MOBILE CONSUMERS AND APPLICATIONS

Essays on Mobile Marketing

Mobile Consumers and Applications
Essays on Mobile Marketing

Mobiele consumenten en applicaties
Essays over mobiele marketing

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
rector magnificus

Prof. dr. F.A. van der Duijn Schouten
and in accordance with the decision of the Doctorate Board.

The public defence shall be held on
Thursday 4 March 2021 at 13.00hrs
by

Zeynep Aydin
born in **Ankara, Turkey.**

Erasmus University Rotterdam

Doctoral Committee

Promotor: Prof.dr.ir. G.H. van Bruggen

Other members: Prof.dr. G. Liberali
Prof.dr. T. Li
Prof.dr. F. Langerak

Copromotor: Dr. B. Ataman

Erasmus Research Institute of Management – ERIM
The joint research institute of the Rotterdam School of Management (RSM)
and the Erasmus School of Economics (ESE) at the Erasmus University Rotterdam
Internet: www.erim.eur.nl

ERIM Electronic Series Portal: repub.eur.nl/

ERIM PhD Series in Research in Management, 519
ERIM reference number: EPS-2021- 519- MKT
ISBN 978-90-5892-599-2

Design: PanArt, www.panart.nl

This publication (cover and interior) is printed by Tuijtel on recycled paper, BalanceSilk®
The ink used is produced from renewable resources and alcohol free fountain solution.
Certifications for the paper and the printing production process: Recycle, EU Ecolabel, FSC®C007225
More info: www.tuijtel.com

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

‘‘The world is moving so fast these days that the man who says it can't be done is generally interrupted by someone doing it.’’ Elbert Hubbard (1856 – 1915)

Now after 28 years since the first text message (‘Merry Christmas.’) has been sent and 13 years since the first touch screen, the speed at which the world changes has reached a new high. Mobile phones have become the constant companions of consumers in today’s connected world. The growing interest in the mobile market combined with advancements in technological infrastructures, especially wireless technology, and the growing smartphone penetration have riveted mobile’s powerful space in users’ daily routines. Collective widespread use of mobile phones has further incentivized users to stay connected and participate in myriad of activities now available in mobile. These activities range from continuous communication with others to remote access of home appliances. To crown it all, the coronavirus has advanced mobile usage by 2 to 3 years accelerating the transition to a mobile-first world even further. Mobile app usage surged 40% compared to last year during COVID – 19 pandemic, reaching an all-time high amidst stay-at-home measures (Appannie, 2020).

New media and new technologies have already transformed traditional marketing and consumers to a great extent. Although internet has initiated this shift, mobile has taken it into a completely new level ever since the penetration of technology into daily lives of users has skyrocketed with the introduction of iPhone in 2007. Mobile marketing is defined as the multi-way communication and promotion of an offer between a firm and its customers using the mobile medium, device, channel, or technology (Shankar and Balasubramanian, 2009). Since then, research has continued to underline the importance of mobile by integrating it within the existing frameworks of retailing or social, digital and interactive marketing, and call for further research on mobile marketing opportunities (Shankar et al., 2010; Ratchford, 2015), how mobile fits in the customer journey and its' interaction with other channels (Kannan and Li, 2017), its' difference compared to other digital or social channels and how to effectively use its unique features (Lamberton and Stephen, 2016). Now, after over a decade, undeniably established presence of mobile in users' daily routine, driven by the changing lifestyle of users offer a fertile ground with multiple directions to go forward for research.

The main players in the broad mobile ecosystem are businesses (ranging from individual app developers to well-known brands), consumers, and platforms; creating close and complex relationships among them.

Businesses, recently provided with a new channel with unique features to approach customers, are one of the foremost players in this ecosystem. Some of these features include accessibility at any time anywhere, location sensitivity, and customization at a very granular level. These features alone paved a way to reach a previously unattainable level of engagement. Consequently, the possibility of engaging with the uninterrupted customer has been the main focus of businesses in the last decade and new media has gained itself considerable space within marketing strategy.

Platforms, although quite new, are also securing their place in the mobile eco-system with their renovated business model strategies. Apple's App Store, for instance, has a 30% cut on the developer revenues, which drops to 15% if a user stays with the app longer than a year (Ramaswamy and Ozcan, 2018). The App Store as such, rather than being a mere platform, becomes a contributor in the eco-system by deliberately enabling interactions between end-user customers of Apple's mobile device and developers, incentivizing successful apps with the revenue split model and influencing users' decisions with various tools it possesses such as featuring and top lists.

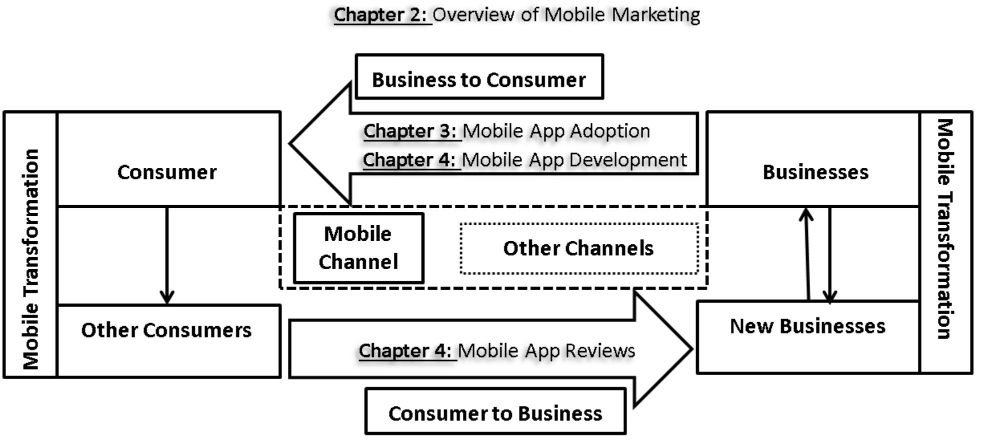
Finally, consumers seem to appear on the receiving end of the bargain; however this intuition is not entirely true. The now seamless integration of mobile phones into the daily routine of consumers has shifted the balance towards consumers in various ways. Consumers have attained an increased bargaining power (Varadarajan, 2010) through their instant access to information, and greater control over pricing, timing and location of their purchases. The realization of this empowerment has revolutionized how consumers act. Firms first need to understand these behavioral changes, and then respond accordingly to their consumers via their renovated marketing strategies.

The multiple players in the eco-system make mobile a complex research domain that contains numerous topics open for exploration. The building blocks of this dissertation are (1) the behavioral changes on the customer side, (2) the evolution of marketing strategies and marketing mix on the firm side and (3) the interaction between mobile consumers and the firms within the surrounding organizational eco-system. I consider multiple sides of the mobile eco-system by combining novel data sets reflecting the actions of mobile businesses and the reactions of mobile users, detailed next in Section 1.1.

1.1 Overview of This Dissertation

Each chapter of this dissertation focuses on different parts of the mobile eco-system. Chapter 2 provides an overview of mobile marketing research by offering an integrated framework and an extensive review of the research in this domain in the last decade. Chapter 3 focuses on the mobile application (app) adoption journey of the user and investigates factors affecting adoption, considering platform controlled, user-side, and developer controlled variables. Chapter 4 concentrates on the organic customer-feedback, product development loop, facilitated through user reviews and mobile application updates and investigates whether and how developers can benefit from the existing user feedback. Figure 1 shows where each chapter fits within the larger mobile ecosystem. Each of these chapters is a separate research project and can be read independently. Next, I introduce each chapter briefly.

Figure 1: Dissertation Overview



The first essay (Chapter 2) in my dissertation provides an extensive research overview and proposes an integrated framework of mobile marketing. Research on mobile marketing continues to grow at an increasing pace. Coupled with the fragmented nature of the mobile marketing domain, the call for an updated unifying framework emerges. Based on a database of 178 published articles over the last decade, I re-formulate this framework that is based on (1) the transformation in consumer behavior originating from the changing lifestyle of users, (2) the transformation of existing and emergence of new businesses thanks to mobile opportunities and (3) the interaction and integration of mobile with existing channels. The classification of each article under various research themes, the type of data collection, and their dependent and independent variables is crucial in constructing the overview. Results from Chapter 2 provide insights on the evolution of the field as well as future research directions.

Chapter 3 puts the mobile application space under the spotlight and offers a framework of the user's journey to mobile app adoption. Since its emergence over a decade ago, the mobile applications market has been attracting the attention of all kinds of businesses due to the lucrative opportunities mobile apps offer and the market's low barriers to entry. Yet, in this crowded space, only a small portion of apps can gain traction with mobile phone users. The challenge developers face did not go unnoticed by scholars and research so far has advanced our understanding of various factors such as user characteristics (Kim et al., 2017), app characteristics (Schulze, Schöler, and Skiera, 2014), app pricing (Arora, Hofstede, and Mahajan, 2017; Carrare 2012; Ghose and Han 2014; Kübler et al., 2018), app updates (Ghose and Han 2014; Kübler et al., 2018), other users' experiences (Ghose and Han 2014; Kübler et al., 2018), and, in the broader mobile eco-system, integration, ownership, and novelty of the apps (Van den Ende, Jaspers and Rijsdijk, 2013) associated with mobile app adoption. Using a novel data set of 979 newly released applications, acquired from a leading mobile analytics company and enriched with publicly available data, I shed light on the factors associated with app downloads during the first year of an app's existence by considering platform-side variables in addition to the user-side and developer-side variables, and investigating their effects over time. Results from time-varying-parameter models estimated separately for free and paid apps reveal that gaining traction with app users shortly after release seems critical for the future performance of apps and app platform owners are influential in these early days. However, as apps mature, affecting the number of downloads becomes increasingly more difficult. The findings of this research add new insights to the growing literature on mobile applications and provide practical implications for mobile application developers over the timeline of their applications.

Chapter 4 considers the mobile app development process wherein app developers operate on an experimental process with no/little guidance on when (timing) to offer and what (nature) to include in their updates. This essay zooms into the dynamic relationship between app users and developers available through reviews (by users) and updates (by developers). Based on an automated text analysis of about 1M reviews and a content analysis of about 3K mobile application updates, observed over 460 apps' first year on the market, I study the effects of incorporating users' voiced concerns, expressed through reviews, into product development stages, assessed through updates, on product evaluations[1]. Specifically, I quantify the rewards or penalties associated with actively responding to or ignoring users' voiced concerns/ requests regarding the product. Moreover, I investigate the extent to which these effects vary over the nature of the product development and time. The results reveal that the rewards associated with responding to user requests and the penalties due to ignoring these requests can be

[1] The apps used in the analysis of Chapter 4 are a subset of the apps used in the analysis of Chapter 3.

substantial and depend on the topic of the feedback and the timing of the response. Our findings provide app developers guidance on the challenge of prioritizing possible development paths: (1) promptly releasing updates in response to users' requests that provide additional benefits or ensure essential functioning of the app to restore and improve ratings; (2) continuously releasing updates that improve existing benefits or ensure compatibility with most recent operating systems and wide range of devices to avoid penalties. The implications may also extend to the broader New Product Development literature especially with respect to the fundamental question of whether and when to pro-act on or re-act to the voice of the customer.

Finally, Chapter 5 summarizes the findings derived from each study described in Chapter 2, Chapter 3 and Chapter 4; discusses their implications for research and practice; and last but not least outlines areas of interest for future research.

1.2 Declaration of Contribution

This dissertation has been written under the supervision of Berk Ataman and Gerrit van Bruggen. Research presented in Chapter 2, Chapter 3 and Chapter 4 have been conducted together with Berk Ataman and Gerrit van Bruggen. I have conducted majority of the work presented in Chapter 2, Chapter 3 and Chapter 4, and have benefited from remarkable feedback from Berk Ataman and Gerrit van Bruggen throughout the research processes.

Chapter 2

The Rise of Mobile Marketing: A Decade of Research in Review

The last decade has been turbulent for businesses and marketers as there have been tremendous changes in the world around us. It may be hard to imagine this turbulence when you consider that the consumer is constantly in the center of marketing activities. However, consumers themselves have faced dramatic changes. After over a decade since the introduction of the iPhone in 2007, mobile phones are the all-time, inseparable companions of consumers. The spread of social media, coupled with the advancements in technology, has created an uninterrupted online consumer, changing consumers' relationships with businesses in various ways. The consumer now has instant access to detailed product information and is connected to businesses and other consumers, attaining an increased bargaining power (Varadarajan et al., 2010) and making it possible to influence others' purchase decisions (Kumar, 2015). The realization of this empowerment has changed how consumers act.

Businesses, on the other hand, need to understand and make sense of these behavioral changes and then respond accordingly to the consumers via their renovated marketing strategies. Although this means a radical transformation for businesses that function in the traditional sense, once they accept the necessity of this transformation, the shift in the daily routine of the users provides businesses with plenty of unique opportunities. Now, businesses can reach out to connected customers at all times, with previously unattainable levels of engagement (with the help of additional information, such as location or behavioral history). Companies such as Amazon, Twitter, and Facebook have successfully revised their strategies in a mobile-first manner and grabbed the opportunity to connect further with on-the-go consumers.

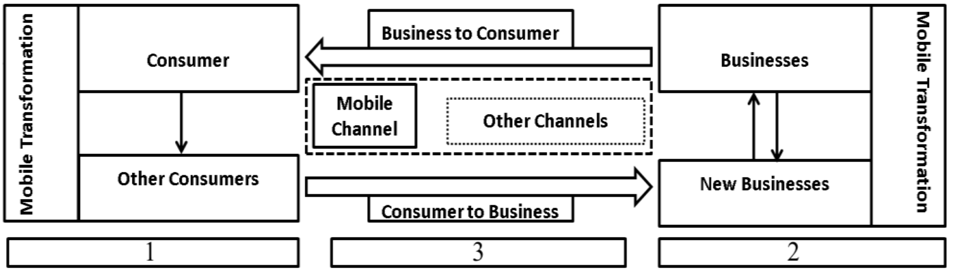
These unique opportunities, together with the dynamics of the mobile medium, also created space for new, innovative businesses to function. Mobile businesses that met an emerging need of consumers in this new routine (i.e., Uber, Netflix, Spotify, M-Pesa, Whatsapp) disrupted prevalent business models.

These changes in consumers' daily lives and the consequent transformation in the business world echoed in the research conducted in the marketing domain. Research on mobile marketing has studied various features of this medium, illuminating different fragments of the mobile ecosystem. The increasing number of articles over the years reflects a growth in the mobile domain at an increasing pace. Consequently, the growing body of knowledge on the subject and the fragmented nature of the mobile ecosystem call for a unifying framework.

In this paper, we aim to reformulate a unifying framework in light of recent studies and summarize research in mobile marketing in the last decade under this framework. So far, researchers have defined mobile marketing and offered an integrative framework (Shankar and Balasubramanian, 2009); positioned it in the next wave of interactive marketing (Ratchford, 2015); and discussed it as part of their proposed digital marketing framework (Kannan and Li, 2017). Recently, Lamberton and Stephen (2016) have provided a thematic exploration of digital, social, and mobile marketing and called for research on the difference of mobile compared to other digital or social channels; how to effectively use its unique features; understanding mobile practices and consumer goals; and building new theories of mobile behavior. We add to their insights by focusing solely on mobile marketing and covering more recent research.

In computer-mediated environments, four key interactions have been identified: consumer-firm, firm-consumer, consumer-consumer, and firm-firm (Yadav and Pavlou, 2014). Reflecting these interactions, we classify and study papers about mobile marketing under three main themes: (1) the transformation in consumer behavior enabled by the mobile shift in consumers' daily routines; (2) the mobile transformation of existing, and the emergence of new, businesses enabled by mobile platforms; and (3) mobile as an interactive channel together with its interaction and integration with other channels. This framework is depicted in Figure 2:

Figure 2: Conceptual Framework



The left-hand side of the framework depicts how mobile transforms conventional consumers and their behavior along with how consumers interact with each other. The right-hand side outlines how this transformation fuels the transformation of traditional businesses and enables new businesses to emerge. In between, we show the effects of mobile on how businesses approach consumers, its interaction with traditional channels to reach consumers, and how consumers approach businesses on the reverse side. In line with Tong et al. (2019), the 'business to consumer interaction' in our framework contains the 4P's of marketing within the mobile marketing mix. We discuss products and pricing in the mobile apps section, and promotion and place in the mobile promotions and advertising section, respectively.

The remainder of this paper is organized as follows: In the next section, we provide an overview of our data. We then discuss the mobile transformation of the consumer as well as the transformation on the business front. Next, we detail the business to consumer interactions and the interaction of mobile with traditional channels. Finally, we discuss the role of mobile on the consumer to business interaction enabled by interactive channels.

2.1 Data Overview

2.1.1 Identifying Relevant Articles

To identify the articles on mobile marketing published in the last decade, we consulted Erasmus Research Institute's (ERIM) journal rankings.[2] The list consists of two subsets of journals, primary and secondary. We focused on the primary set of journals (marked STAR and P), which contain the top publication outlets in the marketing domain (see Table 1 for the list of journals in the primary set). We visited each journal's database and searched papers published between 2009 and 2019, specifically the ones containing the keyword 'mobile' (using the advanced search option). We identified 211 articles containing the keyword and added those to a database for detailed reading and synthesis.

For each article, we recorded the following information: author name(s), article title, journal, year, and keywords defined by the author(s). Upon a detailed reading of the articles, we first identified whether mobile marketing was the primary focus of the article. Of the 211 articles, 33 included the word 'mobile' but did not focus on mobile marketing or on a topic that bears direct relevance to mobile marketing. These articles were then excluded from further analysis. The remaining 178 articles form the basis of this review (see Appendix for the full list).

Table 1: List of Journals Included in the Review

Name Journal	ISSN	EJL Classification	JCR IF 2017
International Journal of Research in Marketing	0167-8116	STAR	2.593
Journal of Consumer Psychology	1057-7408	STAR	2.809
Journal of Consumer Research	0093-5301	STAR	3.535
Journal of Marketing	0022-2429	STAR	7.338
Journal of Marketing Research	0022-2437	STAR	3.854
Journal of the Academy of Marketing Science	0092-0703	STAR	8.488

[2] See https://www.erim.eur.nl/about-erim/erim-journals-list-ejl/ for the full list.

Name Journal	ISSN	EJL Classification	JCR IF 2017
Marketing Science	0732-2399	STAR	2.794
Journal of Advertising	0091-3367	P	2.880
Journal of Interactive Marketing	1094-9968	P	3.864
Journal of Product Innovation Management	0737-6782	P	4.305
Journal of Retailing	0022-4359	P	5.480
Journal of Service Research	1094-6705	P	6.842
Marketing Letters	0923-0645	P	1.350
Quantitative Marketing and Economics	1570-7156	P	1.000

During this pass, we identified common themes in the mobile marketing literature. These themes, which substantially overlap with the authors assigned keywords (yet offer a more concise categorization) are as follows:[3] (1) mobile marketing and opportunities, (2) mobile consumers (including topics such as privacy concerns, user acceptance, mobile social and reviews), (3) mobile businesses (ranging from mobile services to retailing), (4) mobile apps (games, nongame apps, and pricing of apps), (5) mobile and multi/omni-channel, (6) mobile advertising or promotions, (7) cocreation through mobile, and (8) mobile data. In addition to the variables discussed above, we coded the 'theme(s)' of each article.

Moreover, we coded whether the paper is empirical or conceptual (i.e., whether or not data have been collected and analyzed). Interestingly, we have an equal number of empirical and conceptual papers in the final set. For the empirical articles, we further coded the data collection method as well as the dependent and independent variables. We grouped data collection methods under three main categories: (1) survey-based methods (i.e., surveys and qualitative data), (2) field-based methods (i.e., secondary and field data), and (3) experiment-based methods (i.e., lab and field experiments).

As to the coding of the dependent and independent variables of the empirical

[3] The author-assigned keywords are scattered, they are more comprehensive since they can include the methods and data for each article.

articles, we reduced the large number of seemingly disparate variables down to a reasonable number of categories (without losing sight of their theoretical bases or our need to observe meaningful interrelationships among them). Specifically, we observed a natural division among the dependent variables and coded them accordingly. Some articles focus on user acceptance of, and engagement with, mobile products or channels (referred to as 'user acceptance' and 'user engagement' hereafter), whereas others focus on the performance of the mobile product (referred to as 'product performance' hereafter) or the performance of the brand engaging in mobile activities (referred to as 'brand performance'). Moreover, inspired by the classification in Katsikeas et al. (2016), we further categorize the measures of product and brand performance by considering whether the performance indicator is customer-based (e.g., intention to use a mobile app or the likelihood of recommending a brand that launched its mobile app) or market-based (e.g., app rankings or brand sales).

We classify the large number of independent variables in the empirical articles under five main categories: (1) consumer-related variables, (2) mobile application, channel, or service-related variables, (3) mobile promotion or advertising-related variables, (4) user- generated mobile-content-related variables, and (5) contingency factors (including contextual elements and device, product, market, store, firm, and country characteristics). Table 2 shows the main categories and the subcategories of independent variables, with illustrative examples.

