fall under C3 of Table 2 are also useful in understanding this principle (i.e. "To get things done, we tend to complete things we've invested time and energy in"). As the user contributes more to develop his or her social currency, the IKEA effect may set in and, complemented by the corresponding loss aversion biases, could enhance the stickiness and engagement metrics of the digital product offerings. One example of such a tactical operationalization is to introduce avatars or specific profiles to facilitate the investment of time and effort where such social currency can be quantified and compared.

T	Triggers	The triggers principle can draw useful insights from research in biases or heuristics found in quadrants A (Too Much Information) and D (What Should be Remembered?) of Figure 13 and Table 2. To address A1 (i.e. “We notice things already primed in memory or repeated often”), digital entrepreneurs and managers will do well to design nudges that tap into the availability heuristic and the attentional bias. This is particularly instructive for a localization campaign or a design that fits the geographical context, where local preferences for color, layout or designs can be incorporated within the digital product offerings’ user interface. Even the mood-congruent memory bias can provide useful insights for guiding the design of suitable digital nudges. For example, if the mobile application shows content or features that will evoke an anticipated mood or experience, such a bias will reinforce memory recall, which could perhaps strengthen the brand positioning efforts for the digital startup. Also, addressing D3 (i.e. “We reduce events and lists to their key elements”), the recency effect and primacy effect can also be quite instructive for digital practitioners in helping them to create digital nudges that are highly contemporary. Adopting the latest designs or “skins” for game characters that coincide with recent popular phenomena, potentially from current affairs or pop culture, can constitute effective digital nudges for optimal virality, especially in the early stages. For example, digital

		practitioners could incorporate the pinkish color and mix of shapes shown in the recent 2021 Netflix series *Squid Game* – which became a global phenomenon – in the user interface designs of digital products.
E	Emotions	This principle is mostly about the affect heuristic, which I have described at length in Section 6.3.1. Berger (2013) shared that content that evokes strong emotions is particularly effective in promoting virality. Referencing Table 2 once more, it is quite apparent that practitioners can identify effects such as a bizarreness effect or the humor effect, categorized under A2 in Table 2, to potentially derive insights for designing their digital nudges. Loewenstein's (2005) empathy gap, as illustrated in the Section 6.3.1's literature review Table 1, indicating that people's decision-making is "state-dependent" also serves this principle well. A salient example is in the realm of sexual desire, partly explaining why many mobile game developers often adopt highly sexual and suggestive themes in their digital product offerings, with accentuated body curves for their characters, and particularly use specific scenes of voluptuous female models and handsome hunks in digital promotional collaterals, as such high arousal provides a better "triggering" outcome and gives the developers a much higher probability of overcoming the awareness hurdle in the early stages of adoption.

		Furthermore, addressing the tendencies of B6 (i.e. "We project our current mindset and assumptions onto the past and future"), digital practitioners can draw insights from research into self-consistency bias and projection bias, generating content which allows people to experience strong emotions like awe, anger and anxiety; if the target audience situates themselves in similar context, digital practitioners will have a higher chance of overcoming the awareness hurdle and having their produce become viral, especially at the early stage.
P	Public	In addressing this public principle, digital practitioners can seek to reference insights from research in both quadrant A (Too Much Information) and quadrant D (What Should We Remember?) in Table 2. For example, the availability heuristic categorized under A1 and described at length in Table 1 in the literature review under Section 6.3.1, alongside the representative heuristic and salience bias, can provide several insights for digital practitioners to adopt for their design of digital nudges. Another aspect particularly relevant for digital applications where adoption requires scaling a rather steep learning curve, insights from the spacing effect[16] categorized under D1 (i.e. "We edit and reinforce some memories

[16] The spacing effect as described by Dempster (1988) refers to the phenomenon that learning is more effective when study sessions are spaced out.

		after the fact") may be instructive for designing tutorials or guideposts in the user-interface design or wireframing phase. Also, given that the digital context also promotes digital amnesia, as documented by research into the Google effect described by Sparrow et al. (2011), under D1 practitioners may also do well to identify the kind of content that could be omitted or should be included in the design of the user interface, particularly when the "digital real estate" of the mobile screen is so precious, and thus the interface should not be cluttered with superfluous content. Finally, other effects such as the recency effect and primacy effect categorized under D3 can also be instructive for digital practitioners in designing digital nudges, including suitable memes to suit this public principle. This should involve designing topical content, shareable on various public social media channels, such as a Telegram or Facebook group, to achieve maximum virality and optimal top-of-mind brand positioning.
P	Practical Value	The principle of practical value addresses areas of practicality and potentially addresses various biases such as loss or risk aversion described in Table 1 in Section 2.3.1. As the target audience in the digital context is still situated at the awareness Stage 1, the main goal for the digital practitioner is to overcome the awareness hurdle among the cacophony of opinions and potentially fake news that is the internet and social media. As such, the biases and heuristics categorized under A3 (i.e. "We notice when

		something has changed"), such as the distinction bias, contrast effect and framing effect, can serve as excellent guidelines for digital practitioners to design their content or user interface. Lessons from research into the anchoring effect can also be useful at this stage, so that users can be persuaded into conversion at the subsequent purchasing/conversion stage in the digital context. This is also where the framing effect, again sitting under A3, plays a big role in explaining the Rule of 100 previously described by Berger (2013) and explained in Table 4 of Subsection 6.3.1. Also, as described in Subsection 4.5.1, the sharing of useful and relevant content promotes thought leadership, as saliently described in the case study of CBInsights presented by Berger (2021); thus, the authority bias from B2 and the halo effect from B3 can also serve as good signposts for digital practitioners.
S	Stories	As Berger (2013) underscored, stories are particularly important if digital entrepreneurs and managers wish to achieve maximum virality. However, just as lessons or morals are embedded in various fairy tales, fables, urban legends and even gossip, practitioners will do well to identify clearly the key messages they wish to embed within these stories. This principle can draw insights from several quadrants of cognitive biases and heuristics research. Quadrant A of Table 2 highlights the various cognitive biases and heuristics which arise because of "too much information", therefore, the stories that digital practitioners create must be memorable. Insights from