Table 2: Independent Variable (sub)Categories

Main Category	Subcategory	Examples
Consumer-related Variables	Consumer's Prior Behavior/Experience	The nature, extent, intensity, and recency of (mobile) usage
	Consumer Characteristics	Demographics, category spending
	Consumer Traits	Risk acceptance, desire for social contact, coupon proneness, technology readiness
	Consumer Motivation	Search vs. other
	Consumer Location/ Distance/ Proximity	Proximity to other consumers and stores
	Consumer Connectedness	Network features, wireless access
Mobile	Introduction/ Adoption	Introduction or user adoption of a mobile

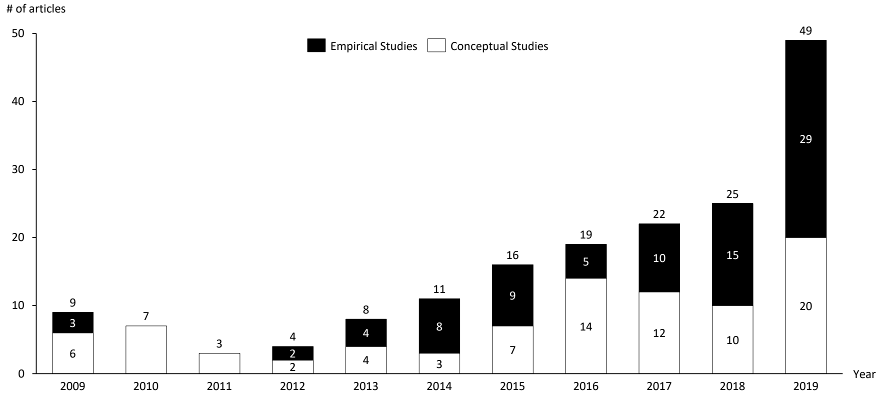
Main Category	**Subcategory**	**Examples**
Application/Channel / Service-related Variables		application, channel, or service
	Characteristics/ Features/ Capabilities	User interaction (e.g., gestures, sounds), User control over information, User specificity (e.g., adaptivity, legibility, personalization, responsiveness), User-to-user interaction (e.g., social interaction), Cost to user (i.e., perceived and actual cost and incentives to reduce), Features (e.g., interactivity, gamification)
	Subjective Evaluation	Usefulness, ease of use, usability, overall attitude, perceived risk
	Quality	Developer reputation, reviews, etc. as quality signals
	Type	Game/ nongame, informational/ experiential, shopping/ nonshopping, fun/ functional
	Life Cycle	Life stages (early vs. late)
Mobile Promotion/ Advertising / Message-related Variables	Exposure	Consumer exposure to a mobile promotion, advertising, or message
	Content and Style	Informative vs. persuasive, informative vs. experiential, intimate vs. not
	Delivery Mode and Frequency	Irritability, interruption, delivery mode and frequency, intrusiveness, format
	Source Credibility	Friends vs. strangers
	Value to User	Discount depth, expiry date, price display format, threshold, coupon order
	Relevance	Customization option, personalization, intimacy, broadcast vs. narrowcast
	User's Subjective Evaluation	Perceived risk, privacy concerns
	Cost to User	Registration costs
	User Control	Control over personal information
User generated mobile-content-related Variables		Trustworthiness of the reviewer, brevity of the review, content (affective vs. concrete)
Contingency Factors	Contextual Factors	Crowdedness, social density, weather, temporal distance, time of day, day of week
	Device Type/ Characteristics	Screen size, haptics
	Product Type/ Characteristics	Utilitarian/hedonic, habitual/impulse, high vs. low involvement
	Market Characteristics	Competitive intensity, complexity
	Store Characteristics	Layout
	Firm Characteristics	Prior experience w/online or mobile, ability to seamlessly integrate mobile
	Country Characteristics	Culture

2.1.2 Evolution of Research on Mobile Marketing

Based on a series of descriptive analyses of the variables coded in the database, we explore the evolution of mobile marketing literature over the last decade.

Figure 3 displays the number of articles published over the years, with a breakdown of conceptual vs. empirical articles. It reveals that the research on mobile marketing has grown at an exponential pace, with an (approximately) fivefold increase in a decade. Although we observed an equal number of conceptual vs. empirical studies in total (88 each), the majority of the work published early on is conceptual.

Figure 3: Distribution of Conceptual vs. Empirical Studies related to Mobile Marketing between 2009-2019



Note: The graph excludes two meta-analyses published between 2009–2019.

Later in the review period, empirical work takes over: the number of empirical studies grows substantially over time, with an approximately tenfold increase over the years. This pattern suggests that the field initially discussed the opportunities and threats that this new channel had to offer, then built up theories and set a research agenda.

The empirical work published early on tests these initial ideas, relying on surveys, qualitative studies, and experiments (see Figure 4). Matching the growth in mobile marketing practices in the industry, the share of empirical studies relying on secondary or field data increased noticeably over time. These studies test the propositions in the early conceptual work and identify additional behavioral regularities to be tested causally.

Causal inference in the mobile marketing domain (i.e., studies relying on laboratory or field experiments) takes off toward the end of the review period.

The transition from the early to later phases is reflected in the publication outlets. Figure 5 displays the distribution of the publication outlet over time, with a breakdown of the journal's FT50 ranking status. We observe that (1) the share of articles published in FT-ranked journals increases over the years and (2) the appearance in FT50 ranked journals coincides with the increased use of experiments and field data. Combined, these observations suggest that specialized journals were the first to cover the innovative and emerging subject of mobile marketing; as its use and importance grew over the years, coverage expanded beyond specialized journals to top-ranked journals.

Figure 4: Distribution of Data Collection Method for Empirical Studies Related to Mobile Marketing between 2009–2019

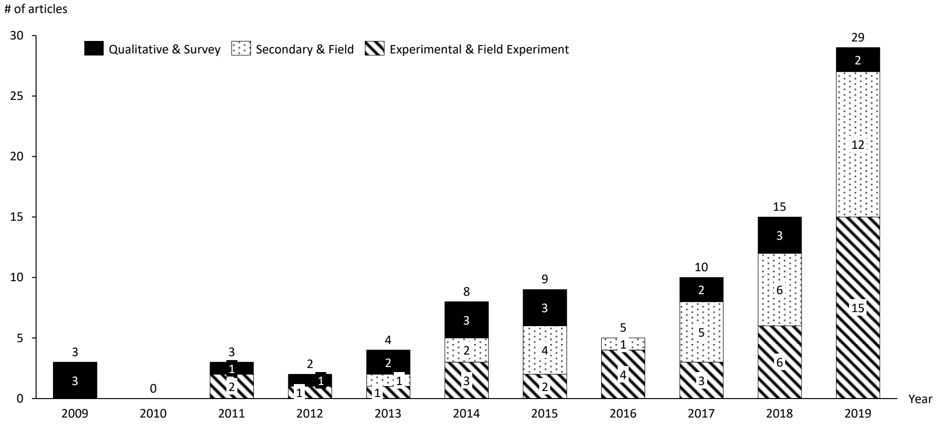


Figure 5: Distribution of Articles in FT-ranked Journals Related to Mobile Marketing between 2009–2019

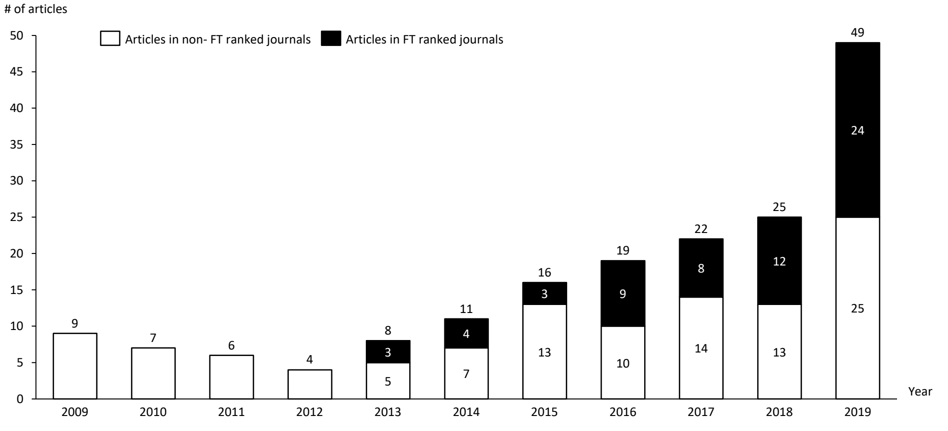


Figure 6: Word Clouds of Titles of Articles related to Mobile Marketing between 2009–2019

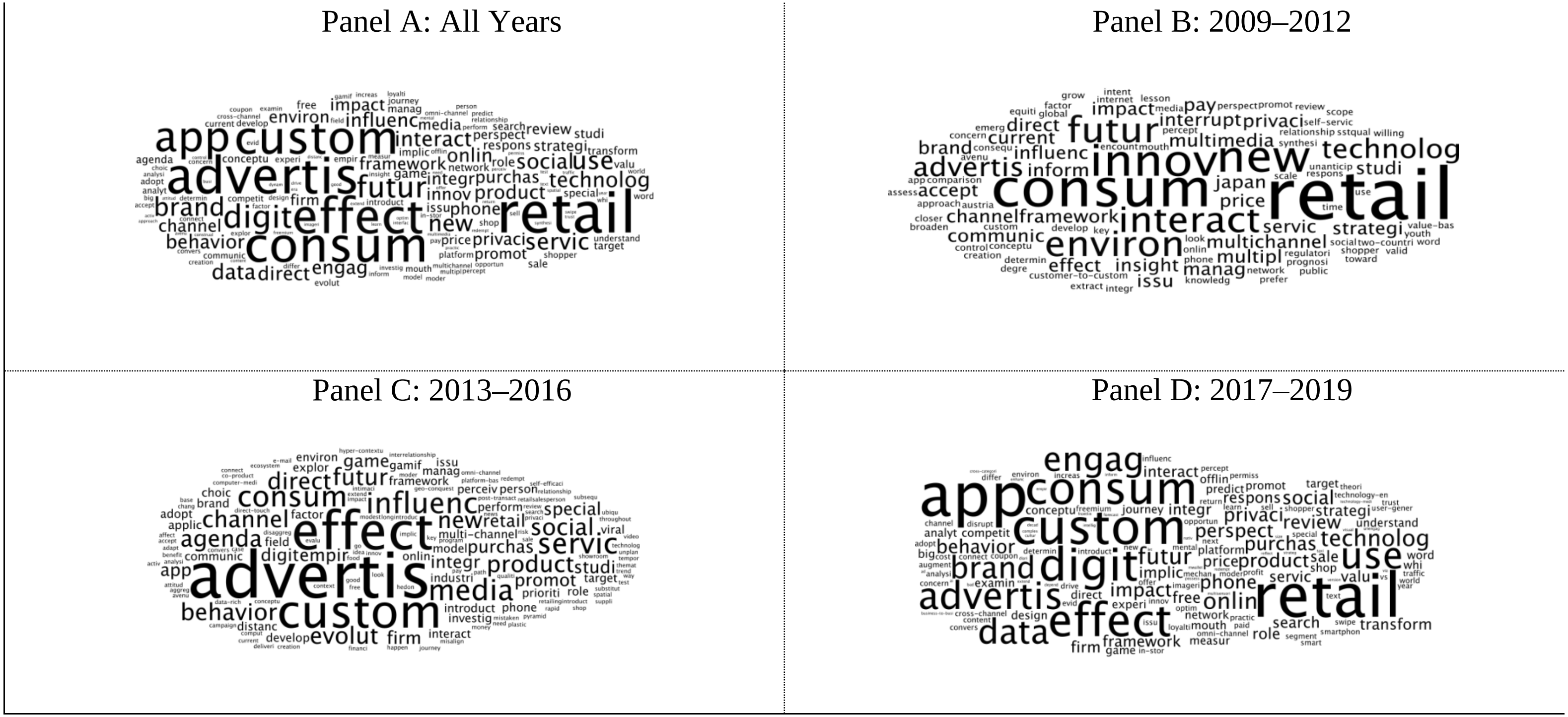
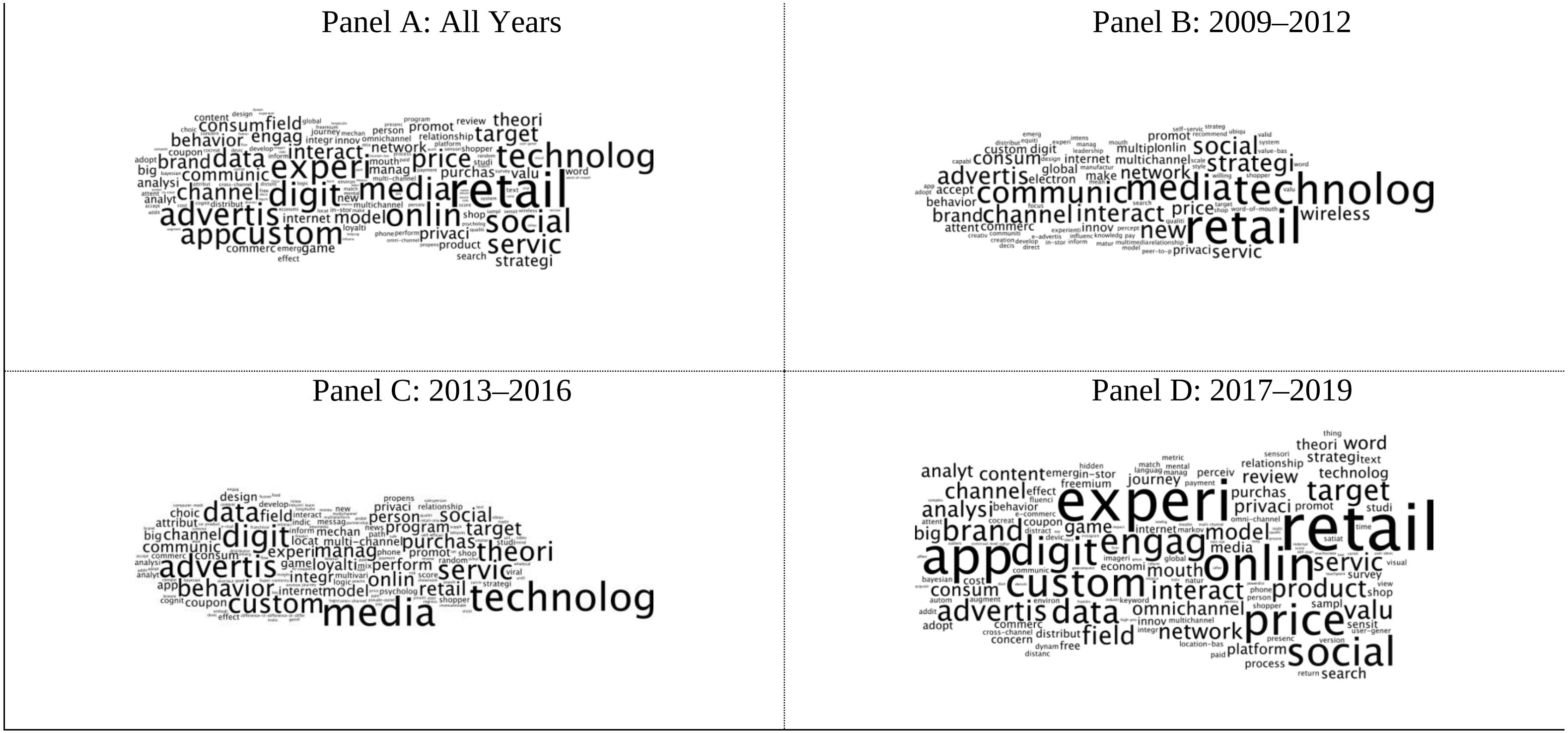


Figure 7: Word Clouds of Author- Assigned Keywords of Articles related to Mobile Marketing between 2009–2019

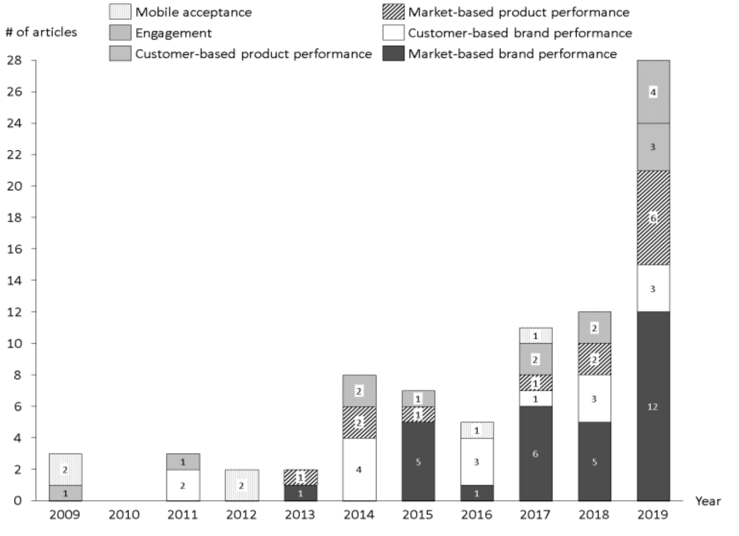


To delineate the prevalent themes of mobile marketing papers and their evolution over time, we explore article titles and author-assigned keywords that contain valuable and concise information about the investigated topics. To that end, we utilize word clouds in three eras over the time span of 2009–2019. Figures 6 and 7 display the resulting word clouds from title words and author-assigned keywords, respectively.

Research published in the first era is mainly concerned with what mobile technology, in general, and this new environment (which offers greater levels of interactivity), in particular, may mean to consumers and how it may impact, specifically, the retailing landscape. These articles, most of which are conceptual pieces, debate the strategic integration of this new and interactive channel to the existing channels of communication (i.e., implications of the changing media landscape) in addition to the existing channels of distribution. Articles published in the second era place greater emphasis on mobile advertising. They explore increased advertising effectiveness through digital data-enabled targeting and examine how mobile technology and mobile marketing influence consumer behavior and the emerging mobile services. The last era of the review period sees a wide variety of topics under investigation. While mobile advertising continues to attract attention in the field, the use of mobile in retailing gains renewed interest. In this period, we observe the emergence of new topics, such as mobile apps and customer engagement, and the use of new data sources, such as online field experiments.

To offer a more refined view of how research on mobile marketing has evolved in the last decade, we investigate the over-time change in the dependent (Figure 8) and the independent variables (Figure 9) used in the empirical articles, and the association between the two (Figure 10). Consistent with our observations, early on the field is primarily interested in the acceptance of, and engagement with, mobile. Mainly using surveys and (to a lesser extent) experiments, marketing scholars have advanced our understanding of which consumers are likely to accept this new channel, why, and under what circumstances. The work published in the early days is dotted with research exploring what drives the performance of a mobile product or a brand engaging in mobile activities. As the field matures, interest in user acceptance wanes, interest in user engagement remains relatively stable, and interest in performance drivers grows substantially.

Figure 8: Distribution of Dependent Variable Categories for Empirical Studies related to Mobile Marketing between 2009–2019



Notes. Ten studies whose dependent variables could not be classified and three theoretical papers are excluded from this figure.

Figure 9: Distribution of Independent Variable Categories for Empirical Studies related to Mobile Marketing between 2009–2019

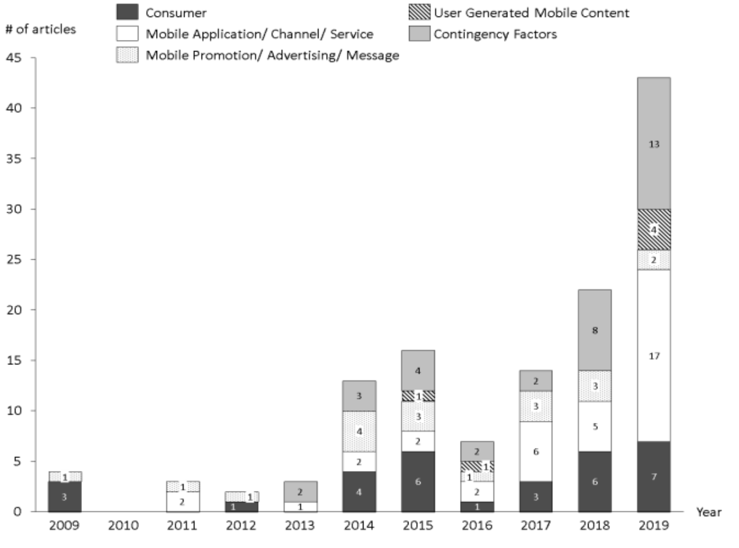
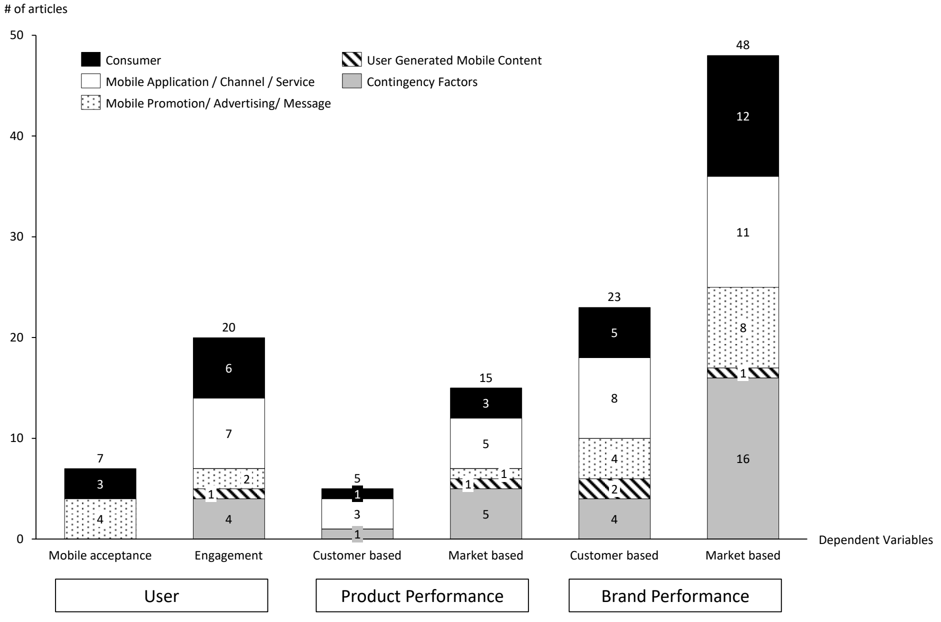


Figure 10: Distribution of Dependent Variable Categories over Independent Variable Categories for Empirical Studies related to Mobile Marketing between 2009–2019



Growing interest in the drivers of a mobile product's performance and, even more so, in the performance of brands embracing the opportunities of mobile technology parallels the growth of mobile marketing practices and the attendant growth in data. The availability and variability of data appears to have enabled the use of different product and brand performance measures, especially market-based measures, and resulted not only in an increased number of studies but also in studies that explore a wide variety of topics.