		quadrant D, which groups together the various effects that result from "what should we remember", are also relevant here. Finally, because of humans' deeply entrenched tendency to look for a narrative, as expounded by Harari (2014), quadrant B of Table 2, which details various biases stemming from "not enough meaning" can also be very instructive for digital practitioners in crafting stories that promote the virality of an application or product. Effects such as time-saving bias, categorized under B6 of Table 2, or the FOMO effect described at length in Table 1 of Section 2.3.1, play a critical role in the digital context, and the insights and managerial implications from research in these fields will also be particularly instructive for digital practitioners.

6.3.3. Conversion Stage 2 – Linking Cognitive Biases to the "REDUCE" Principles for Developing Catalysts

If the STEPPS framework described above is used to promote virality, and to help digital entrepreneurs accomplish virality and achieve an optimal WOM effect, especially in the first awareness stage of consumers' decision-making process in the digital context, it is also important to identify ways to *convert* consumers from awareness to the purchasing of digital apps and offerings, especially premium offerings. This ties in closely with the second, conversion stage of my conceptual framework shown in Figure 5 in Section 2.6 of this dissertation. As an example, my research finding that the endowment effect extends to the digital context lends credence to this effect's efficacy, and the necessity for digital practitioners to consider it. Furthermore, my research finding that the type of strategy (i.e. limited-feature freemium or full-feature free-trial) moderates the level of affect experienced by consumers, thereby increasing their propensity to convert into paying customers, is also especially instructive.

In light of this, I will explore how a more systematic approach can be applied to incorporating an understanding of other behavioral biases in relation to digital product/service design or to designing new digital nudges or growth hacking strategies. More recently, Berger (2020) also introduced the acronym "REDUCE" to summarize a set of principles to guide practitioners, incorporating even more insights from the behavioral economics realm. He described how Aristotle used *logos* (the logical appeal)*, pathos* (the emotional appeal) *and ethos* (the ethical appeal) as the three primary means of persuasion, and that these have been used since ancient times. He also highlighted that *mythos* (the narrative appeal) can also be a very powerful part of persuasion, reinforcing once again what Harari (2014) surmised about humanity's entrenched need for narratives. In this popular treatise, Berger related a story of a SWAT team crisis negotiation scenario to illustrate the difficulties and challenges of persuasion in general. Recognizing that all persuasion is essentially self-persuasion, Berger (2020) also highlighted five key principles, aptly described as the "five horsemen of inertia", that act as major roadblocks obstructing change or action towards a desired behavior or outcome from the practitioner's point of view. Berger (2020) also cautioned against “working harder” at the same operating procedures that only seek to reinforce these enemies of persuasion. Instead, he proposed strategies to design nudges, in order to (pun intended) “reduce” these five major obstacles. In the following table (Table 6), I seek to link the five REDUCE principles back to the cognitive bias codex, and to the key “whys” and humans’ coping mechanisms and tendencies shown in Table 2.

Table 6: Berger’s (2020) REDUCE Principles and the Relevant Cognitive Biases

	Principles	**Description and Berger’s (2020) Proposed Strategies**
R	Reactance	Reactance is actually a psychological bias that is categorized in the cognitive bias codex under C4 in Table 2 (i.e. “To avoid mistakes, we’re motivated to preserve our autonomy and status in a group and to avoid irreversible decisions”). It stems from humans’ natural proclivity to resist whenever they feel that their sense of freedom is deprived or threatened. Such an innate anti-persuasion (Berger, 2020, p. 11) almost compels people to do the opposite of what is desired by the practitioner performing the persuasion. This is also what underpins the essence of Thaler and Sunstein’s (2008) nudge theory, which suggests aversion towards “mandates” or forced requirements. Instead, an allowance for agency seeks to ameliorate the psychological phenomenon of reactance. Berger (2020) suggested the following four key strategies to reduce reactance:

		- Provide a menu: Addressing mostly A3 of Table 2 (i.e. "We notice when something has changed") and A4 (i.e. "We are drawn to details that confirm our own existing beliefs"), practitioners would do well to limit the set of bounded options guiding users or a target audience towards a desired outcome. Berger (2020) warned against providing any more options than a handful, given that offering more options may backfire, since the target audience may simply give up the process of self-persuasion. This bias stems from the less-is-better effect and Occam's razor, both categorized under C5 of Table 2 (i.e. "We favor simple-looking options and complete information over complex, ambiguous options"). - Ask, don't tell: Instead of making proclamations or statements, "facilitate" the target audience to come to their own conclusions by asking the right kind of questions. - Highlight a gap: By addressing the various coping mechanisms categorized under quadrant B (Why) of Table 2, especially B1 (i.e. "We find stories and patterns in sparse data") and B6 (i.e. "We project our current mindset and assumptions onto the past and future"), practitioners achieve their objectives by appealing to this nuanced but entrenched desire to fill a gap. Highlighting a disconnect