When one examines the drivers in question closely, it is striking to see that the increased interest in mobile application/ channel/ service characteristics parallels the emergence of interest in mobile apps. In addition, consumer-related factors are investigated through all eras, including the early eras when mobile acceptance dominated other themes. Finally, we observe that the investigation of contingency factors combining multiple product, country, and contextual characteristics also increased over time.

Figure 10 allows us to observe the association between the independent variables (IV) and the dependent variables (DV) in our data set. We observe the presence of mobile application/ channel/ service-related variables in brand and product performances; this indicates that they are popular outlets both as stand-alone products and for well-known brands. For brand performance-related measures, mobile application/ channel/ service-related variables resemble a close to even distribution, whereas for other IV categories, market-based measures dominate. The high share of mobile/ promotion/ advertising/ message related variables for mobile acceptance underlines the importance of customer acceptance in the advertising domain.

2.2 Mobile Transforms the Consumers

In 2018, adults spent 6.3 hours per day on average using digital devices, with an average 3.6 hours spent on mobile devices and two hours spent on desktop/laptop computers and, for the first time, mobile usage was higher than TV usage (226 vs. 216 minutes) (Meeker, 2019). Mobile exceeds well beyond a channel to be a 'digital friend' to today's consumers (Meyer, 2018). The now seamless integration of mobile into the daily routine of consumers has transformed the traditional consumer in many dimensions.

The beginning of the transformation dates back to the emergence and penetration of the iPhone (Muller, 2019). The 'new-to-the-consumer' features of mobile formed the basis of this transformation. Mobile provided consumers with the feeling of 'always being on.' It offered consumers the possibility of smoothly and seamlessly transitioning to and from tasks, performing these tasks effortlessly, and making thorough examinations at virtually no cost. Moreover, mobile provided continuous access to these possibilities due to the portable nature of the device. Also known as the 'ubiquity of mobile' (Okazaki and Mendes, 2013), this 'anytime, anywhere' nature of mobile meant personalized and uninterrupted connection and communication between the consumer and other consumers and/or firms, as well as a steady flow of information to and about consumers.

By removing the dependence on time and space, one may argue that mobile technologies (1) facilitated digital customer engagement practices (such as learning about a brand by consuming brand-generated content, talking about a brand, and providing feedback on a brand) (Eigenraam et al., 2018); and (2) improved the addressability of (interactive) marketing actions (enabled by practices such as thought and activity tracing)

(Deighton and Kornfeld, 2009). Not surprisingly, mobile is considered to play a vital role in consumers' decision journeys directly as well as through interacting with other drivers boosting or dampening their influences (Batra and Keller, 2016).

The ubiquity of mobile and the attendant implications pertaining to the transformation of consumers can be discussed under three headings: (1) acceptance of mobile (technologies) and consumers' privacy concerns; (2) mobile's influence on consumers and their behaviors, and (3) mobile's influence on consumer-to-consumer interactions.

2.2.1 Consumer Acceptance of Mobile and Privacy Concerns

Although mobile marketing presents itself as a fruitful medium with unique opportunities, users' privacy concerns turn it into a double-edged sword. These concerns should be handled with great care to avoid the risk of mistrust or complete shut down by the consumer. The transparency of user data collection and open communication about consumer permission requests have been intensely debated in the literature. Peltier and colleagues (2009) were among the first to call for research on determining which marketing and data collection activities should require consumer permission and identifying the best way to obtain it. Over time, with increased usage of users' mobile locations and app data, we hear more frequent concerns about privacy. The increase in consumer reactions is parallel to the sophistication of information use (i.e., rich data containing sensitive information such as medical or payment history) in marketing tactics (Martin & Murphy, 2016). Consequently, developing an understanding of the risks associated with new marketing agents, such as mobile apps or electronic point of sale systems (Ferrell, 2017), became inevitable.

Whereas some of the extant research sought to uncover which of these new technologies were more susceptible to privacy concerns (e.g., Inman and Nikolova, 2017 explore new retail technologies, such as mobile applications, self-check-out, proximity marketing), others investigated the role privacy concerns play in consumer acceptance of mobile marketing, user intentions, and/or user permissions (Sultan et al., 2009; Kleijnen et al., 2009; Koenigstorfer and Groeppel-Klein, 2012; Krafft et al., 2017). The antecedents (Song et al., 2016; Okazaki et al., 2009) as well as the consequences of privacy concerns

(Okazaki et al., 2009; Pagani and Malacarne 2017; Krafft et al. 2017) have been studied extensively. For example, Song et al. (2016) find that increased personalization increases consumers' privacy risk perceptions in the email domain, which may have similar implications for mobile. Yet, giving consumers more control over their personal information and adding intimate cues extenuate this increase. Consumer acceptance of mobile activities is closely connected to privacy concerns; such that the consequences of privacy concerns are higher regulatory controls in mobile advertising (Okazaki et al., 2009) or not granting permission to marketing activities (Krafft et al., 2017). Researchers have identified, consumer traits (Sultan et al., 2009; Koenigstorfer and Groeppel-Klein, 2012), consumer motivations (including the activities carried out) (Sultan et al., 2009), network effects and types of mobile services (Kleijnen et al., 2009), types of engagement (Pagani and Malacarne, 2017), and cost-benefit trade-offs (Krafft, 2017) as factors that drive consumers' acceptance of different mobile services and applications (see Table 3 for details).

Table 3: Privacy Concerns and Consumer Acceptance of Mobile (Marketing)

Study	**Independent Variable Group**	**Dependent Variable Group**	**Data Collection Method**	**Key Findings**
	Consumer			
Sultan et al. (2009)	Consumer Traits (risk acceptance, personal attachment to mobile) and motivations (accessing and sharing content or providing information)	Customer-based Mobile Acceptance	Survey	*Risk acceptance and personal attachment influence mobile activities (providing information, sharing content, and accessing content), which in turn lead to acceptance of mobile marketing.*
Kleijnen et al. (2009)	Consumer traits, distance/proximity, experience, connectedness	Customer-based Mobile Acceptance	Experimental	*Personal and similarity attributes precede network positions. Type of mobile services moderates the effect on knowledge creation, which significantly influences intentions to use mobile services.*
Koenigstorfer and Groeppel-Klein (2012)	Consumer characteristics (demographics), experience, traits (innovativeness, desire for social contact, technology optimism)	Customer-based Mobile Acceptance	Experimental	*Innovativeness, low desire for social contact, and technology optimism, in interaction with age and gender, determine acceptance of mobile internet, whereas perceived job-related dependency, gender, and age are direct predictors. Ease of use is negatively perceived over time with usage.*
Okazaki et al. (2009)	Consumer experience, Subjective evaluation	Customer-based Mobile Acceptance	Survey	*Prior negative experiences increased privacy concerns and perceived risk, which in turn lead to stricter regulatory controls in mobile advertising.*

Study	Independent Variable Group	Dependent Variable Group	Data Collection Method	Key Findings
	Application/ Advertisement/ Message			
Krafft et al. (2017)	Costs (Registration costs, Intrusiveness, Privacy concerns) / Benefits (Personal Relevance, Entertainment, Incentive, Lottery, Information Control)	Customer-based Mobile Acceptance	Survey	*Significant effects on permission grants, except for monetary incentives and lottery participation. Entertainment value or personal relevance can extenuate the effects of privacy concerns.*
Pagani and Malacarne (2017)	Type (Personal or social interactive engagement)	Customer-based Engagement	Survey	*Personal engagement affects active usage when privacy concern is high, whereas social interactive engagement affects passive usage.*

2.2.2 Mobile's Influence on Consumers and Their Behaviors

The consequences of the integration of mobile practices in consumers' lives is reflected in consumers' updated sense of self and consumer behavior. Belk (2013) enhances the understanding of the consumer in the digital world and discusses how digital consumption -including mobile- impacts the sense of self and possessions. Digital dimensions ranging from dematerialization (reduced number of possessions, i.e., cameras) to distributed memory (due to digital clutter) alter the cues to self-perception and create an updated, extended self-concept. This change can be traced in various new activities (such as the emergence of new vocabularies, practices, self-presentations, and forms of connection (Kozinets, 2019)).

The transformation of consumer behavior is closely related to (1) the new-to-the-consumer features of mobile and (2) the context in which mobile is being used. For instance, the discrepancy between the user interfaces of traditional and mobile media (i.e., the smaller screen in mobile devices) and the way in which users interact with either of the mediums (i.e., click- vs. gesture-based interaction) has created a new avenue for research. To this end, researchers have investigated the effects of touch and swipe gestures on consumer choices and/or evaluations (e.g., Shen et al., 2016; Kerckhove and Pandelaere, 2018).

A related group of articles investigates how (1) mobile interacts with the context and (2) mobile acts as the context to influence behavior. Among the studies we reviewed, Consiglio et al. (2018) explore how contextual factors (e.g., social density) influence mobile activity. The authors show that high social density situations increase mobile sharing behavior. Sciandra et al. (2019) and Grewal et al. (2018), on the other hand, investigate mobile phone use as a contextual factor and show (the mechanism by which) mobile phone use increases (unplanned) purchases in stores (see Table 4 for details).

Table 4: The Effect of Mobile on Consumer Behavior

Study	**Independent Variable Group**	**Dependent Variable Group**	**Data Collection Method**	**Key Findings**
	User Interaction			
Shen et al. (2016)	Direct-Touch Effect	Customer-based Brand Performance	Experimental	*Touch interfaces encourage hedonic choices.*
Kerckhove and Pandelaere (2018)	Object orientation in swiping movements	Customer-based Brand Performance	Experimental	*Object orientations affect swiping movement evaluations.*
	Contextual Factors			
Consiglio et al. (2018)	Social Density	Customer-based Engagement	Experimental	*Through perceived control, high social density increases sharing behavior.*
Sciandra et al. (2019)	Mobile Phone Usage	Brand Market Performance	Experimental & Field Data	*Mobile phone use increases unplanned purchases (higher risk for higher dependence customers).*
Grewal et al. (2018)	Mobile Phone Usage	Brand Market Performance	Field Experiment & Field Data	*Mobile phone use increases purchases through customer loop diversions, & increased store time, & shelf attention.*

2.2.3 Mobile's Influence on Consumers-to-consumer Communication

The intersection of social media with mobile technologies has created a new channel of interest that revolutionizes consumer-to-consumer (C2C) interactions (Libai et al., 2010). The ever-increasing amount of content generated by users and the widespread use of mobile to search for and/or verify information and self-express has attracted scholars' attention to the possible discrepancies between content generated on mobile devices and elsewhere.

Recent research finds that (1) mobile content is affected by consumer proximity, such that experiencing spatial distance (i.e., authoring a review about a geographically distant restaurant vs. proximate one) and temporal distance (i.e., authoring a review after a lengthy delay vs. immediately) jointly affect review positivity by amplifying consumers' high-level construals (Huang et al., 2016); (2) it is different than nonmobile content (Ransbotham et al., 2019; Melumad et al., 2019; Liu et al., 2019b); and (3) this difference is reflected in other users' review accuracy perceptions and purchase intentions (Grewal and Stephen, 2019; Liu et al., 2019b). The findings of these studies collectively suggest that mobile reviews are more positive, shorter, more concrete, less extreme, less 'liked', less specific, more emotional, more trustworthy, and associated with higher purchase intentions (see Table 5 for details).

Table 5: User Generated Mobile Content

Study	Independent Variable Group	Dependent Variable Group	Data Collection Method	Key Findings
	Consumer			
Huang et al. (2016)	Consumer location / distance / proximity	Customer-based Brand Performance	Field Data	*Experiencing spatial and temporal distance jointly affect review positivity by amplifying consumers' high-level construals.*
	Contingency Factors (Device Type / Characteristics)			
Ransbotham et al. (2019)	Mobile / Nonmobile	Customer-based Engagement	Field Data	*Mobile reviews are more affective, more concrete, less extreme, and have lower consumption value (less likes); this relationship increases with consumer learning (over time).*
Melumad et al. (2019)	Smartphone vs. PC	Other (Review Content)	Experimental & Field Data	*Mobile content is briefer, less specific, and more emotional.*
Grewal and Stephen (2019)	Mobile / NonMobile	Brand Market Performance	Experimental & Field Data	*Mobile reviews require more effort, are associated with higher trustworthiness, are perceived to be more accurate, and lead to higher purchase intention (higher effects in skeptical consumers).*
Liu et al. (2019b)	Mobile vs. PC	Brand Market Performance	Field Data	*Consumers use PC's more to read reviews; mobile reviews are more positive, shorter, more concrete, less extreme, less 'liked', less specific, more emotional, trusted more and associated with higher purchase intentions. Price has a larger effect on mobile.*

The studies reviewed up to this point reveal the emergence of an empowered consumer: one who cares about his/her privacy and is willing to exercise control over the information s/he receives and shares; has instant access to detailed information from a wide variety of sources anytime and anywhere; readily shares his/her experiences with others; and talks back to firms. Accordingly, we may argue that the introduction and penetration of mobile technologies has accelerated a change that was already taking place in the role customers play in business-consumer relationships, one that moves them from a traditional recipient role to a whole new multidirectional role (Hennig-Thurau et al., 2010).

In this new role, consumers are in a better position to act as contributors to the pricing-, place-, and product-related decisions of their purchases. Moreover, fueled by the power of mobile, social networks start to assume greater importance and consumers' influence over other consumers' purchase decisions reaches a new high (Kumar, 2015). As discussed subsequently, the empowerment of consumers reshaped the business landscape (e.g., implications for retailing as discussed in Varadarajan et al., 2010) and led to the development of new frameworks for the execution of marketing strategies (e.g., customer engagement strategies, as discussed in Venkatesan, 2017).

2.3 Mobile Transforms Businesses

Mobile being the 'digital friend' of customers translates into a 'continuously-connected customer' from the business perspective. The widespread use of mobile provides businesses with the opportunity to establish deeper connections with their customers in a personalized manner on a digital base that allows for continuous development. Not only does this opportunity enable existing businesses to redesign their models to integrate mobile medium's unique features, but also gives rise to new businesses engineered to unite mobile features with unmet customer needs. New digital business models impact markets and firm performance through the digital transformation of firm strategies, marketing strategy consequences, and marketing capabilities (Verhoef and Bijmolt, 2019).

Companies such as Amazon, Twitter, or Facebook successfully revised their business strategies in a mobile-first manner and grabbed the opportunity to connect further with on-the-go consumers. For example, Facebook states that "substantially all" of its daily and monthly active users access Facebook on mobile devices (Facebook, 2019). Twitter generated 94% of its advertising revenues from mobile devices in the first half of 2019 (Twitter, 2019). Amazon's mobile app users spent, on average, 12.8 billion minutes per month in the Amazon app in 2018, whereas mobile browser users averaged only 2.4 billion minutes on the site (Business Insider, 2019).

In addition to the transformation of existing business models, these unique opportunities, coupled with the mobile infrastructure, have enabled new businesses to correspond to unmet customer needs. Companies such as Uber, Netflix, Spotify, M-Pesa, and Whatsapp have redefined the rules of their existing industries. Driven by dynamism in the business world, recent studies aim at shedding light on this new area. Originating from a customer need where location is key, the case of Uber and mobile hailing technology has been particularly interesting (Muller, 2019; Wang et al., 2019b).

The retailing and service industry landscapes have experienced particularly recognizable changes. Research has explicitly identified the shift in retailing due to mobile by acknowledging mobile commerce as a new media with new communication approaches (Winer, 2009); proposing a framework of mobile marketing in retailing (Shankar et al., 2010); and updating the view of the mobile shopper's journey (to reflect consumer, employee, and organization perspectives) (Shankar et al., 2016). Researchers attribute this shift to technological changes, including social and mobile localization and personalized offerings (Grewal et al., 2012; Kumar, 2018). Section 5 discusses mobile as a new channel within the retailing industry in greater detail.

Additionally, there have been noteworthy changes in the services industry. Ostrom et al. (2015) highlight that this transformation has led to a number of revolutionary services that change how customers serve themselves, and underline the need for a research-based ground (as opposed to trial and error experimentation) to build appropriate business models for new service technologies. Mobile technologies are crucial enablers in this transformation; and the service industry has seen notable examples, especially in the domain of mobile payments. Specifically, mobile financial services lead this transformation. Researchers acknowledge the transformative effect of M-Pesa ("M" for Mobile, "*PESA*", Swahili for cash), a mobile-phone based money transfer service developed by Vodafone, which has had a high impact in less developed African countries. (Reinartz et al., 2011; Wooder and Baker, 2012). Martin and Hilll (2015) discuss technology-based mobile transactions and call for advancements to meet the needs of impoverished consumers, in addition to 'top of the bottom' customers. Another successful example is the HP i-community Mobile Photo Studio, which enables female entrepreneurs in India to leverage digital photography and printing services in rural areas without a physical location or a web address (from which customers would transact with the retailer) (Reinartz et al., 2011).

The transformed landscape of the payment industry evoked researchers to study the behavioral antecedents and consequences of different payment types, offering mixed results on the benefits and risks of mobile payment. The results from a meta-analysis on the factors influencing acceptance of self-service technologies (mobile banking is one of the prominent applications) emphasize the importance of ease of use and usefulness across multiple theories (i.e. Technology acceptance model, unified theory of acceptance and use of technology, compatibility, trialability, risk etc.) (Blut et al., 2016). In addition, Kumar et al. (2019) show that design and content can play a role in the adoption of technologies.

The consequences of mobile payment offer different perspectives. From the seller's perspective, Xu et al. (2020) show that cash payment leads to higher selling prices compared to mobile payments (through mental imagery and increased desire for money), and that this effect is attenuated when sellers focus on the foregone product. From the consumer's perspective, paying with more painful payment forms (i.e., by cash or check) increases emotional attachment to the product and the likelihood of repeat transactions; mobile payment lies in the less painful part of the spectrum (Shah et al., 2016). This finding raises important implications that need careful consideration in transforming mobile payment. From the retailers' point of view, Kumar et al. (2019) show that higher levels of mobile wallet integration impacts customer engagement through an S-curve (a higher increase in customer engagement with higher levels of integration).

Mobile can facilitate solutions to customer needs in other industries. One example is Mobisol, which provides electricity in rural areas of Africa, or EASY, which offers a mobile solution for service technicians at TOYOTA (Helkkula et al., 2018).

In sum, the mobile platform with unique features offers businesses (whether digital/traditional or existing/new) the opportunity to enhance their existing value propositions, or develop unique value propositions, for their current or potential customers.

Successful examples in the business world have echoed in the academic world, and research continues to increase our understanding of the changing landscapes of businesses. The transformations of consumers, as well as of businesses, point to a new-fangled relationship. Next, we examine this new form of relationship by detailing how mobile acts as a new channel for businesses to reach their customers.

2.4 Mobile Connects Businesses to Consumers

Recently, mobile has proven itself to be an efficient digital and interactive channel, changing what, when, where, and how businesses connect with their customers. This section summarizes changing business to consumer interactions by discussing the literature on mobile applications (one of mobile's innovative and unique platforms), the deployment of the mobile channel and its integration with other channels, mobile promotions, and mobile advertising (with an emphasis on geo- and behavioral targeting).

2.4.1 Applications as Mobile Products

Since its emergence in 2008, the mobile applications market has been growing exponentially. Low barriers to entry and relatively lower costs to develop a mobile application, coupled with the opportunity of frequent and deep user engagement, have resulted in an overcrowded market. Developers, ranging from individuals to well-known brands from various industries, have launched their applications in this attractive market. Mobile apps are powerful tools for online marketers to have a close relationship with their customers (Steinhoff et al., 2019) and build loyalty (programs) (Breugelmans et al. 2015; Kumar et al. 2017).

Based on the identity of their developers, it is possible to view apps as stand-alone products (as in the case of mobile gaming) or as a new channel to reach users (as in the case of branded/retailing apps). Mobile applications (whether stand-alone products or new mediums to reach consumers) and their efficacy present as intriguing research opportunities. In order to provide insights for a new market, research on this subject has been mostly empirical and has increased parallel to market growth. The unique features of the app market have given rise to a growing body of research on various aspects of mobile applications, one of which is its new pricing strategies (discussed in Section 5.1.1).

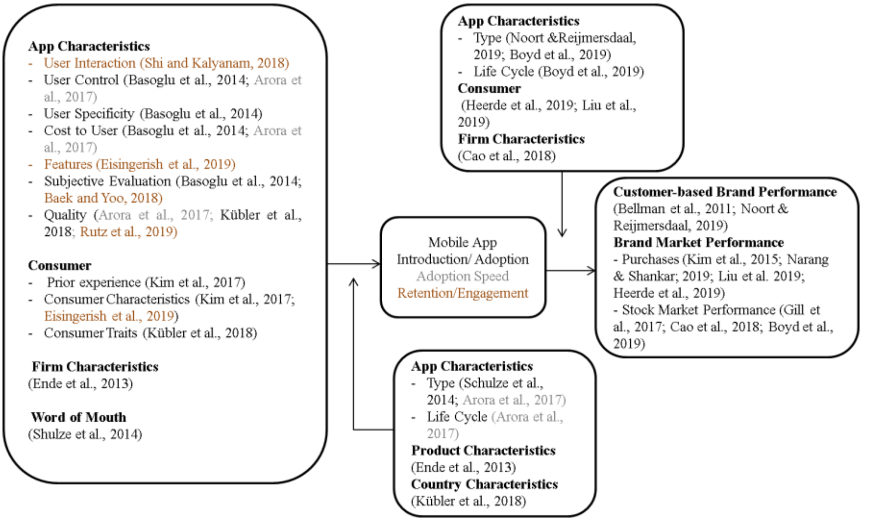
2.4.1.1 Mobile App Pricing Strategies

The structure of the app market allows for different pricing strategies, such as freemium pricing, a concept that has been voiced frequently with digital products. Research on freemium pricing presents mixed results. Different product characteristics and pricing combinations moderate its effect on overall revenue.

While some researchers (Appel et al., 2019b; Li et al., 2019) support the notion that offering free versions can increase revenues, Arora et al. (2017) report lower paid app adoption speed with free apps. This discrepancy can be explained when the boundary conditions are explored. Li et al. (2019) find an increase in sales when the sample quality and the digital product quality are both high. Appel et al. (2019b) indicate that offering a free app version with ads - even if advertisers are not paying for the ads - is profitable: the free version acts as a sample that helps consumers assess their fit with the app. On the other hand, Arora et al. (2017) find a larger decrease in adoption speed of paid apps for hedonic apps (i.e., games) and in the later life stages. Shi et al. (2019) establish optimality for freemium business model for digital products only if the high- and low-end products have asymmetric marginal network effects (such that the high-end product provides larger utility gain from an expansion of the user base). Besides the free samples, Gu et al. (2018) investigate the effects of offering premium alternatives to the freemium line. Their results show an increase in demand for the premium alternative product as well as in overall revenue when the premium alternatives are reasonably priced. The business model choice imposes different routes to awareness and adoption. Bond et al. (2019) show that consumers are more likely to share their opinions of free products than paid products because they feel reciprocity toward the producer; this effect decreased through perceived adoption risk (i.e., low volume and high dispersion of WoM).

Depending on their business models, developers continue to seek either high download figures and/or regular interaction opportunities with users. Consequently, adoption to maximize one-off revenues, retention to enable multiple interactions with users, and engagement to attain deeper interaction with users become important metrics. Therefore, with unique features on a novel platform, whether it is in the domain of branded, retailing, shopping, or gaming apps, researchers have shown interest in determining the antecedents and consequences of mobile app adoption, engagement, and retention. Figure 11 illustrates these relationships, discussed in sections 5.1.2 and 5.1.3.

Figure 11: Conceptual Framework for Mobile Applications



2.4.1.2 Antecedents of App Adoption, Retention, and Engagement

Understanding factors affecting adoption and usage are of critical importance for developers in order to succeed in this crowded and highly competitive market. Research has explored app characteristics (Basoglu et al., 2014; Kübler et al., 2018), consumer characteristics (Kim et al., 2017; Kübler et al., 2018), firm characteristics (Ende et al., 2013), and WoM (Schulze et al., 2014) as antecedents of app adoption. It also explores how these relationships change with app characteristics (Schulze et al., 2014), product characteristics (Ende et al., 2013), and country characteristics (Kübler et al., 2018).

Conditional on adoption, the concepts of retention and engagement start to assume greater importance for app developers. Exploring the drivers of these constructs, Baek and Yoo (2018) find positive effects of branded app usability on app retention. In addition to retention, the concept and measurement of engagement has been intensely debated with the rise of digital products. Engagement, defined as a customer's behavioral manifestations (which have brand or firm focus, beyond purchase, as a result of motivational drivers) (Van Doorn et al., 2010), can have different measures ranging from stay/exist decisions (or time spent on apps) to referral of apps to others. Although there are studies on the effects of app design elements on engagement (Shi and Kalyanam, 2018), the concept of engagement has been particularly important for mobile games (Rutz et al., 2019) and apps with gamification. Gamification, defined as the use of game design elements to enhance nongame goods and services by increasing customer value and encouraging value-creating behaviors such as increased consumption, greater loyalty, engagement, or product advocacy (Hofacker et al. 2016), presents as an efficient tool to enhance customer engagement. Eisingerish et al. (2019) show the effect of gamification principles on engagement through hope and compulsion, whereas Berger et al. (2018) show that highly interactive and optimally challenging gamified interactions enhance self-brand connections through increased emotional and cognitive brand engagement (see Table 6 for details).

Table 6: Antecedents of Mobile Application Adoption, Retention, and Engagement

Study	**Independent Variable**	**Dependent Variable**	**Method**	**Key Findings**
	App Characteristics	*Adoption/Rate of Adoption*		
Basoglu et al. (2014)	Subjective evaluation (usefulness, and ease of use), personalization	Customer-based Brand Performance	Survey	*Adaptivity & information completeness explain ease of use; innovativeness, customization & ease of use explain usefulness; ease of use, usefulness & personalization explain attitude which in turn leads to satisfaction.*
Kübler et al. (2018)	Price, Rating, Volume, Updates	Mobile Product Market Performance	Secondary/ Observa-tional	*Cultural factors & country characteristics moderate the effects of price, valence & volume sensitivity of adoption.*
Arora et al. (2017)	Price (Free version presence), permissions, developer, rating	Mobile Product Market Performance	Field data	*Product type & life cycle of apps moderate the effects of free version presence, developer & rating on paid app adoption. User control over information & quality features are positively associated with paid app adoption.*
Kim et al. (2017)	*Consumer Characteristics* (Online and mobile experience, browsing history)	Brand Market Performance	Field Data	*Online & mobile experience and browsing history of non-shopping apps have positive effects on shopping app adoption.*
Schulze et al. (2014)	*Advertisement/ Message Characteristics* Sharing mechanisms (Source, Delivery Mode and Value of the message)	Mobile Product Market Performance	Field Data	*Product type (utilitarian vs. fun-oriented) moderate the effects of sharing mechanisms on app adoption. Optimum for fun-oriented apps, unsolicited and incentivized broadcast messages from friends are least effective for utilitarian apps.*
Ende et al. (2013)	*Firm characteristics* (Integration and ownership)	Mobile Product Market Performance	Survey	*Novelty of the app moderates the effects of firm characteristics on performance.*

Study	Independent Variable	Dependent Variable	Method	Key Findings
	App Characteristics	*App Retention/ Engagement*		
Baek and Yoo (2018)	*Usability* (User-friendliness, Personalization, Speed, Fun, Omni-presence)	Customer-based Brand Performance	Survey	*Branded app usability has a positive effect on continuance usage and intentions, which in turn increase brand loyalty.*
Shi and Kalyanam (2018)	*Touch Featıres* (Navigational and Informational)	Customer-based Engagement	Field Data	*Informational touch features have an effect on app engagement whereas navigational features do not.*
Rutz et al. (2019)	*Quality Features* (Rating and Volume)	Customer-based Engagement	Secondary	*Quality features increase mean usage of a mobile game*
Eisingerish et al. (2019)	*Gamification Features* (Social interaction, sense of control, goals, progress tracking, rewards, and prompts)	Mobile Product Market Performance	Field Experiment	*Hope positively mediates the relationship between gamification & customer engagement, whereas compulsion may reduce it.*
Berger et al. (2018)	*Gamification Features* (Compulsory play, time pressure)	Customer-based Engagement	Field Data/ Experimen-tal	*Compulsory play decreases emotional brand engagement whereas time pressure decreases cognitive brand engagement; they in turn decrease self-brand connections.*

2.4.1.3 Consequences of App Adoption, Retention, and Engagement

After understanding what drives adoption/retention and engagement, it is important to understand the outcomes. Research has shown the positive effects of app adoption on customer-based outcomes, such as brand attitude or purchase intention (Bellman et al., 2011; Noort & Reijmersdaal, 2019), and on market-based outcomes, such as purchases or stock market performance (Kim et al., 2015; Gill et al., 2017; Cao et al., 2018; Boyd et al., 2019; Liu et al., 2019a; Narang & Shankar, 2019; Van Heerde et al., 2019). However, these effects can vary across apps (Noort &Reijmersdaal, 2019), consumers (Liu et al., 2019a; Van Heerde et al., 2019), and firm characteristics (Cao et al., 2018).

Bellman et al. (2011) and Noort and Reijmersdaal (2019) show that app type moderates the effects of using a branded app on attitudinal outcomes, whereas Kim et al. (2015) show that branded app adoption and usage have an effect on behavioral responses (reflected in purchasing behavior). Grewal et al. (2011) call for research on understanding the effectiveness of mobile applications in the retailing domain; following up on this call, recent research establishes the positive effects of app adoption on the purchasing behavior of customers across channels (Narang and Shankar, 2019) and further explores the moderating effects of customer characteristics (Liu et al., 2019a; Van Heerde et al., 2019).

From firms' perspectives, researchers have established the positive effects of mobile app introductions on annual sales revenues (Gill et al., 2017) and stock market returns (Cao et al., 2018; Boyd et al., 2019). This positive effect increases with customer participation (Gill et al., 2017). For search-related apps (i.e., Home Depot app highlighting its search functions), this effect is more positive for product retailers (vs. service retailers) and small firms (vs. large). For purchase-related apps (i.e., Starbucks app highlighting its purchase functions), this effect is less positive for firms that target younger customers (vs. firms who do not especially target them) (Cao et al., 2018). Moreover, apps emphasizing social-oriented features increase this positive effect, whereas apps emphasizing transaction-oriented features decrease it (Boyd et al., 2019) (see Table 7 for details). Section 5.2 discusses research on the positioning of mobile within the channel mix.

Table 7: Consequences of Mobile Application Adoption, Retention, and Engagement

Study	Independent Variable	Dependent Variable	Method	Key Findings
	Adoption, Retention and Engagement			
Bellman et al. (2011)	Branded app usage	Customer-based Brand Performance	Experimental	*Using apps leads to an increase in brand attitude and a smaller increase in purchase intention, which is larger for informational apps than for experiential apps.*
Noort and Reijmersdaal (2019)	Branded app usage	Customer-based Brand Performance	Experimental/ Field	*An information app enhanced cognitive responses through self-reported elaboration, whereas an entertainment app enhanced affective responses through enjoyment.*
Kim et al. (2015)	Branded app adoption and usage	Brand Market Performance	Field data	*Branded app adoption has a positive effect on purchase behavior that persists for at least six months, which increases with active usage and is cumulative; spending levels increase with repeated usage.*
Narang and Shankar (2019)	Branded retailing app adoption	Brand Market Performance	Field Data	*App adopters buy (and return) more frequently, more items, and spend more compared to nonadopters. Adoption increases online and off-line purchases (36% increase in net monetary value across all channels).*
Liu et al. (2019a)	Branded retailing app adoption	Brand Market Performance	Secondary	*App adopters buy more frequently, more items, and spend more compared to nonadopters; the effects of adoption on order size are stronger for less loyal customers with a lower spending share of high price products.*
Van Heerde et al. (2019)	Branded retailing app adoption	Brand Market Performance	Field Data	*App access generates more incremental value for distant and offline-only customers compared to near and online customers.*

Study	**Independent Variable**	**Dependent Variable**	**Method**	**Key Findings**
Gill et al. (2017)	Business-to-business app adoption	Brand Market Performance	Secondary	*App increased manufacturer's sales revenues and resulted in positive return on engagement initiatives (RoEI), which was higher when buyers created more projects using the app (customer participation).*
Cao et al. (2018)	Branded app introduction announcement	Brand Market Performance	Secondary	*For search-related apps, the market responds more positively to product (vs. service) retailers & to small firms (vs. large). For purchase-related apps, the market responds less positively to firms that target younger customers.*
Boyd et al. (2019)	Branded mobile app introduction announcement	Brand Market Performance	Field	*Branded mobile app introduction announcements increase firm value. Apps emphasizing social-oriented features increase this positive effect (steady over time) whereas apps emphasizing transaction-oriented features decrease it (decrease over time).*

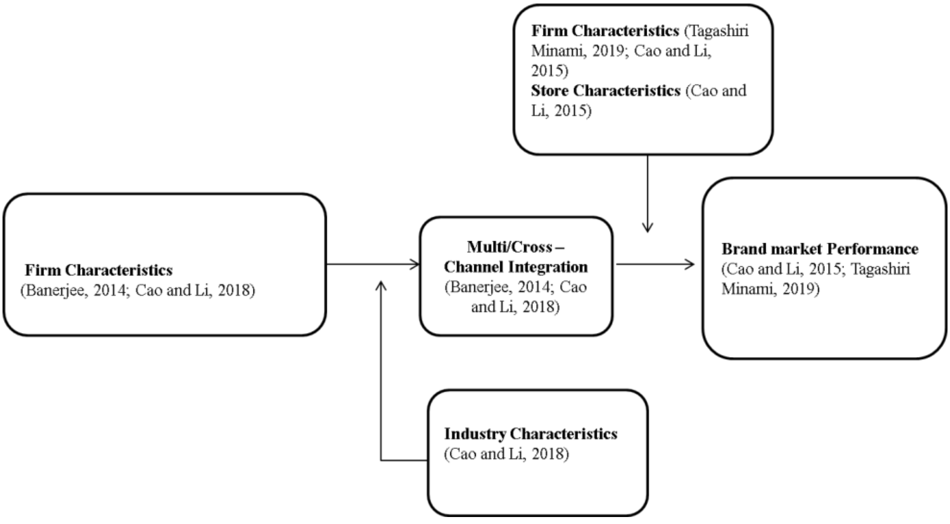
2.4.2. Mobile Channel Deployment and Integration

The proliferation and interaction of channels have given consumers greater control over the time and location of their purchases through different touchpoints (such as web interfaces, mobile applications, and their combinations with different devices). This consumer autonomy implies the emergence of new and personalized customer journeys (Shankar et al., 2011). With the transformation of consumers and businesses, single channel marketing has been replaced by a more complex system with multiple channels. As transition across channels became effortless, the boundaries between channels have become blurry, recently enabling a unified channel front (omni-channel). While this opulence in customer touchpoints presents an opportunity for customers, for businesses it requires a transformation in traditional marketing models and a deeper understanding of these new concepts. This section of the review discusses the interaction of mobile channel with other channels. Specifically, we summarize research that maps mobile within the multichannel environment. Research on the subject falls under three categories: (1) the integration and combination of channels on the firm side; (2) how the interaction of channels affects firm performance; and (3) how consumer behavior varies across channels.

Changes in customer needs and advancements in information technology have given rise to channel multiplicity, which is characterized by multiple information sources and outlets and seamless experiences (Van Bruggen et al., 2010). Consequently, in this new era where channels to reach the consumer have proliferated and transitions among them have become elusive, the decision of whether to add and how to implement a new channel presents as a challenging task for firms. Researchers have thus tried to offer new frameworks for this onset struggle of the firms involving effective multi/omni-channel management (Keller, 2010; Shankar and Yadav, 2010; Van Bruggen et al., 2010). Van Bruggen et al. (2010) discuss channel design and multi-channel management within an evolving channel structure and a broadened view of distribution intensity. Keller (2010) underlines the importance of distribution (metrics are distribution breadth, depth, performance and online findability) while distinguishing between pull and push marketing strategies.

Up to date research on the subject focuses on the drivers (Banerjee, 2014; Cao and Li, 2018) and the impact of cross channel integration on sales growth (Cao and Li, 2015) and cost efficiency (Tagashira and Minami, 2019). Figure 12 illustrates research on this stream in a conceptual framework mapped onto our categorization of independent variables.

Figure 12: Conceptual Framework for Channel to Channel Interactions



Cao and Li (2018) develop a conceptual framework (including technology related factors, organizational characteristics, and environmental context) to identify the drivers of cross-channel integration in a multi-channel environment from an innovation diffusion perspective. The authors find information-technology capabilities and private-label provision to be the most influential drivers. Banerjee (2014) adds the perspectives of the organization, the institutional environment, and the customers and finds that the misalignment between organizational perception, the design of the multichannel system, and customer expectations negatively impacts integration quality. Although scholars establish the positive impact of cross-channel integration on performance (Cao and Li, 2015; Tagashira and Minami, 2019), Cao and Li (2015) find that a firm's online experience and larger physical store presence negatively affect its impact on sales growth, whereas Tagashira and Minami (2019) show that the extent of a retailer's experience with e-commerce and higher in-store service levels reduce its impact on cost efficiency.

In the second research stream, several articles identified the investigation of the interaction of mobile channel with other channels as a relevant topic. Researchers have thus called for research on investigating mobile in relation to other channels in terms of pricing, advertising, content, and information collection and privacy; (Lambrecht et al. 2014), its incremental impact and differences among devices (Kannan et al. 2016); and the effects of using mobile within a store on customer's purchasing behavior and store performance (Verhoef et al., 2015). More specifically, Watson et al. (2015) review the evolution of marketing channels and discuss the role of mobile in disrupting the upstream channel members' dominance. They reveal the concepts of price comparisons, reviews, and easy mobile purchases becoming common place as increased competitive forces. The authors call for research on exploring the most effective strategies for managing hierarchical multichannel structures and mobile disruption on e-commerce channel structures.

Researchers have responded to this call to investigate the effect of mobile channel on other channels and established complementarity of the mobile channel rather than substitution among channels (Xu et al., 2014; Herhausen et al., 2019; Zhang et al., 2019). Xu et al. (2014) find that mobile app adoption increases demand on the corresponding mobile web site visit behavior, indicating complementarity between these two channels. Zhang et al. (2019) find that adding offline to online service platform channels (O2OSP) hurts offline and total profits in the short run, but improves offline and total sales and profits in the long run. Thus, the O2OSP channel can serve as a complement to, rather than a substitute for, the offline channel. Herhausen et al. (2019) propose segmentation based on customers' usage of different touch points in the customer journey in a multichannel environment. The authors identify five segments: (1) store-focused shoppers, (2) pragmatic online shoppers, (3) extensive online shoppers, (4) multiple touchpoint shoppers, and (5) online-to-offline shoppers. These segments differ considerably in their touchpoint and mobile device usage as well as in their search and purchase patterns. The relationships between various loyalty antecedents and customer loyalty differ among the segments. In line with previous research, the authors also suggest complementarity of the mobile channel.

The third stream of research is closely related to the second stream. It investigates how consumer behavior is differentiated across channels. From a brand perspective, Neslin et al. (2014) propose a framework containing firm actions, the consumer's search and choice processes, and consumer learning for the joint study of consumers' decisions of where and what to buy (i.e., channel/ brand combination). In order to further understand the changing scope of consumer behavior, Reinartz et al. (2019) follow a value creation perspective, define new sources of value creation, and list associated perceived customer benefits. The authors state the importance of acknowledging changes in this multichannel environment and give geo-targeting as an example of ‘value ambient embeddedness’ in an embedded communication process. Similarly, Lemon and Verhoef (2016) discuss an integrated process model of customer experience and customer journey by considering the ownership of multiple touch points. Mobile brings in a complexity to the customer journey by adding a new channel and a touch point with unique features. The authors call for research on the use of mobile and touch devices and their impact on customer decisions.

Responding to this call, researchers have investigated how mobile impacts customer decisions (Wang et al., 2015; De Haan et al., 2018). Wang et al. (2015) find that the adoption of mobile shopping has a positive effect on customer purchase behavior. For low-spending customers, the size and rate of their orders increase as they become accustomed to mobile shopping. In addition, the authors find that mobile shoppers tend to use mobile devices to shop for products that they have a history of purchasing. De Haan et al. (2018) find that moving from a more mobile to a less mobile device increases conversion. The authors also find that this effect increases with product category-related perceived risk and product price, and when a customer has less experience with the product category and the online retailer. Their results imply that mobile channel facilitates a consumer’s information search. On a related note, initiated by the search motivations of mobile consumers within conventional stores, a recent phenomenon called ‘showrooming’ emerges. Rapp et al. (2015) investigate the showrooming from the salespeople’s perspective and find negative relationships between perceived showrooming and salesperson self-efficacy and performance, decreased by salesperson coping and cross-selling strategies.

In addition, Verhoef et al. (2017) draw attention to the multidimensionality of connectivity by stating that mobile oriented technologies enable connection with people, objects, and their physical environments. The authors place mobile in the center of omni-channel marketing as it plays an integral role in bringing people together with objects and the physical environment. They call for further research on the long term effectiveness of mobile marketing campaigns. There have been numerous responses to this call, and in section 5.3, we discuss how mobile can help enhance the effectiveness of mobile promotions and advertising.

2.4.3 Mobile Advertising and Promotions

Kumar and Gupta (2016) conjecture that there is/will be an irreversible change in the way customers and firms interact, transact, and engage with each other as mobile rises as the most prominent channel. This irreversible change is most apparent in the ways firms promote/advertise. The use of location data (Liu-Thomkins, 2019), personalization of messages, and interactivity of the communication platforms are the most prominent features of mobile that can be utilized to increase the efficacy of ads and promotions. Hence, researchers propose detailed frameworks in order to reflect the changing landscape of advertising and promotions due to mobile embracement (Grewal et al., 2016; Kumar and Gupta, 2016), and discuss the associated risks and benefits for stakeholders (Andrews et al., 2016a). Because this is a relatively new yet broad area (which has been quite dynamic recently), scholars have called for research on the interrelationships among different forms of ads (i.e., banner, search, mobile, social media ads etc.) (Shankar and Batra, 2009); the gamification of advertising in the digital platforms (Terlutter and Capella, 2013); consumer inferences from and reactions to mobile advertising (Johar, 2016); cultural comparisons (Chang et al., 2019); and the relevance of personalization, time, and location or effectiveness of sales promotion where mobile applications serve as technological enablers (Grewal et al., 2011). In this section, we will first discuss attitudes toward mobile advertising and then review research on the effectiveness of mobile promotions and mobile targeting.

Although early research reveals negative consumer attitudes to mobile advertising (Liu et al., 2012), or lower attitudinal outcomes of advertising exposure (Acquisti and Spiekermann, 2011) over time, studies discover *when* these effects are positive (Bart et al., 2014; Pescher et al., 2014; Osinga et al., 2019). This evolution points back to the transformation in consumer behavior, as mobile secures its place in consumers' daily lives. Acquisti and Spiekermann (2011) show that despite increased brand awareness, consumer willingness to pay for an advertised brand is lower for brands with interruptive advertising. However, Bart et al. (2014) show that mobile display advertising campaigns significantly increased consumers' favorable attitudes and purchase intentions when the products were higher (vs. lower) involvement and utilitarian (vs. hedonic). Interestingly, Osinga et al.