		between the target audience's thoughts and actions is a useful route towards self-persuasion. - Start with understanding: This involves developing trust with the target audience. Berger (2020) underscores the fact that before someone will change, they have to first show a propensity to listen. Practitioners can potentially showcase various anecdotes or customer testimonies and reviews, as discussed in the STEPPS framework, to establish such trust, instead of adopting an overly aggressive approach to trumpeting their products' superiority and features over those of their competitors. These strategies repurpose this principle of reactance by changing the role of the target audience from a listener who is thinking of a "push-back" counter argument to an opinion and potential desired response to the call to action.
E	Endowment	Endowment is a principle that a substantial part of this research focuses on. In fact, Berger (2020) derived this principle from the research done by pioneering behavioral economists, particularly on the various effects, such as the endowment effect, loss aversion and the sunk cost fallacy, addressing item C3 in Table 2 (i.e. "To get things done, we tend to complete things we've invested time and energy in"). Furthermore, Berger (2020) suggested strategies such as freemium and trialability to lower the perceived cost of

		experimentation in order to guide the self-persuasion process of the target audience. He also identified the status quo bias, under C4 of Table 2 (i.e. “To avoid mistakes, we’re motivated to preserve our autonomy and status in a group and to avoid irreversible decisions”) as a primary hurdle, and proposed two major ways to address this, namely: - Surfacing the cost of inaction: By saliently highlighting the potential costs of inaction, practitioners can make loss aversion bias work in their favor and “nudge” the potential customer towards a desired course of action. - Burning the ships: Berger (2020) suggested that if inertia is too strong, practitioners may need to force the change, lest such inertia causes more problems for the company. For example, in the digital context, even though there may still be users who are wedded to a particular kind of application system or user-interface design, digital entrepreneurs may need to make the decision to do an entire overhaul instead of incurring additional costs to service the minority group of users at the expense of rapid scaling. Notwithstanding this, I am cognizant that such an action would not technically constitute a nudge, but would still be required if the situation calls for it, as is evident in many systems upgrades

		"forced" upon users by high-tech titans like Microsoft and the Android and iOS operating systems.
D	Distance	Berger (2020) indicated that distance as a principle is not restricted to physical distance per se. He was referring to the different positions on a field or spectrum regarding a particular topic. He likened people's different beliefs or ideological positions to locations on a "football field of beliefs" and encouraged practitioners to identify the target audience's region of rejection and zone of acceptance, so as to be more efficient and effective in catalyzing desired actions, particularly for resource-strapped digital practitioners. Referencing Benson and Manoogian's (2018) cognitive bias codex and Table 2, practitioners can utilize effects such as the false consensus effect or the Dunning-Kruger effect,[17] categorized under C1 of Table 2. This can then be reinforced further by other effects such as the confirmation bias, categorized under A4 (i.e. "We are drawn to details that confirm our own existing beliefs"). Berger

[17] According to Dunning (2011), the Dunning-Kruger effect is a form of cognitive bias in which people believe that they are smarter, better and more capable than they really are.

		(2020) proposed three key strategies to bridge the understanding between the persuader and the target audience, namely: - Finding the movable middle: This segment will yield the best results for conversion relative to people on the other extreme. - Ask for less: Instead of being straightforward and jumping into a big ask, break this down into multiple smaller asks. Berger (2020) highlighted that this will bridge the distance on the field of beliefs, and it resonates with Cialdini's (2016) strategy of negotiation via the "death by a thousand cuts" approach. - Switching the field to find an unsticking point: Berger (2020) used various anecdotes of politicians crossing the aisle, related to the deep divisions between the Democrats and Republicans in the United States political scene, and suggested ways of initially highlighting things that people already agree on before proceeding to nudge the target audience towards a particular goal. This pre-persuasion method of establishing common ground also coincides with Cialdini's (2008) principles to establish trust and eventually bridge the proverbial distance between the persuader and the target audience.

U	Uncertainty	This principle, uncertainty, is a major roadblock to the growth hacker's playbook, according to Berger (2020), because humans hate uncertainty. In fact, the entire literature review presented in Chapter 2 is primarily dedicated to the evolution of the research into consumers' decision-making under uncertain conditions. Practitioners in the digital context would do well to reference the various cognitive biases incorporated under item C3 in Table 2, to identify various strategies suggested by prior researchers for mitigating biases such as loss aversion. Berger (2020) suggested several approaches: - Harnessing freemium and trialability to reduce uncertainty: This is closely examined in the research undertaken for this dissertation and is also discussed at length in Chapter 3. - Reducing up-front costs: I suggest that other biases categorized under C5 can also be instructive. For example, the Occam's razor effect and the less-is-better effect may assist digital practitioners in moving towards simple designs for user interfaces and guiding tutorial screen-flow, as this can lower the perceived cost of the adoption of digital offerings in the form of learning effort. This strategy would constitute a digital nudge in the choice architecture framework suggested by Thaler and Sunstein (2008).

		- Drive discovery: This involves getting people to be aware of a product offering's existence. This is discussed at length in Subsection 6.3.1 under the STEPPS framework, the goal of which is to help digital practitioners overcome this awareness hurdle in the first stage of the digital consumer decision-making process. - Make it reversible: Berger (2020) suggested that an option with a backup plan often seems more desirable. This is saliently demonstrated in the Acura (5-day money-back guarantee) example in his book. The cognitive biases involved can largely be categorized under C3, with effects like loss aversion and zero-risk bias coming into play. As Keskin (2021) highlighted, a "satisfaction guarantee is a promise a brand makes to assure a buyer that a refund will be issued if the buyer is not satisfied with a product or service within a certain timeframe". She elucidated seven kinds of guarantee commonly deployed by various companies and seen in the digital context: the lifetime guarantee, the free-trial guarantee, the first-time guarantee, the lowest price guarantee, the happiness guarantee, the fun guarantee and the branded guarantee. All these are potentially instructive for digital practitioners in designing products or using suitable digital nudges in their offerings to

		address this major "uncertainty" roadblock underscored by Berger (2020).
CE	Corroborating Evidence	Berger's (2020) fifth major "horseman of inertia" is the principle of corroborating evidence. This gels strongly with the confirmation bias and subjective validation bias categorized under item A4 in Table 2 (i.e. "We are drawn to details that confirm our own existing beliefs"). He proposed that different approaches should be used to target different kinds of target audience personas by first identifying whether audience members are "pebbles" or "boulders". For less opinionated people, a "sprinkler" approach to evidence would suffice, whereas a "hose" strategy would be required for those with deep entrenched beliefs or practices. This could be particularly instructive for digital practitioners in designing their relevant digital nudges: - For the "pebbles", practitioners can direct such people to relevant web articles, or produce dedicated blog posts to feed these individuals' confirmation bias (categorized under A4 of Table 2) or other biases such as anchoring (categorized under A3). Directing them to third- party sites might be a useful way to persuade them and also to mitigate the uncertainty roadblock discussed when elaborating the uncertainty principle above.

		- For the "boulders", practitioners can potentially facilitate deeper engagement, such as inviting them to join a special-interest group or a Telegram/WhatsApp group-chat, where digital practitioners can engage community managers or administrators to answer any enquiries. As Beller (n.d.) highlighted, highly scalable digital startups today cannot avoid the development of highly engaged communities who can assist in mutually educating each other about the company's development. In fact, this strategy could be supported by using guidance from the various biases categorized under item B2 of Table 2, including the authority bias and the bandwagon effect. Digital practitioners could draw on insights from research into these well-documented biases to achieve the difficult task of converting "boulders".

6.3.4. Putting it Together

As elucidated in the preceding subsections, it would be daunting for resource-constrained and time-strapped digital practitioners to dive headlong into the deep ocean of literature and research into various cognitive biases and heuristics. In the literature review covered in Section 2.3.1, I selected the prominent key effects, heuristics and biases commonly used and observed in the digital context. In addition, I have provided a purpose-driven framework to join together Benson and Manoogian's (2018) comprehensive cognitive bias codex, as shown in Figure 13, to Berger's (2013) STEPPS and Berger's (2020) REDUCE principles to help practitioners promote greater virality in the awareness stage as well as executing better conversion in the second stage of my conceptual framework, shown in Figure 5.

By carefully referring to the four main quadrants of “why” a bias occurred, as presented in Table 2, digital practitioners can focus on the 20 categories listing “how” humans cope with the corresponding reason “why”, shown in Table 2. The respective cognitive biases and heuristics within each category are all captured in Table 8 under Appendix 3. Practitioners can then identify the appropriate effects to be applied in their design of digital nudges and strategies. Furthermore, the prior subsections also showcased several case studies on how the STEPPS and REDUCE principles have been used to apply various effects, heuristics and biases with great success, which digital practitioners can emulate. These principles can also potentially contribute to early-stage ideation exercises for digital entrepreneurs to discover what new capacities can be unlocked, such as how Uber unlocked the unused capacities of privately owned automobiles and drivers’ time, or how Airbnb unlocked the capacities of spare bedrooms or units in privately owned residential dwellings.

All these highly practical action steps may be particularly helpful in overcoming the “cold start” problem noted by Chen (2021), that when startups do not gain momentum with an “atomic network” of early users, the digital product and its corresponding awareness will dwindle and die. A good example is the employment of the social proof effect to assist in the acquisition of new customers, such as in the case of PayPal, where users sending money via electronic email to their contacts prompt these contacts to adopt the new digital product as well. Through this type of approach, an early network of users can be greatly scaled up, thereby increasing the probability of creating a highly successful platform company in the digital age.

My research on the ZPE and the endowment effect in the digital context focused on just a small segment of the whole universe of behavioral biases and effects. Using the purpose-driven framework presented in this chapter to identify the "whys" before zooming into the 20 categories of "hows" within the cognitive bias codex, digital practitioners can be more surgical in reviewing the relevant literature to assist in their design of digital nudges or strategies across the two stages (i.e. the awareness and conversion stage) of my conceptual framework for a digital consumer's decision-making process. In addition, in the realm of marketing and growth hacking, it is often not the quantity of choices that consumers look out for, but rather assurance that the "right" choice has been made. It is with this objective that I hope this purpose-driven framework, which marries Benson and Manoogian's (2018) cognitive bias codex as well as Berger's (2013, 2020) STEPPS and REDUCE principles, can help to achieve.

Chapter 7: Conclusion and Key Contributions

As the wise adage goes, “In the land of the blind, the one-eyed man is king”; but I will argue that “perhaps the man who *says* he has one eye is the king”, since there is no one to validate that claim if it is truly the land of the blind! Many rules need to be rewritten for or “spoken” to the proverbial “blind” in this new digital economy. We have heard many new proverbs in recent years, such as “data is the new oil”, and artificial intelligence (AI) and machine learning (ML) are potentially the new “electricity”. This is not dissimilar to what the world witnessed in the early 20th century, when traditional home appliances like the iron and the kettle began to be electrified. As we navigate these exciting waters in the upcoming decades, cognitive processes that influence consumer choices will play an increasingly important role in the design of digital products and services delivered on the mobile platform. In the modern digital economy, many of us recognize that the “free” offerings today come with certain hidden costs, be these a user’s privacy, time, attention or exposure to advertisements. Notwithstanding this, understanding how the nuanced variations of each “reference point”, such as the category or strategies (freemium/free-trial), moderate the corresponding behavioral effects (zero-price and endowment effect) can be particularly instructive.