(2019) show that mobile banner ads positively affect offline sales (persistent in the long run) as opposed to online. Finally, Pescher et al. (2014) examine responses to mobile viral ad campaigns closely by separating them into reading, interest, and referral stages and examining each stage in detail.

Digital advertising gives rise to novel concepts such as native advertising (Sahni and Nair, 2019) or keywords advertising (Wang et al., 2019c), whose impacts have been investigated on mobile. Sahni and Nair (2019) do not find any differential effects in advertising format (i.e., native advertising) on user behavior, meaning there are no signs of deception on the user's end due to native advertising. Wang et al. (2019c) find that mobile keywords increase direct sales more compared to online keywords; however, they generate lower indirect sales (see Table 8 for details).

Table 8: Attitudes toward Mobile Advertising

Study	**Independent Variable**	**Dependent Variable**	**Method**	**Key Findings**
Liu et al. (2011)	Mobile promotion content and style, delivery mode and frequency, value	Customer-based Mobile Acceptance	Survey	*Japanese customers are irritated more by mobile advertising compared to Austrian customers. For both markets, determinants of advertising value are infotainment and credibility.*
Acquisti and Spiekermann (2011)	Mobile promotion delivery mode and frequency	Customer-based Brand Performance	Experimental (Conducted on prototype desktop version of a mobile phone game)	*Although brand awareness may be increased, the willingness to pay is lower for advertised brands with interruptive advertising. Providing users with control over the interruptions doesn't mitigate this negative effect.*
Bart et al. (2014)	Product type, mobile promotion content and style	Customer-based Brand Performance	Field experiment	*Mobile display advertising campaigns (banners on mobile web and apps) significantly increased consumers' favorable attitudes and purchase intentions only when the products were higher (vs. lower) involvement and utilitarian (vs. hedonic).*

Study	Independent Variable	Dependent Variable	Method	Key Findings
Pescher et al. (2014)	Mobile promotion value, consumer characteristics, connectedness	Customer-based Engagement	Field experiment	*Three stages of responses to mobile viral ad campaigns are reading, interest, & referral. Entertainment value significantly influences all stages; purposive value significantly influences interest and decision to refer stages, but the reading stage. Tie strength has a negative influence on reading and the decision to refer stages.*
Osinga et al. (2019)	Mobile banner ad exposure	Brand Market Performance	Field experiment	*Mobile banner ads positively affect offline sales –whose impact persists in the long run- whereas the authors find no significant effect on online sale.*
Sahni and Nair (2019)	Delivery mode and frequency (format)	Brand Market Performance	Field experiment (on a mobile restaurant search platform)	*No differential effects of advertising format – native advertising on user behavior meaning no signs of deception on the user's end.*
Wang et al. (2019c)	Delivery mode and frequency (format), Device Type/ Characteristics	Brand Market Performance	Experimental/ Field experiment	*Mobile(vs. online) keyword increase direct sales more, but generate lower indirect sales. Keyword cost lowers the positive effect on direct sales; keyword specificity and cost lowers the negative effect on indirect sales.*

In addition to mobile advertising, mobile promotions and coupons have also provided researchers with ample research opportunities. The effects of several promotion (Danaher et al., 2015; Park et al., 2018) and consumer (Danaher et al., 2015; Mills and Zamudio, 2018) characteristics on redemption probabilities have been researched. Danaher et al. (2015) find coupon characteristics (time and location of delivery, expiry length, etc., and face value, price format) as well as consumer characteristics (previous purchases), product category, and calendar time characteristics (day of the week, time of the day) affect the likelihood of redemption. Mills and Zamudio (2018) investigate consumer response to competing brands' offers. The authors reveal two consumer classes: brand loyal and deal-seeking customers. They find that the coupon-redemption probabilities can differ substantially between these classes. Park et al. (2018) compare the effects of the type of mobile promotions on purchases over time, and find that both price discount and free sample coupons increase customers' purchase likelihood and amount during the coupon redemption period. Previous price discount coupons increase the short-term impact of the current coupons, whereas free sample coupons increase purchase tendency in the long term (see Table 9 for details).

The effectiveness of mobile promotions and/or advertising can be improved by targeting consumers better. In addition to behavioral targeting (based on prior experiences (Fong et al., 2019)), a prevalent concept that has proved useful in increasing the efficacy of both mobile advertising and mobile promotions is location-based (or geo) targeting. The level of personalization that can be achieved using location information has the potential to redefine targeting. Kumar et al. (2017) propose that mobile targeting will be the most important location strategy for retailers (instead of geographic location selection).

Recent research on geo-targeting has investigated the following comprehensive set of scenarios: where geo-targeting is aimed at competitor locations (Fong et al., 2015); when competitor response is present (Chen et al. 2017; Dube et al., 2017); when consumer colocations are considered (Zubcsek et al., 2017); where front traffic and spatial competition are investigated (Wang et al., 2019a); and when the effect of temporal and spatial proximity is dependent on ad type and relevance measure (Goh et al., 2015). In addition, Wakefield and Wakefield (2018) shed light on the consumer behavior side of geo-targeting by using the construal level theory to explain how distance (who (near vs. far social distance), when (near vs. far temporal distance), and where (spatial distance)) influence the price sensitivity and perceived value of the experience services.

Furthermore, the contextual factors surrounding the communication of promotions and advertising has been of interest recently. Several studies have examined the effects of contextual factors, such as physical crowdedness (Andrews et al., 2016b) and weather (Li et al., 2017) on mobile advertising and promotion effectiveness (see Table 9 for details). As the importance of context (when the consumer is approached) has been established, the multiscreening literature has also evolved (see Segijn and Eisend, 2019 for a recent a meta-analysis). Last but not least, Shavitt and Barnes (2019) underline the effects of cultural factors in response to mobile promotions.

Table 9: Mobile Promotions and Targeting

Study	**Independent Variable**	**Dependent Variable**	**Method**	**Key Findings**
Danaher et al. (2015)	Mobile coupon (content & style, delivery frequency, value), consumer (prior behavior, distance), product & calendar time characteristics	Brand Market Performance	Field Experiment	*Coupon characteristics, such as time and location of delivery, expiry length etc., as well as consumer, product, and calendar time characteristics affect redemption likelihood.*
Mills and Zamudio (2018)	Consumer prior experience, traits	Brand Market Performance	Field Experiment	*Consumer response to competing brands' offers is based on two classes: brand loyal customers (80%) using internal reference prices & deal seeking customers using stimulus based prices. Depending on the targeted segment, a $.50 mobile coupon has a redemption probability ranging from 30% to 80%.*
Park et al. (2018)	Delivery mode and frequency (format)	Brand Market Performance	Secondary	*Price discount and free sample coupons increase customers' purchase likelihood & amount during the coupon redemption period. Previous price discount coupons increase the short-term impact of the current coupons on the purchase amount and free sample coupons increases the purchase tendency in the long term.*
Targeting				
Fong et al. (2019)	Consumer prior experience (behavioral targeting)	Mobile Product Market Performance	Field experiment	*Targeted mobile promotions can decrease cross-genre purchases due to decreased search activity of nontargeted products.*

Study	Independent Variable	Dependent Variable	Method	Key Findings
				Targeting to maximize direct promotional response instead of total sales results in less overall revenue.
Fong et al. (2015)	Consumer location/ distance/ proximity, mobile promotion value	Brand Market Performance	Field experiment	*Competitive locational targeting of mobile coupons produced increasing returns to promotional discount depth, whereas targeting the focal location produced decreasing returns to deep discounts, indicating saturation effects and profit cannibalization.*
Dube et al. (2017)	Consumer location/ distance/ proximity; mobile promotion value	Brand Market Performance	Field experiment	*Competing firms can create profits by targeting their competitor's location, but returns to coupons are decreased when competitor also offers targeted mobile coupons.*
Chen et al. (2017)	Consumer location/ distance/ proximity	Brand Market Performance	Theoretical	*A firm's profit can be higher under mobile geo-targeting than uniform or traditional targeted pricing.*
Zubcsek et al. (2017)	Consumer location/ distance/ proximity	Brand Market Performance	Field Experiment	*There's a significant positive relationship between colocated consumers' response to coupons in the same product category.*
Wang et al. (2019a)	Consumer location/ distance/ proximity; industry characteristics	Brand Market Performance	Theoretical	*Higher front traffic is not always favorable to retailers. Considering consumer movements along with competition intensity while adjusting mobile advertising strategies is suggested.*
Goh et al. (2015)	Consumer location/ distance/ proximity; motivation; mobile promotion content and style	Customer-based Engagement	Secondary	*The effect of spatial proximity is dependent on the ad type and the measure used to assess relevance.*
Wakefield &Wakefield (2018)	Consumer location/ distance/ proximity	Customer-based Brand Performance	Field Experiment	*Buyers perceive greater value when the time and location of the event are near, indicating a direct application in the geo-*

Study	Independent Variable	Dependent Variable	Method	Key Findings
				targeting practice customized for the location and time of the purchase.
	Contextual Factors			
Andrews et al. (2016b)	Physical Crowdedness	Brand Market Performance	Field Experiment/ Survey	*Commuters in crowded (vs. noncrowded) subway trains are more likely to respond to a mobile offer by making a purchase. On average, the purchase rates of 2.1% increased to 4.3% when # of people increased from less than two to five per* m^2.
Li et al. (2017)	Weather; mobile promotion content and style	Brand Market Performance	Field Experiment	*Purchase responses to promotions are higher & faster in sunny (vs. cloudy) weather, whereas lower & slower in rainy weather. The prevention frame (vs. neutral) ad copy decreases the positive effect in sunny weather, but increases the initial promotion drop in rainy weather.*

2.5 Mobile Connects Consumers to Businesses

The now seamless integration of social media into the daily lives of users has transformed the traditional relationship models with customers; Malthouse et al. (2013) underline these changes and discuss how traditional customer relationship management needs to adapt to integrate social media. Specifically, the rise of social media (enabled by technological developments) together with the design of the mobile ecosystem have redefined the customer-business relationship. The mostly one-way reach of firms to customers has now turned into a loop; the reverse direction is made effortless by the user’s ability to reach out to firms through interactive channels.

This ‘reaching out’ of customers to firms can present in different forms, such as coproduction, cocreation, or customer feedback; these help slide the balance in favor of the consumer. Bacile et al. (2014) define coproduction as a form of consumer empowerment, disrupting the power balance toward consumers and away from firms by allowing for more consumer assertiveness. The authors show that coproduced mobile promotions increase attitudes toward the communication, coupon proneness, and hence, purchase intent while decreasing perceived risk.

Similarly, Ramaswamy and Ozcan (2018) define digitalized interactive platforms (i.e., Apple's ecosystem) and outline the interactional value creation aspects through them. Users, through reviews and ratings, provide feedback to developer/customers who, in turn, can interact with users through their updates. Apple increases the share of revenue split for developers when a user keeps an app for more than a year. As such, Apple's platform incentivizes app quality and allows developers for continuous development to integrate user feedback. In a first attempt to explore this unique interaction (enabled by the mobile applications platform), Jang and Chung (2015) propose an integrative conceptual framework to investigate interaction activities among customers (C2C), among customers to firms (C2B), and among firms to customers (B2C) on market performance in the mobile applications market. Their results show that C2C and C2B communication activities impact sales and R&D activities. Research can continue exploring the new relationships between customers and firms that have been made readily accessible through mobile.

2.6 Mobile Data

Digitization has considerably increased the amount of available data and created new ways to collect it. Although storing, managing, and mining big data can be challenging for companies, advancements in data and software engineering have yielded fruitful outcomes. Mobile data is a crucial element of the so-called big data and offers unique insights to enhance our understanding of customers. Several papers concede the importance of mobile data usage in marketing research. The proliferation of digital data (where mobile constitutes a crucial role, with unique insights) has been acknowledged by marketing researchers (Wedel and Kannan, 2016; Bradlow et al., 2017; Malthouse and Li, 2017).

With the aim of highlighting the new available sources of mobile data, researchers have proposed novel ways of collecting it, such as mobile diaries (Lovett and Peres, 2018), mobile image data (Klostermann et al., 2018), screencast videography (Kawaf, 2019), or event-based tracking data in a fragmented and anonymous way to protect the privacy of consumers (Kakatkar and Spann, 2019).

Methodological papers, on the other hand, help leverage the use of available data. Feit et al. (2013) follow a Bayesian approach to merge digital individual data with traditional aggregate data, whereas Hui (2017) proposes a Bayesian approach for data augmentation at the individual level to utilize publicly available data. In addition, several papers lay out the utilization of available data sources; Liu-Thompkins and Malthouse (2017) offer a guide on using behavioral data for causal advertising research, whereas Humphreys and Wang (2018) present an overview of automated text analysis for consumer research.

2.7 Conclusion and Future Research

Mobile marketing has gone through a vibrant decade where practice has initiated to blaze the trail based on a trial-based strategy on this relatively new platform. Research in early years, hence, has mostly concentrated on concept/ theory development. Later, experimental and field studies have increased in number, offering empirical validations for developed theories and providing practice with important implications. From where we stand, although the field of mobile marketing seems to be maturing, its digital base allows for continuous developments. Sridhar and Fang (2019) summarize marketing strategy evolving around three D’s as digital, data-rich and developing. Being in the center of a digital, data-rich and open to development space, mobile marketing will continue to evolve in the coming years.

Researchers have identified several future directions for mobile marketing. Of several future research opportunities, the intersection of mobile and social (Grewal et al., 2019); evolving in-store technologies in retailing (Dekimpe, 2019; Grewal et al., 2020); mobile as an enabler of AR configurations (Heller et al., 2019b); and its sensory communication ability (Appel et al., 2019a; Hadi and Valenzuela, 2019; Petit et al., 2019) stand out.

Fueled by the ability to respond to the evolving needs of its users, mobile has literally become an extension of today’s consumers. Mobile applications’ interactive and digital base enables continuous development to keep up with the changing needs of consumers and seize new opportunities. Coupled with mobile-social (which enables instant connection to others and emphasizes social presence), it allows for the integration of new technologies (e.g., AR and VR applications; sensory communications) and keeps mobile applications relevant over time. Research has already started to identify the positive effects of AI on sales (Shankar, 2018) or the positive effects of retail transaction auditory confirmation (RTAC) on trust and purchase intention (Reynolds-McIlnay & Morrin, 2019). Future research should continue shedding light on consumer interactions with the evolving integrated technologies of mobile.

In addition, the landscape of retailing has undergone a substantial change with the redefinition of location of purchases and the availability of geo-targeting. This transformation seems to continue, creating new research avenues to investigate the integration of new technologies to retailing as well as how to effectively manage the multiple evolving channels and their interactions. Finding the right balance between high levels of personalized offerings, while respecting user privacy, has been one of many challenges for brands. Although the acceptance of mobile is established so far, this issue needs to be revisited with the integration of new technologies. Future research should keep recognizing customers' boundaries when it comes to how much they are willing to reveal and at what cost. On the bright side, the ability to connect instantly with users allows for open communication and makes it possible to benefit from user input through customer collaboration (enabled C2B interaction).

Finally, in the larger mobile eco-system, platforms (i.e., mobile application, marketplaces) have gained undeniable and increasing power functioning as a portal to access the valuable mobile user base. Consequently, several brands aim to create a platform by consolidating different features and services to maintain regular engagement opportunities with users. As platform empowerment increases, the concept of when users opt into a platform vs. when disintermediation occurs is a promising research avenue.

Appendix: List of Articles in the Database

Acquisti, A., & Spiekermann, S. (2011). Do Interruptions Pay off? Effects of Interruptive Ads on Consumers' Willingness to Pay. *Journal of Interactive Marketing.* 25(4), 226-240. doi: 10.1016/j.intmar.2011.04.003.

Ailawadi, K., & Farris, P. (2017). Managing Multi- and Omni-Channel Distribution: Metrics and Research Directions. *Journal of Retailing.* 93(1), 120-135. doi: 10.1016/j.jretai.2016.12.003.

Andrews, M., Goehring, J., Hui, S., Pancras, J., & Thornswood, L. (2016a). Mobile Promotions: A Framework and Research Priorities. *Journal of Interactive Marketing.* 34, 15-24. doi: 10.1016/j.intmar.2016.03.004.

Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2016b). Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness. *Marketing Science.* 35(2), 201-340. doi: 10.1287/mksc.2015.0905.

Appel, G., Grewal, L., Hadi, R., & Stephen, A. (2019a). The Future of Social Media in Marketing. *Journal of the Academy of Marketing Science*. 48, 79-95. doi: 10.1007/s11747-019-00695-1.

Appel, G., Libai, B., Muller, E., & Shachar, R. (2019b). On the Monetization of Mobile Apps. *International Journal of Research in Marketing*. 37(1), 93-107. doi: 10.1016/j.ijresmar.2019.07.007

Arora, S., ter Hofstede, F., & Mahajan, V. (2017). The Implications of Offering Free Versions for the Performance of Paid Mobile Apps. *Journal of Marketing*. 81, 62-78. doi: 10.1509/jm.15.0205.

Bacile, T., Ye, C., & Swilley, E. (2014). From Firm-Controlled to Consumer-Contributed: Consumer Co-Production of Personal Media Marketing Communication. *Journal of Interactive Marketing.* 28(2), 117-133. doi: 10.1016/j.intmar.2013.12.001.

Baek, T. H., & Yoo, C. (2018). Branded App Usability: Conceptualization, Measurement, and Prediction of Consumer Loyalty. *Journal of Advertising.* 47, 70-82. doi: 10.1080/00913367.2017.1405755.

Banerjee, M. (2014). Misalignment and Its Influence on Integration Quality in Multichannel Services. *Journal of Service Research*. 17(4), 460-474. doi: 10.1177/1094670514539395.

Bart, Y., Stephen, A. & Sarvary, M. (2014). Which Products Are Best Suited to Mobile Advertising? A Field Study of Mobile Display Advertising Effects on Consumer Attitudes and Intentions. *Journal of Marketing Research*. 51, 270-285. doi: 10.1509/jmr.13.0503.

Barwitz, N., & Maas, P. (2018). Understanding the Omnichannel Customer Journey: Determinants of Interaction Choice. *Journal of Interactive Marketing*. 43, 116-133. doi: 10.1016/j.intmar.2018.02.001.

Basoglu, N., Daim, T., & Polat, E. (2014). Exploring Adaptivity in Service Development: The Case of Mobile Platforms. *Journal of Product Innovation Management*. 31(3), 501-515. doi: 10.1111/jpim.12110.

Batra, R., & Keller, K. (2016). Integrating Marketing Communications: New Findings, New Lessons and New Ideas. *Journal of Marketing*. 80(6), 122-145. doi: 10.1509/jm.15.0419.

Belk, R. (2013). Extended Self in a Digital World. *Journal of Consumer Research*. 40(3), 477-500. doi: 10.1086/671052.

Bellman, S., Potter, R., Treleaven-Hassard, S., Robinson, J., & Varan, D. (2011). The Effectiveness of Branded Mobile Phone Apps. *Journal of Interactive Marketing*. 25(4), 191-200. doi: 10.1016/j.intmar.2011.06.001.

Berger, A., Schlager, T., Sprott, D., & Herrmann, A. (2018). Gamified Interactions: Whether, When, and How Games Facilitate Self–brand Connections. *Journal of the Academy of Marketing Science*. 46, 652–673. doi: 10.1007/s11747-017-0530-0.

Blut, M., Wang, C., & Schoefer, K. (2016). Factors Influencing the Acceptance of Self-Service Technologies: A Meta-Analysis. *Journal of Service Research*. 19(4), 396-416. doi: 10.1177/1094670516662352.

Bond, S., He, S., & Wen, W. (2019). Speaking for "Free": Word of Mouth in Free-and Paid-Product Settings. *Journal of Marketing Research.* 56(2), 276-290. doi: 10.1177/0022243718821957.

Boyd, D., Kannan, P. K., & Slotegraaf, R. (2019). Branded Apps and Their Impact on Firm Value: A Design Perspective. *Journal of Marketing Research*. 56(1), 76-88. doi: 10.1177/0022243718820588.

Bradlow, E., Gangwar, M. & Kopalle, P., & Voleti, S. (2017). The Role of Big Data and Predictive Analytics in Retailing. *Journal of Retailing*. 93(1), 79-95. doi: 10.1016/j.jretai.2016.12.004.

Breugelmans, E., Bijmolt, T., Zhang, J., Basso, L., Dorotic, M., Kopalle, P., Minnema, A., Mijnlieff, W., & Wünderlich, N. (2015). Advancing Research on Loyalty Programs: A Future Research Agenda. *Marketing Letters*. 26, 127-139. doi: 10.1007/s11002-014-9311-4.

Cao, L., & Li, L. (2015). The Impact of Cross-Channel Integration on Retailers’ Sales Growth. *Journal of Retailing*. 91(2), 198-216. doi: 10.1016/j.jretai.2014.12.005.

Cao, L., & Li, L. (2018). Determinants of Retailers’ Cross-channel Integration: An Innovation Diffusion Perspective on Omni-channel Retailing. *Journal of Interactive Marketing*. 44, 1-16. doi: 10.1016/j.intmar.2018.04.003.

Cao, L., Liu, X., & Cao, W. (2018). The Effects of Search-Related and Purchase-Related Mobile App Additions on Retailers’ Shareholder Wealth: The Roles of Firm Size, Product Category, and Customer Segment. *Journal of Retailing*. 94(4), 343-351. doi: 10.1016/j.jretai.2018.08.003.

Chang, C., Lee, W. & Liu-Thompkins, Y. (2019). Advertising in Asia: Theories and

Implications for Practice. *Journal of Advertising*. 48(5), 417-436. doi: 10.1080/00913367.2019.1675103.

Chen, Y., Li, X., & Sun, M. (2017). Competitive Mobile Geo Targeting. *Marketing Science*. 36(5), 645-812. doi: 10.1287/mksc.2017.1030.

Consiglio, I., Deangelis, M., & Costabile, M. (2018). The Effect of Social Density on Word of Mouth. *Journal of Consumer Research*. 45(3), 511–528. doi: 10.1093/jcr/ucy009.

Danaher, P., Smith, M., Ranasinghe, K., & Danaher, T. (2015). Where, When, and How Long: Factors That Influence the Redemption of Mobile Phone Coupons. *Journal of Marketing Research.* 52(5), 710-725. doi: 10.1509/jmr.13.0341.

De Haan, E., Kannan, P. K., Verhoef, P., & Wiesel, T. (2018). Device Switching in Online Purchasing: Examining the Strategic Contingencies. *Journal of Marketing*. 82.(5), 1-19. doi: 10.1509/jm.17.0113.

Deighton, J., & Kornfeld, L. (2009). Interactivity's Unanticipated Consequences for Marketers and Marketing. *Journal of Interactive Marketing.* 23(1), 4-10. doi: 10.1016/j.intmar.2008.10.001.

Dekimpe, M. (2019). Retailing and Retailing Research in the Age of Big Data Analytics. *International Journal of Research in Marketing*. 37(1), 3-14. doi: 10.1016/j.ijresmar.2019.09.001.

Dube, J.P., Fang, Z., Fong, N., & Luo, X. (2017). Competitive Price Targeting with Smartphone Coupons. *Marketing Science.* 36(6), 813-1017. doi: 10.1287/mksc.2017.1042.

Eigenraam, A., Eelen, J., Lin, A., & Verlegh, P. (2018). A Consumer-based Taxonomy of Digital Customer Engagement Practices. *Journal of Interactive Marketing.* 44, 102-121. doi: 10.1016/j.intmar.2018.07.002.

Eisingerich, A., Marchand, A., Fritze, M., & Dong, L. (2019). Hook vs. Hope: How to Enhance Customer Engagement through Gamification. *International Journal of Research in Marketing.* 36(2), 200-214. doi: 10.1016/j.ijresmar.2019.02.003.

Ende, J., Jaspers, F., & Rijsdijk, S. (2013). Should System Firms Develop Complementary Products? A Dynamic Model and an Empirical Test. *Journal of Product Innovation Management.* 30(6), 1178-1198. doi: 10.1111/jpim.12053.

Feit, E., Wang, P., Bradlow, E. & Fader, P. (2013). Fusing Aggregate and Disaggregate Data with an Application to Multi-Platform Media Consumption. *Journal of Marketing Research.* 50(3), 348-364. doi: 10.1509/jmr.11.0431.

Ferrell, O. (2017). Broadening Marketing’s Contribution to Data Privacy. *Journal of the Academy of Marketing Science*. 45, 160-163. doi: 10.1007/s11747-016-0502-9.

Fong, N., Fang, Z., & Luo, X. (2015). GEO-Conquesting: Competitive Locational Targeting of Mobile Promotions. *Journal of Marketing Research.* 52(5), 726-735. doi: 10.1509/jmr.14.0229.

Fong, N., Zhang, Y., Luo, X., & Wang, X. (2019). Targeted Promotions on an E-Book Platform: Crowding Out, Heterogeneity, and Opportunity Costs. *Journal of Marketing Research.* 56(2), 310-323. doi: 10.1177/0022243718817513.

Gielens, K., & Steenkamp, J.B. (2019). Branding in the Era of Digital (Dis)intermediation. *International Journal of Research in Marketing.* 36(3), 367-384. doi: 10.1016/j.ijresmar.2019.01.005.

Gill, M., Sridhar, S., & Grewal, R. (2017). Return on Engagement Initiatives: A Study of a Business-to-Business Mobile App. *Journal of Marketing.* 81(4), 45-66. doi: 10.1509/jm.16.0149.

Goh, K.Y., Chu, J., & Wu, J. (2015). Mobile Advertising: An Empirical Study of Temporal and Spatial Differences in Search Behavior and Advertising Response. *Journal of Interactive Marketing.* 30, 34-45. doi: 10.1016/j.intmar.2014.12.002.

Grewal, D., Ailawadi, K., Gauri, D., Hall, K., Kopalle, P., & Robertson, J. (2011). Innovations in Retail Pricing and Promotions. *Journal of Retailing.* 87(1), 43-52. doi: 10.1016/j.jretai.2011.04.008.

Grewal, D., Roggeveen, A., Compeau, L., & Levy, M. (2012). Retail Value–Based Pricing Strategies: New Times, New Technologies, New Consumers. *Journal of Retailing*. 88(1), 1-6. doi: 10.1016/j.jretai.2011.12.001.

Grewal, D., Bart, Y., Spann, M., & Zubcsek, P. (2016). Mobile Advertising: A Framework and Research Agenda. *Journal of Interactive Marketing.* 34, 3-14. doi: 10.1016/j.intmar.2016.03.003.

Grewal, D., Roggeveen, A., & Nordfält, J. (2017). The Future of Retailing. *Journal of Retailing.* 93(1), 1-6. doi: 10.1016/j.jretai.2016.12.008.

Grewal, D., Ahlbom, C.P., Beitelspacher, L., Noble, S., & Nordfält, J. (2018). In-Store Mobile Phone Use and Customer Shopping Behavior: Evidence from the Field. *Journal of Marketing.* 82(4), 102-126. doi: 10.1509/jm.17.0277.

Grewal, D., Hulland, J., Kopalle, P., & Karahanna, E. (2019). The Future of Technology and Marketing: A Multidisciplinary Perspective. *Journal of the Academy of Marketing Science.* 48, 1-8. doi: 10.1007/s11747-019-00711-4.

Grewal, D., Noble, S., Roggeveen, A., & Nordfält, J. (2020). The Future of In-store Technology. *Journal of the Academy of Marketing Science*. 48, 96-113. doi: 10.1007/s11747-019-00697-z.

Grewal, L., & Stephen, A. T. (2019). In Mobile We Trust: The Effects of Mobile Versus Nonmobile Reviews on Consumer Purchase Intentions. *Journal of Marketing Research*, 56(5), 791–808. doi: 10.1177/0022243719834514.

Gu, X., Kannan, P. K., & Ma, L. (2018). Selling the Premium in Freemium. *Journal of Marketing.* 82(6), 10-27. doi: 10.1177/0022242918807170.

Hadi, R., & Valenzuela, A. (2019). Good Vibrations: Consumer Responses to Technology-Mediated Haptic Feedback. *Journal of Consumer Research*. 47(2), 256–271. doi: 10.1093/jcr/ucz039.

Helkkula, A., Kowalkowski, C., & Tronvoll, B. (2018). Archetypes of Service Innovation: Implications for Value Cocreation. *Journal of Service Research.* 21(3), 284-301. doi: 10.1177/1094670517746776.

Heller, J., Chylinski, M., De Ruyter, K., Mahr, D., & Keeling, D. (2019a). Let Me Imagine That for You: Transforming the Retail Frontline Through Augmenting Customer Mental Imagery Ability. *Journal of Retailing.* 95(2), 94-114. doi: 10.1016/j.jretai.2019.03.005.

Hennig-Thurau, T., Malthouse, E., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The Impact of New Media on Customer Relationships. *Journal of Service Research.* 13(3), 311-330. doi: 10.1177/1094670510375460.

Herhausen, D., Kleinkercher, K., Verhoef, P.C., Emrich, O., & Rudolph, T. (2019). Loyalty Formation for Different Customer Journey Segments. *Journal of Retailing.* 95(3), 9-29. doi: 10.1016/j.jretai.2019.05.001

Hofacker, C., De Ruyter, K., Lurie, N., Manchanda, P., & Donaldson, Je. (2016). Gamification and Mobile Marketing Effectiveness. *Journal of Interactive Marketing.* 34, 25-36. doi: 10.1016/j.intmar.2016.03.001.

Huang, N., Burtch, G., Hong, Y., & Polman, E. (2016). Effects of Multiple Psychological Distances on Construal and Consumer Evaluation: A Field Study of Online Reviews. *Journal of Consumer Psychology.* 26(4), 474-482. doi: 10.1016/j.jcps.2016.03.001.

Hui, S. (2017). Understanding Repeat Playing Behavior in Casual Games Using a Bayesian Data Augmentation Approach. *Quantitative Marketing and Economics.* 15, 29-55. doi: 10.1007/s11129-017-9180-2.

Hui, S., Inman, J., Huang, Y., & Suher, J. (2013). The Effect of In-Store Travel Distance on Unplanned Spending: Applications to Mobile Promotion Strategies. *Journal of Marketing*. 77(2), 1-16. doi: 10.2307/23487410.

Humphreys, A., & Wang, R. (2018). Automated Text Analysis for Consumer Research. *Journal of Consumer Research.* 44(6), 1274-1306. doi: 10.1093/jcr/ucx104.

Inman, J., & Nikolova, H. (2017). Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns. *Journal of Retailing.* 93(1), 7-28. doi: 10.1016/j.jretai.2016.12.006.

Jang, S., & Chung, J. (2015). How Do Interaction Activities among Customers and between Customers and Firms Influence Market Performance and Continuous Product Innovation? An Empirical Investigation of the Mobile Application Market. *Journal of Product Innovation Management.* 32(2), 183-191. doi: 10.1111/jpim.12170.

Johar, G. (2016). Mistaken Inferences from Advertising Conversations: A Modest Research Agenda. *Journal of Advertising.* 45(3), 318-325. doi: 10.1080/00913367.2016.1217810.

Kahn, B. (2017). Using Visual Design to Improve Customer Perceptions of Online Assortments. *Journal of Retailing.* 93(1), 29-42. doi: 10.1016/j.jretai.2016.11.004.

Kakatkar, C., & Spann, M. (2019). Marketing Analytics Using Anonymized and

Fragmented Tracking Data. 36(1), 117-136. *International Journal of Research in Marketing.* doi: 10.1016/j.ijresmar.2018.10.001.

Kannan, P. K., Reinartz, W., & Verhoef, P. (2016). The Path to Purchase and Attribution Modeling: Introduction to Special Section. *International Journal of Research in Marketing.* 33(3), 449-456. doi: 10.1016/j.ijresmar.2016.07.001.

Kannan, P. K., & Li, A. (2017). Digital Marketing: A Framework, Review And Research Agenda. *International Journal of Research in Marketing.* 34(1), 22-45. doi: 10.1016/j.ijresmar.2016.11.006.

Kawaf, F. (2019). Capturing Digital Experience: The Method of Screencast Videography. *International Journal of Research in Marketing.* 36(2), 169-184. doi: 10.1016/j.ijresmar.2018.11.002.

Keller, K. (2010). Brand Equity Management in a Multichannel, Multimedia Retail Environment. *Journal of Interactive Marketing.* 24(2), 58-70. doi: 10.1016/j.intmar.2010.03.001.

Kerckhove, A., & Pandelaere, M. (2018). Why Are You Swiping Right? The Impact of Product Orientation on Swiping Responses. *Journal of Consumer Research*. 45(3), 633–647. doi: 10.1093/jcr/ucy013.

Kim, M., Kim, J., Choi, J., & Trivedi, M. (2017). Mobile Shopping Through Applications: Understanding Application Possession and Mobile Purchase. *Journal of Interactive Marketing.* 39, 55–68. doi: 10.1016/j.intmar.2017.02.001

Kim, S. J., Wang, R., & Malthouse, E. (2015). The Effects of Adopting and Using a Brand's Mobile Application on Customers' Subsequent Purchase Behavior. *Journal of Interactive Marketing*. 31, 28-41. doi: 10.1016/j.intmar.2015.05.004.

Kleijnen, M., Lievens, A., De Ruyter, K., & Wetzels, M. (2009). Knowledge Creation Through Mobile Social Networks and Its Impact on Intentions to Use Innovative Mobile Services. *Journal of Service Research.* 12(1), 15-35. doi: 10.1177/1094670509333238.

Klostermann, J., Plumeyer, A., Böger, D., & Decker, R. (2018). Extracting Brand Information From Social Networks: Integrating Image, Text, And Social Tagging Data. *International Journal of Research in Marketing.* 35(4), 538-556. doi: 10.1016/j.ijresmar.2018.08.002.

Koenigstorfer, J., & Groeppel-Klein, A. (2012). Consumer Acceptance of the Mobile Internet. *Marketing Letters.* 23, 917-928. doi: 10.1007/s11002-012-9206-1.

Kozinets, R. V. (2019). Consuming Technocultures: An Extended JCR Curation. *Journal of Consumer Research.* 46(3), 620–627. doi: 10.1093/jcr/ucz034.

Kozlenkova, I., Hult, G. T. M., Lund, D., Mena, J., & Kekec, P. (2015). The Role of Marketing Channels in Supply Chain Management. *Journal of Retailing.* 91(4), 586-609. doi: 10.1016/j.jretai.2015.03.003.

Krafft, M., Arden, C., & Verhoef, P. (2017). Permission Marketing and Privacy Concerns - Why Do Customers (Not) Grant Permissions?. *Journal of Interactive Marketing*. 39, 39-54 doi: 10.1016/j.intmar.2017.03.001.

Kumar, V. (2015). Evolution of Marketing as a Discipline: What Has Happened and What to Look Out For. *Journal of Marketing.* 79(1), 1-9. doi: 10.1509/jm.79.1.1.

Kumar, V. (2018). Transformative Marketing: The Next 20 Years. *Journal of Marketing*. 82(4), 1-12. doi: 10.1509/jm.82.41.

Kumar, V., & Gupta, S. (2016). Conceptualizing the Evolution and Future of Advertising. *Journal of Advertising.* 45(3), 302-317. doi: 10.1080/00913367.2016.1199335.

Kumar, V., Keller, K., & Lemon, K. (2016). Introduction to the Special Issue—Mapping the Boundaries of Marketing: What Needs to Be Known. *Journal of Marketing.* 80(6), 1-5. doi: 10.1509/jm.80.6.1.

Kumar, V., Anand, A., & Song, H. (2017). Future of Retailer Profitability: An Organizing Framework. *Journal of Retailing.* 93(1), 96-119. doi: 10.1016/j.jretai.2016.11.003.

Kumar, V., Nim, N., & Sharma, A. (2019). Driving Growth of Mwallets in Emerging Markets: a Retailer's Perspective. *Journal of the Academy of Marketing Science*. 47, 747–769. doi: 10.1007/s11747-018-0613-6.

Kübler, R., Pauwels, K., Yildirim, G., & Fandrich, T. (2018). App Popularity: Where in the World Are Consumers Most Sensitive to Price and User Ratings?. *Journal of Marketing.* 82(5), 20-44. doi: 10.1509/jm.16.0140.

Lamberton, C., & Stephen, A. (2016). A Thematic Exploration of Digital, Social Media, and Mobile Marketing Research's Evolution from 2000 to 2015 and an Agenda for Future Research. *Journal of Marketing.* 80(6), 146-172. doi: 10.1509/jm.15.0415.

Lambrecht, A., Goldfarb, A., Bonatti, A., Ghose, A., Goldstein, D., Lewis, R., Rao, A., Sahni, N., & Yao, S. (2014). How Do Firms Make Money Selling Digital Goods Online?. *Marketing Letters.* 25, 331-341. doi: 10.1007/s11002-014-9310-5.

Lemon, K., & Verhoef, P. (2016). Understanding Customer Experience throughout the Customer Journey. *Journal of Marketing.* 80(6), 69-96. doi: 10.1509/jm.15.0420.

Li, A., Jain, S., & Kannan, P. K. (2019). Optimal Design of Free Samples for Digital Products and Services. *Journal of Marketing Research.* 56(3), 419-438. doi: 10.1177/0022243718823169.

Li, C., Luo, X., Zhang, C., & Wang, X. (2017). Sunny, Rainy, and Cloudy with a Chance of Mobile Promotion Effectiveness. *Marketing Science*. 36(5), 645-812. doi: 10.1287/mksc.2017.1044.

Libai, B., Bolton, R., Bügel, M., De Ruyter, K., Götz, O., Risselada, H., & Stephen, A. (2010). Customer-to-Customer Interactions: Broadening the Scope of Word of Mouth Research. *Journal of Service Research.* 13(3), 267-282. doi: 10.1177/1094670510375600.

Lin, C., & Hsieh, P. L. (2011). Assessing the Self-service Technology Encounters: Development and Validation of SSTQUAL Scale. *Journal of Retailing.* 87(2), 194-206. doi: 10.1016/j.jretai.2011.02.006.

Liu, C., Sinkovics, R., Sinkovics, N., & Haghirian, P. (2012). Determinants of Consumer Perceptions toward Mobile Advertising - A Comparison between Japan and Austria. *Journal of Interactive Marketing.* 26(1), 21-32. doi: 10.1016/j.intmar.2011.07.002.

Liu, H., Lobschat, L., Verhoef, P., & Zhao, H. (2019a). App Adoption: The Effect on Purchasing of Customers Who Have Used a Mobile Website Previously. *Journal of Interactive Marketing.* 47, 16-34. doi: 10.1016/j.intmar.2018.12.001.

Liu, X., Lee, D., & Srinivasan, K. (2019b). Large-Scale Cross-Category Analysis of Consumer Review Content on Sales Conversion Leveraging Deep Learning. *Journal of Marketing Research.* 56(6), 918-943. doi: 10.1177/0022243719866690.

Liu-Thompkins, Y. (2019). A Decade of Online Advertising Research: What We Learned and What We Need to Know. *Journal of Advertising.* 48(1), 1-13. doi: 10.1080/00913367.2018.1556138.

Liu-Thompkins, Y., & Malthouse, E. (2017). A Primer on Using Behavioral Data for Testing Theories in Advertising Research. *Journal of Advertising.* 46(1), 213-225. doi: 10.1080/00913367.2016.1252289.

Lovett, M. J., & Peres, R. (2018). Mobile Diaries – Benchmark Against Metered Measurements: An Empirical Investigation. *International Journal of Research in Marketing.* 35(2), 224-241. doi: 10.1016/j.ijresmar.2018.01.002.

Malthouse, E., & Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing Customer Relationships in the Social Media Era: Introducing the Social CRM House. *Journal of Interactive Marketing.* 27(4), 270–280. doi: 10.1016/j.intmar.2013.09.008.

Malthouse, E., & Li, H. (2017). Opportunities for and Pitfalls of Using Big Data in Advertising Research. *Journal of Advertising*. 46(2), 227-235. doi: 10.1080/00913367.2017.1299653.

Malthouse, E., & Shankar, V. (2009). A Closer Look into the Future of Interactive Marketing. *Journal of Interactive Marketing*. 23(2), 105-107. doi: 10.1016/j.intmar.2009.02.008.

Marchand, A., & Hennig-Thurau, T. (2013). Value Creation in the Video Game Industry: Industry Economics, Consumer Benefits, and Research Opportunities. *Journal of Interactive Marketing.* 27(3),141-157. doi: 10.1016/j.intmar.2013.05.001.

Martin, K., & Hill, R. (2015). Saving and Well-Being at the Base of the Pyramid. *Journal of Service Research.* 18(3), 405-421. doi: 10.1177/1094670514563496.

Martin, K., & Murphy, P. (2016). The Role of Data Privacy in Marketing. *Journal of the* Academy of Marketing Science. 45, 135–155. doi: 10.1007/s11747-016-0495-4.

Mäkinen, S.J., Kanniainen, J., & Peltola, I. (2014). Investigating Adoption of Free Beta Applications in a Platform-Based Business Ecosystem. *Journal of Product Innovation Management.* 31(3), 451-465. doi: 10.1111/jpim.12107.

Melumad, S., Inman, J., & Pham, M. (2019). Selectively Emotional: How Smartphone Use Changes User-Generated Content. *Journal of Marketing Research.* 56(2), 259-275. doi: 10.1177/0022243718815429.

Meyer, R. (2018). Reflections on “Transformative Marketing: The Next 20 Years”. *Journal of Marketing.* 82(4), 13-14. doi: 10.1509/jm.82.42.

Mills, P., & Zamudio, C. (2018). Scanning For Discounts: Examining The Redemption Of Competing Mobile Coupons. *Journal of the Academy of Marketing Science*. 46(5), 964-982. doi: 10.1007/s11747-018-0592-7.

Muller, E. (2019). Delimiting Disruption: Why Uber Is Disruptive, But Airbnb Is Not. *International Journal of Research in Marketing.* 37(1), 43-55. doi: 10.1016/j.ijresmar.2019.10.004.

Narang, U., & Shankar, V. (2019). Mobile App Introduction and Online and Offline Purchases and Product Returns. *Marketing Science.* 38(5), 733-912. doi: 10.1287/mksc.2019.1169.

Neslin, S., Jerath, K., Bodapati, A., Bradlow, E., Deighton, J., Gensler, S., Lee, L., Montaguti, E., Telang, R., Venkatesan, R., Verhoef, P., & Zhang, Z. (2014). The Interrelationships Between Brand and Channel Choice. *Marketing Letters.* 25, 319-330. doi: 10.1007/s11002-014-9305-2.

Noort, G., & Reijmersdal, E. (2019). Branded Apps: Explaining Effects of Brands' Mobile Phone Applications on Brand Responses. *Journal of Interactive Marketing.* 45, 16-26. doi: 10.1016/j.intmar.2018.05.003.

Okazaki, S., Li, H., & Hirose, M. (2009). Consumer Privacy Concerns and Preference for Degree of Regulatory Control. *Journal of Advertising.* 38(4), 63-77. doi: 10.2753/JOA0091-3367380405.

Okazaki, S., & Mendez, F. (2013). Perceived Ubiquity in Mobile Services. *Journal of Interactive Marketing.* 27(2), 98-111. doi: 10.1016/j.intmar.2012.10.001.

Osinga, E., Zevenbergen, M., & Zuijlen, M. (2019). Do Mobile Banner Ads Increase Sales? Yes, in the Offline Channel. *International Journal of Research in Marketing.* 36(3), 439-453. doi: 10.1016/j.ijresmar.2019.02.001.