By embedding such insights into their growth hacking strategies, and focusing on achieving rapid user traction and growth, digital practitioners will be well positioned and more likely to secure early-stage funding from the venture capital industry to transit to the next stage of development for their business.

I summarize the key contributions of this dissertation in Table 7 below.

Table 7: Contributions of the Study

A. Theoretical Contribution	
To	**Comments**
Nudge theory, with a specific focus on zero price theory (considered a subset of prospect theory)	Contribution to nudge theory-specific choice architecture in the digital context, especially on how zero-price "nudges" consumer decision-making, with a special focus on how categories (specifically, games, media-streaming and productivity) and the type of strategies moderate choice proportions and the level of affect. Endowment effect was also measured and studied.
Benson and Manoogian's (2018) Cognitive Bias Codex	Formal proposal for the inclusion of zero-price effect (ZPE) into Benson and Manoogian's (2018) codex to be categorized under C5 of Table 8 (Comprehensive Cognitive Biases Table) (i.e. "We favor simple-looking options and complete information over complex, ambiguous options").
B. Contribution to the Body of Knowledge: Quantitative	
Relationships Between	**Comments**
Choice and categories (awareness stage)	- Empirical and quantitative study into the nuanced "reference points" within the digital context, including how three categories – games, media-streaming, and productivity – as well as the choice of free-related strategies (whether a limited-feature freemium or the full-feature free-trial strategy) moderate the choice proportions as well as the level of affect as measured by the Net Promoter Score (NPS) via an online survey with 381 complete and valid responses, during the awareness Stage 1 of my conceptual framework. - Results show that the ZPE truly extends to the digital context, and that the ZPE measured by choice proportions and the level of affect varies according to the category of app.

	- The “reference point” in the case of the productivity app category and media-streaming category is more codified than that of the games category, which may potentially “nudge” a digital consumer more (i.e. a stronger ZPE) to download the app with a free offering.
Level of affect/NPS and categories	- From the affect/NPS perspective, at the price of zero/free, results indicate that consumers do feel significantly different towards apps from both the games and productivity category.
Choice + NPS and the types of free-related strategies	- Examination of the results for both the choice proportions and NPS of respondents in the freemium vs free-trial study suggests that for the category of games, practitioners may be better off using the limited-feature freemium strategy, whereas for the categories of media-streaming and productivity, practitioners may wish to consider the full-feature free-trial strategy instead.
Choice and categories (conversion/purchasing stage), as part of endowment effect study	- Results show that the endowment effect truly extends to the digital context . - Furthermore, the endowment effect is moderated by the “category”, eliciting a stronger positive affect/influence if an app (as appropriately categorized) is deemed to be embedded in the consumer’s workflow or lifestyle, as in the case of a productivity app or media-streaming app. - As such, the full-feature free-trial version will trigger a more positive affect (as measured by a higher mean NPS shown in the productivity category, compared to the media-streaming category which, in turn, is higher than the games category). For games, which are potentially perceived to be trivial and less embedded into the consumer’s daily lifestyle or having any relevance to a consumer’s workflow, a limited-feature freemium strategy may be preferred.

C. Contributions to the Body of Knowledge: Qualitative	
Types of Contribution	**Comments**
Literature review (descriptive)	- An evolutionary history of consumer decision-making theories from classical economics theory to prospect theory and, more recently, nudge theory and zero price theory.
Literature review (descriptive)	- Descriptive literature review of the key heuristics and cognitive biases identified in the digital context (tabulated format).
Literature review (critical)	- Critical review of ZPE and freemium-related literature.
Conceptual framework to study consumer behavior (for the digital context)	- Development of a conceptual framework for the consumer decision-making process in the digital context (specifically the mobile software application store context) as shown in Figure 5, involving two major stages: an "awareness" stage (Stage 1) that is determined by the willingness to download, and a "purchasing" stage (Stage 2) that is determined by the willingness to pay/purchase.
Growth hacking framework for practitioners	- Development of a purpose-driven framework for digital practitioners to growth hack by utilizing my two-stage conceptual framework, and selecting suitable biases and heuristics from Benson and Manoogian's (2018) cognitive bias codex coupled with Berger's (2013) STEPPS principles for promoting virality at the awareness stage and Berger's (2020) REDUCE principles with the goal of conversion at Stage 2. This will ensure a more systematic approach in facilitating practitioners to reference the deep reservoir of literature in the realm of cognitive biases and heuristics for designing and developing new digital nudges.
D. Methodological Contributions	

Construct Measure	Comments
Using NPS as a proxy for the typical 5-point scale used for measuring affect, to better reflect the digital context	- Instead of using Shampanier et al.'s (2007) single-item 5-point scale to measure "affect", I propose the use of the popular 11-point Net Promoter Score® or NPS® by researchers, to more closely mirror conditions of the digital context, given that this NPS scale is widely used by most digital practitioners.

Just as Google unlocked new untapped capacities of the online advertising inventory with products like AdWords and AdSense, or Facebook unlocked personal data capacity for analytical purposes from cookies stored in the caches of users' personal computers and mobile devices in the early 2000s, and as Uber and Airbnb unlocked previously untapped capacities of private cars and living space in the decade that followed, I hope this study charts a path for practitioners that will herald a new age of unlocking new potential or discovering previously untapped capacities, potentially through the behavioral economics lens, to achieve greater success in their entrepreneurial journeys. I also hope that this dissertation sets the stage for future studies into other cognitive biases and effects and contribute to an even better understanding of the consumer decision-making process in the digital context, thereby shaping new digital nudges or strategies in different contexts including charity, or areas to foster environmental consciousness, bringing the realm of applied behavioral economics to the next level.

~ End ~

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Appendices

Appendix 1: Participant Information Form

The following material was included in all the online survey links sent out to potential respondents.

Project Title

Applied Behavioral Economics in the Digital Age - Examining Choices around the idea of "Free"

Researcher

Name	Wilson Wang
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Supervisor

Name	Dr Craig Applegate

Project Aim

The aim of this research is to understand better on how behavioral economics influence decisions in the digital context.

Benefits of the Project

The information gained from the research will be used to inform startup entrepreneurs and product managers in designing their products and strategies in the digital context.

General Outline of the Project

The project will involve the testing of hypotheses made by the researcher, pertaining to choices based on scenarios associated with the downloading and potential purchase decisions around the premium offerings of digital offerings made available on the mobile application stores.

Participant Involvement

Participants who agree to participate in the research will be asked to:

1. Read and imagine themselves in described scenarios and

2. Make selections among choices presented to the participant based on the particular scenario

Participation in the research is completely voluntary and participants may, without any penalty, decline to take part or withdraw at any time without providing an explanation or refuse to answer a question.

Confidentiality

Only the researcher/s will have access to the individual information provided by participants. Privacy and confidentiality will be assured at all times. The research outcomes may be presented at conferences and written up for publication. However, in all these publications, the privacy and confidentiality of individuals will be protected.

Anonymity

All reports and publications of the research will contain no information that can identify any individual and all information will be kept in the strictest confidence.

Data Storage

The information collected will be stored securely on a password protected computer throughout the project and then stored at the University of Canberra for the required five-year period after which it will be destroyed according to university protocols.

Ethics Committee Clearance

The project has been approved by the Human Research Ethics Committee of the University of Canberra (HREC – 9098).

Queries and Concerns

Queries or concerns regarding the research can be directed to the researcher and/or supervisor. Contact details are at the top of this form.
If you have any complaints or reservations about the ethical conduct of this research, you may contact the University of Canberra's Research Ethics & Integrity Unit team via telephone 02 6206 3916 or email humanethicscommittee@canberra.edu.au or researchethicsandintegrity@canberra.edu.au

If you would like some guidance on the questions you could ask about your participation please refer to the Participants' Guide located at http://www.canberra.edu.au/ucresearch/attachments/pdf/a-m/Agreeing-to-participate-in-research.pdf

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Appendix 2: Online Quantitative Survey Questions

Experiment – Online Quantitative Survey Questions

For Stage 1, with the objective of achieving maximum willingness to download, how do consumers perceive zero-priced vs bargain-priced digital offerings?

1. *Is this homogenous across the three main different categories/genres of games, media-streaming applications such as music-streaming platforms (e.g. Spotify), and productivity applications such as cloud-storage solutions (e.g. Dropbox).*

Category: Games

Study 1

Variant 1 – Free vs Premium ($9.99)

Imagine that you are looking for a mobile app, specifically a casual puzzle video game on the Google's Android PlayStore or Apple's AppStore, to occupy your time. There are two different versions of the game:

1. a basic one that is free but only up to 10 levels of gameplay (It is estimated that this will provide entertainment for up to 20 hours, i.e. Approximately 10 days at 2 hours of game-play per day), delivering a ***moderate level*** of entertainment value to the user
- another premium version with all 100 levels of gameplay, translating to 180 hours of gameplay (or an approximately 3 months of 2hr/day game play) along with gift-packs of character-enhancement attributes which will deliver a ***substantial level*** of entertainment value to the user

Question 1 - Which Option Would You Choose:

1. **Basic Option for Free; 2. Do Nothing; 3. Premium Option for $9.99**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Study 2 – If given a choice between a fully-featured version of the game but free for a limited time period of 1 week, and a free basic limited-feature version, which will you prefer?

1. **Fully-Featured Version, Free for 1 Week, $9.99 afterwards, else not able to use**
2. **Free basic limited-feature version, no time-limit**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Variant 2 – Bargain Price of ($0.99) vs Premium ($9.99)

Imagine that you are looking for a mobile app, specifically a casual puzzle video game on the Google's Android PlayStore or Apple's AppStore, to occupy your time. There are two different versions of the game:

- a basic one that costs $0.99 but only up to 10 levels of gameplay (It is estimated that this will provide entertainment for up to 20 hours, i.e. Approximately 10 days at 2 hours of game-play per day), delivering a ***moderate level*** of entertainment value to the user
- another premium version with all 100 levels of gameplay, translating to 180 hours of gameplay (or an approximately 3 months of 2hr/day game play) along with gift-packs of character-enhancement attributes which will deliver a ***substantial level*** of entertainment value to the user

Which Option Would You Choose:

1. **Basic Option for $0.99; 2. Do Nothing; 3. Premium Option for $9.99**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Study 2 – If given a choice between a fully-featured version of the game but free for a limited time period of 1 week, and a free basic limited-feature version, which will you prefer?

1. **Fully-Featured Version, Free for 1 Week, $9.99 afterwards, else not able to use**
2. **Free basic limited-feature version, no time-limit**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Category: Media-Streaming

Variant 1 – Free vs Premium ($9.99)

Imagine that you are looking for a mobile app, specifically a music streaming application on the Google's Android PlayStore or Apple's AppStore, to listen to a large library of music of different genres whenever you wish as long as there is an internet connection. There are two different versions of the digital app offering:

- a basic one that is free, but user can only select from a limited library of music selections from different genres, and users can only listen to a maximum of only 1 minute of the selected song. No offline usage.
- another premium version that costs $9.99 with a much larger library of music selections from different genres which also allow for downloads of up to 100 songs for offline usage for use in areas without internet connectivity

Which Option Would You Choose:

1. **Basic Option for Free; 2. Do Nothing; 3. Premium Option for $9.99**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Study 2 – If given a choice between a fully-featured version of the music-streaming app but free for a limited time period of 1 week, and a free basic limited-feature version, which will you prefer?