Ostrom, A., Parasuraman, A. P., Bowen, D., Patrício, L., & Voss, C. (2015). Service Research Priorities in a Rapidly Changing Context. *Journal of Service Research.* 18(2), 127-159. doi: 10.1177/1094670515576315.

Pagani, M., & Malacarne, G. (2017). Experiential Engagement and Active vs. Passive Behavior in Mobile Location-based Social Networks: The Moderating Role of Privacy. *Journal of Interactive Marketing.* 37, 133-148. doi: 10.1016/j.intmar.2016.10.001.

Park, C. H., Park, Y.H., & Schweidel, D. (2018). The Effects of Mobile Promotions on Customer Purchase Dynamics. *International Journal of Research in Marketing*. 35(3), 453-470. doi: 10.1016/j.ijresmar.2018.05.001.

Peltier, J., Milne, G., & Phelps, J. (2009). Information Privacy Research: Framework for Integrating Multiple Publics, Information Channels, and Responses. *Journal of Interactive Marketing.* 23(2), 191-205. doi: 10.1016/j.intmar.2009.02.007.

Pescher, C., Reichhart, P., & Spann, M. (2014). Consumer Decision-making Processes in Mobile Viral Marketing Campaigns. *Journal of Interactive Marketing*. 28(1), 43-54.

doi: 10.1016/j.intmar.2013.08.001.

Petit, O., Velasco, C., & Spence, C. (2019). Digital Sensory Marketing: Integrating New Technologies Into Multisensory Online Experience. *Journal of Interactive Marketing.* 45, 42-61. doi: 10.1016/j.intmar.2018.07.004.

Ramaswamy, V., & Ozcan, K. (2018). Offerings as Digitalized Interactive Platforms: A Conceptual Framework and Implications. *Journal of Marketing.* 82(4), 19-31. doi: 10.1509/jm.15.0365.

Ransbotham, S., Lurie, N., & Liu, H. (2019). Creation and Consumption of Mobile Word of Mouth: How Are Mobile Reviews Different?. *Marketing Science.* 38(5), 733-912. doi: 10.1287/mksc.2018.1115.

Rapp, A., Baker, T., Bachrach, D., Ogilvie, J., & Beitelspacher, L. (2015). Perceived Customer Showrooming Behavior and the Effect on Retail Salesperson Self-Efficacy and Performance. *Journal of Retailing.* 91(2), 358-369. doi: 10.1016/j.jretai.2014.12.007.

Ratchford, B. (2015). Some Directions for Research in Interactive Marketing. *Journal of Interactive Marketing.* 29, 5-7. doi: 10.1016/j.intmar.2015.01.001.

Reinartz, W., Dellaert, B., Krafft, M., Kumar, V. & Varadarajan, R. (2011). Retailing Innovations in a Globalizing Retail Market Environment. *Journal of Retailing.* 87, 53-66. doi: 10.1016/j.jretai.2011.04.009.

Reinartz, W., Wiegand, N., Imschloss, M. (2019). The Impact of Digital Transformation on the Retailing Value Chain. *International Journal of Research in Marketing.* 36(3), 350-366. doi: 10.1016/j.ijresmar.2018.12.002.

Reynolds-McIlnay, R., & Morrin, M. (2019). Increasing Shopper Trust in Retailer Technological Interfaces via Auditory Confirmation. *Journal of Retailing.* 95(4), 128-142. doi: 10.1016/j.jretai.2019.10.006.

Rodgers, S., & Thorson, E. (2018). Special Issue Introduction: Digital Engagement with Advertising. *Journal of Advertising.* 47(1), 1-3. doi: 10.1080/00913367.2017.1414003.

Rutz, O., Aravindakshan, A., & Rubel, Ol. (2019). Measuring and Forecasting Mobile Game App Engagement. *International Journal of Research in Marketing.* 36(2), 185-199. doi: 10.1016/j.ijresmar.2019.01.002.

Sahni, N., & Nair, H. (2019). Sponsorship Disclosure and Consumer Deception: Experimental Evidence from Native Advertising in Mobile Search. *Marketing Science.* 39(1). doi: 10.1287/mksc.2018.1125.

Schulze, C., Schöler, L., & Skiera, Bernd. (2014). Not All Fun and Games: Viral Marketing for Utilitarian Products. *Journal of Marketing.* 78(1), 1-19. doi: 10.1509/jm.11.0528.

Sciandra, M., Inman, J., & Stephen, A. (2019). Smart Phones, Bad Calls? The Influence of Consumer Mobile Phone Use, Distraction, and Phone Dependence on Adherence to Shopping Plans. *Journal of the Academy of Marketing Science.* 47, 574–594. doi: 10.1007/s11747-019-00647-9.

Segijn, C, & Eisend, M. (2019). A Meta-Analysis into Multiscreening and Advertising Effectiveness: Direct Effects, Moderators, and Underlying Mechanisms. 48(3), 313-332. *Journal of Advertising.* doi: 10.1080/00913367.2019.1604009.

Shah, A., Eisenkraft, N., Bettman, J., & Chartrand, Tanya. (2016). 'Paper Or Plastic?': How We Pay Influences Post-Transaction Connection. *Journal of Consumer Research.* 42(5), 688-708. doi: 10.1093/jcr/ucv056.

Shankar, V. (2016). Mobile Marketing: The Way Forward. *Journal of Interactive Marketing*. 34, 1-2. doi: 10.1016/j.intmar.2016.03.005.

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. *Journal of Retailing.* 94(4), 6-11. doi: 10.1016/S0022-4359(18)30076-9.

Shankar, V., & Balasubramanian, S. (2009). Mobile Marketing: A Synthesis and Prognosis. *Journal of Interactive Marketing.* 23(2), 118-129. doi: 10.1016/j.intmar.2009.02.002.

Shankar, V., & Batra, R. (2009). The Growing Influence of Online Marketing Communications. *Journal of Interactive Marketing.* 23(4), 285-287. doi: 10.1016/j.intmar.2009.07.006.

Shankar, V., Venkatesh, A., Hofacker, C, & Naik, P. (2010). Mobile Marketing in the Retailing Environment: Current Insights and Future Research Avenues. *Journal of Interactive Marketing.* 24(2), 111-120. doi: 10.1016/j.intmar.2010.02.006.

Shankar, V., & Yadav, M. (2010). Emerging Perspectives on Marketing in a Multichannel and Multimedia Retailing Environment. *Journal of Interactive Marketing*. 24(2), 55-57. doi: 10.1016/j.intmar.2010.02.003.

Shankar, V., Inman, J., Mantrala, M., Kelley, E., & Rizley, R. (2011). Innovations in Shopper Marketing: Current Insights and Future Research Issues. *Journal of Retailing*. 87(1), 29-42. doi: 10.1016/j.jretai.2011.04.007.

Shankar, V., Kleijnen, M., Ramanathan, S., Rizley, R., Holland, S., & Morrissey, S. (2016). Mobile Shopper Marketing: Key Issues, Current Insights, and Future Research Avenues. *Journal of Interactive Marketing.* 34, 37-48. doi: 10.1016/j.intmar.2016.03.002.

Shavitt, S., & Barnes, A. (2019). Culture and the Consumer Journey. *Journal of Retailing.* 96(1), 40-54. doi: 10.1016/j.jretai.2019.11.009.

Shen, H., Zhang, M., & Krishna, A. (2016). Computer Interfaces and the "Direct-Touch" Effect: Can iPads Increase the Choice of Hedonic Food?. *Journal of Marketing Research.* 53(5), 745-758. doi: 10.1509/jmr.14.0563.

Shi, S., & Kalyanam, K. (2018). Touchable Apps: Exploring the Usage of Touch Features and Their Impact on Engagement. *Journal of Interactive Marketing.* 44, 43-59. doi: 10.1016/j.intmar.2018.06.001.

Shi, Z., Zhang, K., & Srinivasan, K. (2019). Freemium as an Optimal Strategy for Market Dominant Firms. *Marketing Science*. 38(1). doi: 10.1287/mksc.2018.1109.

Song, J. H., Kim, H., Kim, S., Lee, S., & Lee, J. H. (2016). Effects of Personalized E-Mail Messages on Privacy Risk: Moderating Roles of Control and Intimacy. *Marketing Letters.* 27, 89-101. doi: 10.1007/s11002-014-9315-0.

Sridhar, S., & Fang, E. (2019). New Vistas For Marketing Strategy: Digital, Data-Rich, And Developing Market (D3) Environments. 47, 977–985. *Journal of the Academy of Marketing Science.* doi: 10.1007/s11747-019-00698-y.

Steinhoff, L., Arli, D., Weaven, S., & Kozlenkova, I. (2019). Online Relationship Marketing. *Journal of the Academy of Marketing Science*. 47, 69-393. doi: 10.1007/s11747-018-0621-6.

Sultan, F., Rohm, A., & Gao, T. (2009). Factors Influencing Consumer Acceptance of Mobile Marketing: A Two-Country Study of Youth Markets. *Journal of Interactive Marketing.* 23(4), 308-320. doi: 10.1016/j.intmar.2009.07.003.

Tagashira, T., & Minami, C. (2019). The Effect of Cross-Channel Integration on Cost Efficiency. *Journal of Interactive Marketing*. 47, 68-83. doi: 10.1016/j.intmar.2019.03.002.

Terlutter, R., & Capella, M. (2013). The Gamification of Advertising: Analysis and Research Directions of In-Game Advertising, Advergames, and Advertising in Social Network Games. *Journal of Advertising.* 42, 95-112. doi: 10.1080/00913367.2013.774610.

Tong, S., Luo, X., & Xu, B. (2019). Personalized Mobile Marketing Strategies. *Journal of the Academy of Marketing Science.* 48, 64-78. doi: 10.1007/s11747-019-00693-3.

Van Bruggen, G., Antia, K. Jap, S., Reinartz, W., & Pallas, F. (2010). Managing Marketing Channel Multiplicity. *Journal of Service Research*. 13(3), 331-340. doi: 10.1177/1094670510375601.

Van Heerde, H., Dinner, I., & Neslin, S. (2019). Engaging the Unengaged Customer: The Value of a Retailer Mobile App. *International Journal of Research in Marketing*. doi: 10.1016/j.ijresmar.2019.03.003.

Varadarajan, R., Srinivasan, R., Vadakkepatt, G., Yadav, M., Pavlou, P., Krishnamurthy, S., & Krause, T. (2010). Interactive Technologies and Retailing Strategy: A Review, Conceptual Framework and Future Research Directions. *Journal of Interactive Marketing.* 24(2), 96-110. doi: 10.1016/j.intmar.2010.02.004.

Venkatesan, R. (2017). Executing on a Customer Engagement Strategy. *Journal of the Academy of Marketing Science.* 45, 289-293. doi: 10.1007/s11747-016-0513-6.

Verhoef, P., & Kannan, P. K., & Inman, J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing. *Journal of Retailing.* 91(2), 174-181. doi: 10.1016/j.jretai.2015.02.005.

Verhoef, P., Stephen, A., Kannan, P. K., Luo, X., Abhishek, V., Andrews, M., Bart, Y., Datta, H., Fong, N., Hoffman, D., Hu, M., Novak, T., Rand, W., & Zhang, Y. (2017). Consumer Connectivity in a Complex, Technology-enabled, and Mobile-oriented World with Smart Products. *Journal of Interactive Marketing.* 40, 1-8. doi:

10.1016/j.intmar.2017.06.001.

Verhoef, P., & Bijmolt, T. (2019). Marketing Perspectives on Digital Business Models: A Framework and Overview of the Special Issue. *International Journal of Research in Marketing.* 36(3), 341-349. doi: 10.1016/j.ijresmar.2019.08.001.

Wakefield, L., & Wakefield, K. (2018). An Examination of Construal Effects on Price Perceptions in the Advance Selling of Experience Services. *Journal of Service Research.* 21(2), 235-248. doi: 10.1177/1094670517738367.

Wang, R., Malthouse, E., & Krishnamurthi, L. (2015). On the Go: How Mobile Shopping Affects Customer Purchase Behavior. *Journal of Retailing*. 91(2), 217-234. doi: 10.1016/j.jretai.2015.01.002.

Wang, W., Li, G., Fung, R., & Cheng, T.C.E. (2019a). Mobile Advertising and Traffic Conversion: The Effects of Front Traffic and Spatial Competition. *Journal of Interactive Marketing.* 47, 84-101. doi: 10.1016/j.intmar.2019.02.001.

Wang, Y., Wu, C., & Zhu, T. (2019b). Mobile Hailing Technology and Taxi Driving Behaviors. *Marketing Science*. 38(5), 734-755. doi: 10.1287/mksc.2019.1187.

Wang, F., Zuo, L., Yang, Z., & Wu, Y. (2019c). Mobile Searching Versus Online Searching: Differential Effects of Paid Search Keywords on Direct and Indirect Sales. *Journal of the Academy of Marketing Science.* 47, 1151-1165. doi: 10.1007/s11747-019-00649-7.

Watson, IV. G., Worm, S., Palmatier, R., & Ganesan, S. (2015). The Evolution of Marketing Channels: Trends and Research Directions. *Journal of Retailing*. 91(4), 546-568. doi: 10.1016/j.jretai.2015.04.002.

Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing*. 80(6), 97-121. doi: 10.1509/jm.15.0413.

Winer, R. (2009). New Communications Approaches in Marketing: Issues and Research Directions. *Journal of Interactive Marketing.* 23(2), 108-117. doi: 10.1016/j.intmar.2009.02.004.

Wooder, S., & Baker, S. (2012). Extracting Key Lessons in Service Innovation. *Journal of Product Innovation Management.* 29(1), 13-20. doi: 10.1111/j.1540-5885.2011.00875.x.

Xu, J., Forman, C., Kim, J., & Ittersum, K. (2014). News Media Channels: Complements or Substitutes? Evidence from Mobile Phone Usage. *Journal of Marketing*. 78(4), 97-112. doi: 10.1509/jm.13.0198.

Xu, X., Chen, R., & Jiang, L. (2020). The Influence of Payment Mechanisms on Pricing: When Mental Imagery Stimulates Desire for Money. *Journal of Retailing.* 96(2), 178-188. doi: 10.1016/j.jretai.2019.08.002.

Yadav, M. S., & Pavlou, P. (2014). Marketing in Computer-Mediated Environments: Research Synthesis and New Directions. *Journal of Marketing.* 78(1), 20-40. doi: 10.1509/jm.12.0020.

Yadav, M. S., & Pavlou, P. (2020). Technology-Enabled Interactions in Digital Environments: A Conceptual Foundation for Current and Future Research. *Journal of the Academy of Marketing Science.* 48, 132-136. doi: 10.1007/s11747-019-00712-3.

Zhang, S., Pauwels, K., & Peng, C. (2019). The Impact of Adding Online-to-Offline Service Platform Channels on Firms' Offline and Total Sales and Profits. *Journal of Interactive Marketing.* 47, 115-128. doi: 10.1016/j.intmar.2019.03.001.

Zijun, S., Zhang, K., Srinivasan, K. (2019). Freemium as an Optimal Strategy for Market Dominant Firms. *Marketing Science*. 38(1). doi: 10.1287/mksc.2018.1109.

Zubcsek, P., Katona, Z., & Sarvary, M. (2017). Predicting Mobile Advertising Response Using Consumer Co-Location Networks. *Journal of Marketing.* 81(4), 109-126. doi: 10.1509/jm.15.0215.

Chapter 3

There's an App for That!
Understanding the Drivers of Mobile Application Downloads[4]

Since its emergence in July 2008, the mobile application (app hereafter) space has been growing at an astonishing rate. The Apple App Store has gone from just 500 apps in July 2008, the month of its launch, to 1 million apps in the fall of 2013 and reportedly reached 2 million apps by 2018 (Apple Insider, 2018). Its competitor, the Google Play Store, offered 2.5 million different apps in 2018 (AppBrain, 2019). Global downloads from app stores exceeded 194 billion in 2018. Total app revenues, including revenues from paid downloads, in-app purchases and in-app subscriptions, hit $101 billion in 2018, up 75% from its level in 2016 (AppAnnie, 2019). As apps become increasingly more popular among consumers, worldwide app store revenues are forecasted to reach $156.5 billion in 2022 (AppAnnie, 2018).

The growth of the app market is not surprising, because continuing advances in wireless technologies and the growing smartphone penetration have provided businesses with a new channel with unique features to approach customers (e.g., accessibility at anytime and anywhere, customization at a granular level, and location sensitivity). Apps

[4] This chapter was published in the Journal of Business Research: Aydin Gokgoz, Z.., Ataman, M.B.., & van Bruggen, G. H. (2021) There's an app for that! Understanding the drivers of mobile application downloads. Journal of Business Research, 123, 423-437.

offer businesses, big and small, an opportunity to connect with on-the-go consumers in various ways. First, apps can become an integral – or even core – part of a firm's business model and operate as an additional channel or a platform generating most of the traffic and (ad) revenues (e.g., Facebook, Twitter, Amazon). Some firms start mobile first and operate almost entirely through their apps (e.g., Uber, Instagram). Second, with the increasing importance of apps in consumers' daily lives, apps provide firms a new medium for advertising and a platform to create and maintain brand engagement (e.g., Ruffles AmiGo, IKEA Place).

This emerging market with low entry barriers and lucrative business opportunities continues to attract businesses diverging from individual developers to well-established brands and the app market has become increasingly crowded over the years. However, only a small portion of apps can gain traction with mobile phone users. In 2018, 74% of all apps were downloaded less than 1,000 times, up from 70% in 2014. In contrast, 80% of the downloads in 2019, up from 76% in 2014, are generated by the top 1% of publishers in the Apple App Store or the Google Play Store (SensorTower, 2019). Moreover, the average app loses 77% of its daily active users within the first three days after download, whereas top apps have significantly higher retention rates (Chen, 2018). Consequently, the majority of apps don't generate the anticipated revenues, and some are even withdrawn from the market after a while.

Apps such as Everpix (a high quality app that sorts, organizes, and cloud-stores photos) and Vine (an app for sharing short videos) that satisfy unique customer needs in the first place, have learnt the importance of having the right business model, adapting to the changing landscape of the market place and to evolving consumer needs, and the power of marketing the hard way. Both apps made a promising entrance to the market and were shutdown later with great disappointment and despair (Smart Insights, 2019). Despite these challenges, firms continue developing new apps. In order to increase the success rates of apps, it is important to understand the factors that are associated with app downloads, especially in the early stages of an app's lifecycle. In this paper, we aim to contribute to developing this understanding by studying factors that are related to app adoption.

Based on a review of related studies in the literature and a detailed analysis of a user's decision journey in the path to app adoption, we identify a set of factors potentially associated with downloads. The literature review revealed a set of variables under the developer's control and variables reflecting current users' views, while the analysis of a user's decision journey revealed additional factors under the platform owner's control, whose effects are yet unexplored. Also unexplored in the literature are whether and how this comprehensive set of variables' effects differ across app types (i.e., free and paid apps) and, more importantly, vary over time in the first year following an app's release. To investigate how all variables jointly affect downloads over the first year following an app's release, we assemble a unique data set by combining daily-level transactional data for 979 apps obtained from one of the foremost mobile analytics companies with publicly available data from the Apple App Store. We observe each app since its release and study the evolution of the impact of the factors on downloads over time separately for free and paid apps . By doing so, we can offer insights customized to an app's business type and time on market. We also explore the sensitivity of our findings in other pertinent sub-samples of apps.

Our findings show that the mere appearance in top apps charts have the largest effect on downloads of free and paid apps alike, followed by appearing on a top featured list, especially for paid apps. These results highlight the influence that platform owners have on users. Updates released by developers have positive effects on downloads and their effects increase proportional to the amount of improvement. Further investigation of these effects' evolutions reveals that a majority of the factors matter especially early-on following an app's release.

This paper continues as follows. In Section 2, we review the literature on apps and discuss how this study adds to the current knowledge. In Section 3, we develop the conceptual framework for our study and a series of expectations for the explored relationships. Since the field of mobile marketing is in its early stages and theory development so far seems non-existent or at least scarce, we refrain from developing formal hypotheses. In Section 4, we describe the unique data set we have compiled for the sake of this study, the specification of the model, and the operationalization of our variables of interest. Sections 5 and 6, respectively, present the results of our analyses and conclusions with the ensuing implications.

3.1 Research Background

Although research in marketing and human computer interaction has advanced our knowledge of the mobile consumer (Nysveen, Pedersen, and Thorbjørnsen, 2005), mobile commerce (Shankar et al., 2010), usability of and user experience with mobile devices (Zhang and Adipat, 2005), mobile usage behavior (Ghose, Goldfarb and Han, 2013), and mobile marketing (Shankar and Balasubramanian, 2009), research related to app markets is still in its infancy. Research on apps can be discussed under two main headings: the antecedents of app adoption and the consequences of app introduction.

Starting with the latter, the effectiveness of this medium has particularly been of interest to researchers. Current research shows the positive effects of app introduction/adoption on brand attitudes and purchase intentions (Bellman et al., 2011; McLean et al., 2020), cognitive and affective brand responses (Van Noort and Van Reijmersdaal, 2019), subsequent purchases (Liu et al., 2019; Van Heerde, Dinner, and Neslin, 2019), and even firm value (Boyd, Kannan, and Slotegraaf 2019; Cao, Liu, and Cao, 2018; Gill, Sridhar, and Grewal., 2017).

As to the antecedents of app adoption, previous research has advanced our understanding of the impact of user characteristics (Kim et al., 2017), app characteristics (Schulze, Schöler, and Skiera, 2014), app pricing (Arora, Hofstede, and Mahajan, 2017; Carrare 2012; Ghose and Han 2014; Kübler et al., 2018), app updates (Ghose and Han 2014; Kübler et al., 2018), other users’ experiences (Ghose and Han 2014; Kübler et al., 2018), and, in the broader mobile eco-system, integration, ownership, and novelty of the apps (Van den Ende, Jaspers and Rijsdijk, 2013). Our research is in line with the empirical studies focusing on the antecedents of app adoption and differs from them in the following respects (see Table 10).