1. **Fully-Featured Version, Free for 1 Week, $9.99 afterwards, else not able to use**
2. **Free basic limited-feature version, no time-limit**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Variant 2 – Bargain Price of ($0.99) vs Premium ($9.99)

Imagine that you are looking for a mobile app, specifically a music streaming application on the Google's Android PlayStore or Apple's AppStore, to listen to a large library of music of different genres whenever you wish as long as there is an internet connection. There are two different versions of the digital app offering:

- a basic one that costs $0.99 but user can only select from a limited library of music selections from different genres, and users can only listen to a maximum of only 1 minute of the selected song. No offline usage.
- another premium version that costs $9.99 and allow for downloads of up to 100 songs for offline usage for use in areas without internet connectivity

Which Option Would You Choose:

2. **Basic Option for $0.99; 2. Do Nothing; 3. Premium Option for $9.99**

Follow on NPS Question – “On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?”

0 1 2 3 4 5 6 7 8 9 10

Study 2 – If given a choice between a fully-featured version of the music-streaming app but free for a limited time period of 1 week, and a free basic limited-feature version, which will you prefer?

1. **Fully-Featured Version, Free for 1 Week, $9.99 afterwards, else not able to use**
2. **Free basic limited-feature version, no time-limit**

Follow on NPS Question – “On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?”

0 1 2 3 4 5 6 7 8 9 10

Category: Productivity tool

Variant 1 – Free vs Premium ($9.99)

Imagine that you are a specialized knowledge worker, looking for a mobile app, specifically a work-enhancement specialized productivity tool on the Google’s Android PlayStore or Apple’s AppStore, to assist you in your daily work tasks. There are two different versions of the digital app offering:

- a basic one that is free but has only limited features, and can only improve your work productivity **moderately**
- another premium version that costs $9.99 with full features that will improve your work productivity **substantially**

Which Option Would You Choose:

1. **Basic Option for Free; 2. Do Nothing; 3. Premium Option for $9.99**

Follow on NPS Question – “On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?”

0 1 2 3 4 5 6 7 8 9 10

Study 2 – If given a choice between a fully-featured version of the productivity app but free for a limited time period of 1 week, and a free basic limited-feature version, which will you prefer?

1. **Fully-Featured Version, Free for 1 Week, $9.99 afterwards, else not able to use**
2. **Free basic limited-feature version, no time-limit**

Variant 2 – Bargain Price of ($0.99) vs Premium ($9.99)

Imagine that you are a specialized knowledge worker, looking for a mobile app, specifically a work-enhancement specialized productivity tool on the Google's Android PlayStore or Apple's AppStore, to assist you in your daily work tasks. There are two different versions of the digital app offering:

- a basic one that costs only $0.99 but has only limited features, and can only improve your work productivity by at most 5%.
- another premium version that costs $9.99 with full features that will improve your work productivity by at least 20%

Which Option Would You Choose:

1. **Basic Option for $0.99; 2. Do Nothing; 3. Premium Option for $9.99**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Study 2 – If given a choice between a fully-featured version of the productivity app but free for a limited time period of 1 week, and a free basic limited-feature version, which will you prefer?

1. **Fully-Featured Version, Free for 1 Week, $9.99 afterwards, else not able to use**
2. **Free basic limited-feature version, no time-limit**

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

The following section is For Stage 2 - does the endowment effect apply for mobile applications?

1. *Is this effect homogenous across the aforementioned 3 main categories?*
2. *Does the endowment effect impact the freemium/freeware model the same as the free-trial/trialware model with respect to willingness to pay?*
3. *In the context of a free-trial for a full-featured application in each of the categories, what is the optimal "trial-period" for users before it is deemed reasonable to charge?*

Study 3 – Testing for Endowment Effect wrt Willingness to Pay

(Repeat the same questions for 3 Categories – Games, Music-Streaming App, Productivity App)

Unendowed Group

Assuming that you are brought aware of a mobile casual game on the AppStore, which is advertised to be very entertaining. For the purpose of this research, please assume that competing premium versions of applications priced similarly at $9.99 also deliver the same level of entertainment value. Would you:

1. Pay $9.99 to upgrade to the Premium Version of the App?
2. Do Nothing?

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Endowed Group with Limited-Feature Freemium App

Assuming that you are brought aware of a mobile game on the AppStore, which is advertised to be very entertaining. You have downloaded the limited-feature basic version and played for approximately 1 week, and understandably for its limited features, it has delivered only a marginal level of entertainment value. Would you:

1. Pay $9.99 to upgrade to the Premium Version of the App?
2. Keep using the Limited-feature basic version?

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Endowed Group with Fully-featured App with 1 week Free-Trial period

Assuming that you are brought aware of a mobile game on the AppStore, which is advertised to be very entertaining. For the purpose of this research, please assume that competing premium versions of applications priced similarly at $9.99 also deliver the same level of entertainment value. You have downloaded the Free-trial version and tried out the entire trial period of 1 week, it has truly delivered its advertised or expected level of entertainment value from your perspective. Would you:

1. Pay $9.99 to download the Full-featured version of the App?
2. Not Pay and Delete the App?

Follow on NPS Question – "On a scale of zero to ten, how likely are you to recommend this app to a friend or colleague?"

0 1 2 3 4 5 6 7 8 9 10

Appendix 3: Comprehensive Cognitive Bias Codex

Table 8: Comprehensive Compilation of Benson and Manoogian's (2018) Cognitive Bias Codex

A. Too Much Information	**B. Not Enough Meaning**
1. We notice things already primed in memory or repeated often	1. We find stories and patterns even in sparse data
- Availability heuristic	- Confabulation
- Attentional bias	- Clustering illusion
- Illusory truth effect	- Insensitivity to sample size
- Mere-exposure effect	- Neglect of probability
- Context effect	- Anecdotal fallacy
- Cue-dependent forgetting	- Illusion of validity
- Mood-congruent memory bias	- Masked-man fallacy
- Frequency Illusion	- Recency illusion
- Baader-Meinhof phenomenon	- Gambler's fallacy
- Empathy gap	- Hot-hand fallacy
- Omission bias	- Illusory correlation
- Base rate fallacy	- Pareidolia
	- Anthropomorphism
2. Bizarre/funny/visually-striking/ anthropomorphic things that stick out more than mediocre stuff	2. We fill in characteristics from stereotypes, generalities and prior histories
- Bizarreness effect	- Group attribution error
- Humor effect	- Ultimate attribution error
- Von Restorff effect	- Stereotyping
- Picture superiority effect	- Essentialism
- Self-relevance effect	- Functional fixedness
- Negativity bias	- Moral credential effect
3. We notice when something has changed	- Just-world hypothesis
	- Argument from fallacy
- Anchoring	- Authority bias
- Conservatism	- Automation bias
- Contrast effect	- Bandwagon effect
- Distinction bias	- Placebo effect
- Focusing effect	
- Framing effect	3. We imagine things and people we're familiar with or fond of as "better"
- Money illusion	
- Weber-Fechner law	- Out-group homogeneity bias
	- Cross-race effect
4. We are drawn to details that confirm our own existing beliefs	- In-group favoritism
	- Halo effect
- Confirmation bias	- Cheerleader effect
- Congruence bias	- Positivity effect

- Post-purchase rationalization - Choice-supportive bias - Selective perception - Observer-expectancy effect - Experimenter's bias - Observer effect - Expectation bias - Ostrich effect - Subjective validation - Continued influence effect - Semmelweis reflex 5. We notice flaws in others more easily than flaws in ourselves - Bias blind spot - Naïve cynicism - Naïve realism	- Not invented here - Reactive devaluation - Well-travelled road effect 4. We simplify probabilities and numbers make them easier to think about - Mental accounting - Appeal to probability fallacy - Normalcy bias - Murphy's law - Zero sum bias - Survivorship bias - Subadditivity effect - Denomination effect - The magical number 7+-2 5. We think we know what other people are thinking - Illusion of transparency - Curse of knowledge - Spotlight effect - Extrinsic incentive error - Illusion of external agency - Illusion of asymmetric insight 6. We project our current mindset and assumptions onto the past and future - Self-consistency bias - Restraint bias - Projection bias - Pro-innovation bias - Time-saving bias - Planning fallacy - Pessimism bias - Impact bias - Declinism - Moral luck - Outcome bias - Hindsight bias
C. Need to Act Fast	**D. What Should We Remember?** 1. We edit and reinforce some memories after the fact

1. To act, we must be confident we can make an impact and feel what we do is important
- Peltzman effect
- Risk compensation
- Effort justification
- Trait ascription bias
- Defensive attribution hypothesis
- Fundamental attribution error
- Illusory of control
- Actor-observer bias
- Self-serving bias
- Barnum effect
- Forer effect
- Optimism bias
- Egocentric bias
- Dunning-Kruger effect
- Lake Wobegon effect
- Hard-easy effect
- False consensus effect
- Third-person effect
- Social desirability bias
- Overconfidence effect

2. To stay focused, we favor the immediate, relatable thing in front of us
- Identifiable victim effect
- Appeal to novelty
- Hyperbolic discounting

3. To get things done, we tend to complete things we've invested time and energy in
- Backfire effect
- Endowment effect
- Processing difficulty effect

- Spacing effect
- Suggestibility
- False memory
- Cryptomnesia
- Source confusion
- Misattribution of memory

2. We discard specifics to form generalities
- Fading affect bias
- Negativity bias
- Prejudice
- Stereotypical bias
- Implicit stereotypes
- Implicit association

3. We reduce events and lists to their key elements
- Suffix effect
- Serial-position effect
- Part-set cuing effect
- Recency effect
- Primacy effect
- Memory inhibition
- Modality effect
- Duration neglect
- List-length effect
- Serial recall effect
- Misinformation effect
- Levelling and sharpening
- Peak-end rule

4. We store memories differently based on how they were experienced
- Top of the tongue phenomenon
- Google effect

- Pseudocertainty effect
- Disposition effect
- Zero-risk bias
- Unit bias
- IKEA effect
- Loss aversion
- Generation effect
- Escalation of commitment
- Irrational escalation
- Sunk cost fallacy

4. To avoid mistakes, we're motivated to preserve our autonomy and status in a group and to avoid irreversible decisions

- Status quo effect
- Social comparison effect
- Decoy effect
- Reactance
- Reverse psychology
- System justification

5. We favor simple-looking options and complete information over complex, ambiguous options

- Less-is-better effect
- Occam's razor
- Conjunction fallacy
- Law of triviality
- Bike-shedding effect
- Rhyme-as-reason effect
- Belief bias
- Information bias
- Ambiguity bias
- **Zero-price effect**

- Next-in-line effect
- Testing effect
- Absent-mindedness
- Levels-of-processing effect