Table 10: Comparison of Empirical Studies on App Performance

Study	App Store	Number of Apps	Sampling Criteria	Sampling Time Frame	App Performance (Operationalization)	Developer-controlled Variables	User-side Variables	Platform-controlled Variables	Contingency Factors
Carrare (2012)	Apple	912	Top 100 Apps (Free and Paid)	1/1/2009 – 6/16/2009 (166 daily obs. per app)	Sales (Inferred from rank and market shares)	Price Update	--	--	--
Ghose and Han (2014)	Google Apple	2,624 4,706	Top 400 Apps (Free and Paid)	9/5/2012 – 1/10/2013 (daily obs. for 4 months)	Demand (Estimated sales quantities)	Price Update	Valence Volume	--	Consumer Characteristics
Lee and Raghu (2014)	Apple	7,579	Top 300 Apps (Free, Paid, Grossing)	12/2010 – 09/2011 (39 weekly obs. per app)	Appearance, duration, and number of apps by developer in Top Charts	Update Discount	Valence Volume	--	--
Kübler et al. (2018)	Apple	20	Ranked in Top 100 paid apps in at least 80% of 60 countries and remains in this ranking during the observation period	6/5/2011 – 3/27/2012 (276 daily obs. per app)	Popularity (Sales rank data)	Price Update	Valence Volume Dispersion	--	Cultural, Economic, Structural Factors and Category
This Study	Apple	979	Stratified random sample from 40,000 new free of paid apps released between 1/1/2012 and 5/31/2012	Release dates ranging from 1/1/2012 to 5/31/2012 (365 daily obs. per app)	Downloads (Estimated by a leading mobile analytics company)	Update Type Price Discount	Valence Volume	Feature Lists Top Apps Charts	Time and Business Model

Notes: The studies listed herein also control for app characteristics (e.g., app size, description length, etc.) and developer characteristics (e.g., number of previous successful apps, number of categories in which the developer offers apps, etc.) among other things. We do not list these for brevity.

First, our study differs from other empirical studies in terms of the *set of drivers influencing downloads*. Decisions and actions of three players in the app market, as suggested by Hao et al. (2011), have the potential to drive downloads. These are app developers, app users, and app platform owners. So far, research sheds light on the important roles developers and users play in app performance. We add to this knowledge by considering the unexplored role of app platform owners. Platform-controlled variables impact the visibility and discoverability of apps and have the potential to increase downloads to a great extent (see Section 3 for more details). Specifically, we study the impacts of three types of updates, price, and discounting decisions by developers, word-of-mouth activity (valence and volume) by users, and appearance on featured lists and position in top apps charts by platform-owners on downloads. Not having to use ranking as a proxy for success, because we have access to download numbers, enables us to quantify the additional effect of merely appearing in top apps charts on downloads. In sum, our selection of variables is more comprehensive than up to date research, yet limited by the availability and extractability of the data.

Second, our study differs from existing research in terms of the *nature and composition of apps under investigation*. Previous studies almost exclusively use 'being ranked in a Top Apps Chart' as one of the sampling criteria. The use of such a sampling criterion may introduce success bias, as it takes quite a high number of downloads to enter these charts[5]. Though these studies have advanced our understanding of the drivers of relatively mature apps' downloads, the problem of generating downloads is more acute for newly released apps. As our results show, download performance early-on is critical for overall downloads. Our access to download figures allows us to study factors associated with a new app's performance from its release date onwards independent of the app's ranking status. Moreover, we believe that including low-download generating apps as well as high-download generating apps in our sample helps us develop a broader understanding of the app market dynamics.

Finally, our study differs from extant literature in terms of its *main focus*. Whereas past research mainly deals with the problem of estimating app demand (from

[5] For a few statistics on this, please see https://www.pocketgamer.biz/comment-and-opinion/67142 (last accessed on 12/14/2019) and https://www.apptweak.com/aso-blog/infographic-number-of-downloads-to-reach-top-rankings (last accessed on 12/14/2019).

rankings), the impact of price and its variation across cultural, economic, and structural factors, our goal is to develop an understanding of a comprehensive set of variables that are related to downloads for different app types (i.e., free and paid) and, more importantly, whether and how the effects of these factors *vary over time in the first year following an app's release* on the market[6]. To our knowledge, our paper is the first to link all these variables to downloads and investigate the evolution of their effects.

3.2 Conceptual Framework and Expectations

To identify the drivers of app downloads, it is vital to consider the user's decision journey that leads to app adoption (i.e., the decision to download) and factors that facilitate/hinder progression through journey stages. In what follows, we first outline the user's decision journey, which is built upon the classic demand chain or purchase funnel (Lavidge and Steiner, 1961) and is further modified with the specifics of the app market, the design of the store, and the behaviors of users therein. We then discuss the sources of information users rely on while sequencing through the decision journey and identify the drivers of downloads. We conclude this section with a discussion on the evolution of an app through its lifecycle and the unique challenges imposed by its business model to arrive at differential predictions for variables associated with downloads.

3.2.1 The Path to App Adoption and Variables Affecting Users' Decisions

A user's decision journey starts with the *recognition of a need* for an app, which triggers an app search in the store. At times, the user is relatively less certain about the need, and at times, more certain because s/he has heard about an app through offline word-of-mouth or other channels. Depending on how certain the user is, s/he pursues either a browse path (i.e., browsing the app store navigated by the user interface) or a search path (i.e., searching for an app by typing in the search box). The search path is further divided into two inherently different types in terms of the specificity of the queries, indicating more refined variation around need uncertainty. These are navigational search (i.e., searching

[6] The set of factors associated with downloads change across app business models. Whereas boosting downloads by adjusting prices and offering discounts is possible for paid app developers, developers of free apps only have control over the value proposition of the app. Given this structural difference, we choose to explore the relationships separately for free and paid apps.

with a specific app name, such as 'Angry Birds') and categorical search (i.e., searching with generic phrases, such as 'free games')[7]. Through the browse and the categorical search paths, the user arrives at pages listing several apps. We refer to this milestone in the journey as *app discovery* (i.e., the user becomes aware of apps that may satisfy her/his need).

For users following the browse path and, to a lesser extent, the categorical search path[8], the design and information display of the store's landing page as well as those of category landing pages will play a critical role in app discovery. Prominently displayed on these pages are, *featured lists* and *top apps charts*. Although an app's appearance in a featured list or its position on a top apps chart is determined by underlying app characteristics (e.g., design, uniqueness, business model type, media coverage) and app performance (e.g., past revenues, downloads, engagement, retention (Engström and Forsell, 2018)), these lists are created by platform owners. For that reason, we refer to them as *platform-controlled variables* associated with downloads.

Following app discovery, the user chooses which app(s) to evaluate in detail (i.e., the decision to click on one of the apps in the list). We refer to this milestone as *app consideration*. Those conducting navigational search are likely to transition in and out of the consideration stage swiftly. However, as app stores list similar items alongside the app searched for, these users may also discover the mere presence of rival apps.
Users decide which apps they would like to evaluate in detail based on the information available to them on the app list page. In addition to the app's icon, name, and position on the list, the only other pieces of information available on these pages are the app's average rating scores, the number of reviews, and price – determined by the developer. Ratings and number of reviews reflect previous adopters' views about the app and correspond to the online word-of-mouth measures of *valence* and *volume* (Dellarocas, 2003). Therefore, we refer to them as *user-side variables* associated with downloads. The findings in Colicev et al. (2018) support the notion that WoM volume and valence are effective in the transition to the consideration stage.

[7] 51% of smartphone users in the U.S. learn about apps because their friends/family are using them and 48% discover apps by browsing the app store (Google, 2016). According to Apple (2020), the search path drives majority of downloads with 65% and most of the search queries are branded (i.e., navigational).
[8] The more generic the categorical search query is, the closer the resulting list becomes to lists from browsing top apps charts.

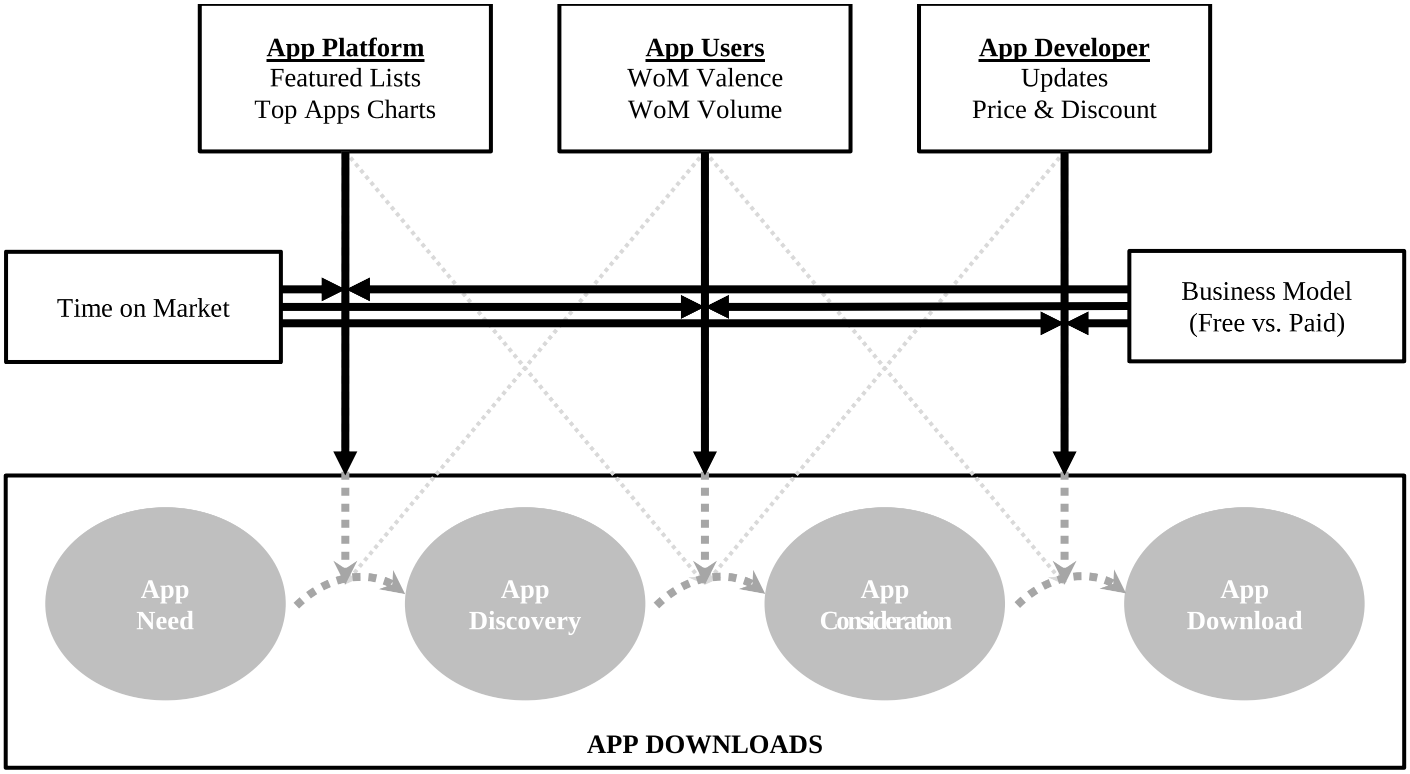
App evaluation takes place on the app description page. These pages show the app's price, average rating score, the number of times it has been reviewed with an option to access individual ratings and reviews, static or dynamic visual and verbal descriptions of the app, and information on what's new in the most up-to-date version of the app with an option to review update history. Using these pieces of information, the user evaluates whether the app can satisfy her/his need and whether the price s/he needs to pay, if any, for gaining access to the app is acceptable. The user, then, decides whether or not to *download the app*. The decision to download terminates the journey, whereas the decision to not download may lead the user to return to earlier stages.

In addition to the *user-side variables* (i.e., WoM valence and volume), all other factors that facilitate the user's progression to the journey's end stage are directly under the control of the developer. Accordingly, we refer to them as *developer-controlled variables* associated with downloads and group them under the app's value proposition, which the developer seeks to improve by means of *updates*, and its *price* (including discounting, if any)[9].

In sum, variables under different app-market-players' controls – platform owners, users, and developers – influence a potential adopter's decision to download an app. Platform-controlled variables are primarily operational on early transitions in the journey, user-side variables on mid- and to late-stage transitions, and developer-controlled variables largely on late-stage transitions. The user's journey to app adoption along with our conceptual framework is presented in Figure 13.

[9] When asked about how important various factors are when making a decision about which app to download, smartphone users in the U.S. rank price first with 85% (Top 2 Box) followed by privacy or security of information (84%), how much they'll use the app (71%), description (71%), memory used (66%), reviews (61%), and ratings (60%) (Google, 2016). The factors listed between price and WoM variables are directly related to the efficient and effective delivery of the app's value proposition. Colicev et al. (2018) finds that social media metrics corresponding to WoM valence are strongly associated with customer satisfaction.

Figure 13: Conceptual Framework



Notes: The grey circles show the journey stages of an individual decision maker on the path to app adoption, curved grey dashed arrows the transitions, straight grey dashed arrows the factors most effective on the transitions, and thin light-grey dashed arrows the factors effective to a lesser extent on the transitions. The black solid boxes and the variables listed therein show the relationships (black solid arrows) explored in this study.

3.2.2 Expectations

3.2.2.1 Platform-controlled Variables

Platform owners can create attention for apps through the *featured lists* they publish on the landing pages. Being featured helps more users discover an app in a crowded environment through its impact on visibility. Holding all else constant, discovery by a larger group of users should boost download numbers. Though empirical research on the antecedents of app adoption or the drivers of app performance has not studied the effect of being featured, research in other domains shows a substantial effect on sales of highlighting a product in its category and featuring/displaying it in a prominent position (e.g., Blattberg, Briesch, and Fox, 1995).

Likewise, as browsing through *top apps charts* is a prominent way of app discovery, appearance and the position of an app in one of these charts can attract greater attention to the app and boost downloads. Studies trying to uncover the ranking algorithms of app stores and the relationship between rankings and downloads reveal interesting insights pertaining to appearances and positions of apps in these charts. Comparing the effects of WOM metrics and app rankings for a data set of 42 days in the Google Play Store, Engström and Forsell (2018) find that a 10-percentile increase in displayed rankings increases downloads by 20%. Carrare (2012), investigating the effect of current rank on future demand based on a data set of 166 days of top 100 free and paid apps in Apple App Store, finds that consumers' willingness to pay is $4.50 higher for a top ranked app compared to an unranked app and declines steeply as the ranking of an app drops. Carrare (2012) also discovers natural breakpoints in rankings corresponding to top 5, top 25 and top 50. Findings of Garg and Telang (2013) complement those of Carrare (2012): a top ranked app for iPhone (iPad) earns 95 (110) times more revenue compared to a top 200 ranked app. Accordingly, we expect appearing in the top ranks of these charts to speed up adoption, with more prominent positions being more strongly associated with downloads.

3.2.2.2 User-side Variables

The impact of *word-of-mouth* on consumer decisions has increased with the emergence of online feedback mechanisms. Word-of-mouth has been shown to be an important factor in determining the success of experience goods (De Vany and Walls, 1996) as well as goods in other industries (e.g., Anderson and Magruder, 2012; Chevalier and Mayzlin, 2006; Dhar and Chang, 2009; Duan, Gu and Whinston, 2011). As to the impact of WoM on app performance, both valence and volume have been shown to have a positive impact on app demand (Ghose and Han, 2014; Hao et al., 2011; Kübler et al., 2018). Accordingly, we expect to find a relationship in the same direction.

3.2.2.3 Developer-controlled Variables

Developer-controlled variables, especially the app’s value proposition, are effective in sealing the deal for potential adopters. Though an app’s value proposition is determined prior to launch, *updates* serve as a tool for further development of the app. In fact, the dynamics of the app market puts pressure on developers to update apps often and on a regular basis. Fortunately, the continuous feedback from app users provides developers with the opportunity to offer customized and swift responses and enjoy favorable response as a result (Aydin Gokgoz, Ataman, and Van Bruggen, 2020).

Previous research agrees on the positive impact of updates on app performance: the demand is higher for apps that are regularly updated (Carrare, 2012; Ghose and Han, 2014; Kübler et al., 2018). Accordingly, we expect a positive relationship between updates and downloads. Though developers may generate additional downloads by means of updates, we expect the nature of the update to matter. In some updates, the developers add new features and functionalities to their apps – referred to as major updates hereafter – with the goal of improving their app’s value propositions. In others, they improve the existing features – referred to as intermediate updates hereafter – or implement development tweaks and bug fixes – referred to as minor updates hereafter – to ensure effective and efficient delivery of the value proposition, respectively. We expect major updates to have a greater impact on downloads than minor updates.

Finally, developers of paid apps can influence downloads with *price* changes and the *discounts* they offer. Unlike traditional markets where regular price changes are relatively infrequent, experimenting with different price points to arrive at the right one, especially in the early life cycle of the apps, is a common practice in this market[10]. The app

[10] See https://mashable.com/2011/08/17/price-mobile-app/ for more details. In our sample, we observe sufficient variation in regular price and discounting variables. Specifically, 50.4% of paid applications undergo at least one regular price change over the first year of the app’s existence and more apps change regular prices in the first six months of the data. Moreover, 45.9% of all apps in the sample offer at least one discount.

store provides developers with the opportunity to move smoothly between price points by allowing them to schedule price changes. Developers can alter price points permanently as soon as they realize that they have chosen a price point that is too high for their potential user base or they can temporarily offer discounts to expand the user base.

The effects of prices and discounts on downloads have been investigated in several studies. For instance, Kübler et al. (2018) find that the demand for apps is sensitive to prices and price sensitivity varies across countries with different economic and cultural backgrounds as well as app categories (e.g., games and non-games). Ghose and Han (2014) investigate the competition between Apple and Google stores and find that discounting increases app demand more in Google Play Store than Apple App Store. Accordingly, we expect to find a negative (positive) relationship between price (discounts) and downloads.

We summarize our expectations for the signs of the effects of all variables on downloads and how we expect these effects to vary over an app's lifecycle and across business models, discussed subsequently, in Table 11.

Table 11: Expected Effects of Download Drivers

	Prediction		Evolution
Variable	Free Apps	Paid Apps	
Platform-controlled Variables			
Appearance on Featured Lists	++	+	Decrease over time
Position in Top App Charts	++	+	Decrease over time
User-side Variables			
Valence of WOM	+	++	Decrease over time
Volume of WOM	+	++	Decrease over time
Developer-controlled Variables			
Updates	+	++	Increase over time
Price	NA	-	Decrease over time
Discount	NA	+	Increase/Constant over time

Notes: ++ indicates that the association between a variable and downloads is stronger for a specific app type compared to the other. As for the over-time effect of price on downloads, we expect a reduction in the magnitude of price elasticity. Accordingly, a decrease over time means that price elasticity, which is negative, moves closer to zero (i.e., demand becomes less sensitive to prices).

3.2.3 Changes over an App's Lifecycle and Differences between Business Models

Apps and their potential adopters experience changes over the lifecycle and different conditions across app business models on three fronts: (1) the source and the amount of information available, (2) the nature and the extent of risks perceived, and (3) the perceptions and expectations of the untapped potential. As a result, the strength of the association between the variables and downloads can evolve over the phases of an app's lifecycle and be different for free vs. paid apps.

First, the source and the amount of information available vary over time and across apps. Because the number of users who have downloaded the app is likely to be lower in the early days of an app's lifecycle (i.e., low observability), the likelihood of discovering the app through channels other than the app store itself will be lower early on (Rogers, 2003). As an app matures and increasingly more users download it, potential adopters will gain access to more information and from various sources (e.g., offline WoM, press coverage, publicity, etc.). Moreover, the amount of information that potential adopters need to process on the platform varies substantially across free and paid apps. As 90% of Apple App Store apps are free, the adoption decision is more taxing for users looking to download a free app. The relative complexity of the free apps sub-market means greater information overload and higher search costs (Payne, Bettman, and Johnson, 1993). To reduce search costs and deal with the undesirable consequences of complexity, potential adopters of free apps may engage in selective information processing and utilize heuristics on the path to choice more than those of paid apps (Bettman, Luca, and Payne, 1998). One readily accessible source of information that may ease the burden of app discovery and app consideration is the prominence of the app in the store (Ghose, Goldfarb, and Han, 2013). Accordingly, we expect the effects of platform-controlled variables to be highest early on and decrease over time, and to be greater for free apps than paid apps.

Second, perceived risks associated with the acquisition of an app evolve over the lifecycle and vary across free and paid apps. Among the various types, two strongly correlated risks are relevant for the purposes of our study: functional risk and financial risk (Jacoby and Kaplan, 1972). Perceived functional risk is higher early on in a new product's lifecycle because it is quite difficult to anticipate product performance in the early days.

However, uncertainty about the product's performance reduces as it matures and potential adopters who are on the market in the later phases of the product's lifecycle perceive lower functional risk (Babić Rosario et al., 2016). Moreover, a crucial difference between the two business models is the monetary risk associated with the purchase. While potential users of paid apps face this risk, those of free apps don't. The mere presence of a monetary risk implies paid apps score lower on trialability compared to free apps (Rogers, 2003). As consumers rely on WoM taking place on the app store to deal with perceived risks (Babić Rosario et al., 2016; Shen, 2015), we expect the effectiveness of user-side drivers of downloads to decline over time. We also expect the relationship to be weaker for free apps than paid apps, as users can readily try free apps without any transactional costs. For paid apps, on the other hand, potential users perceive greater risk and the reviews of past users can provide them with useful additional information.

Third, the composition of potential adopters and, consequently, the variety of needs the developer should satisfy evolve over an app's lifecycle and across business models. Assuming away app discovery bottlenecks on the path to app adoption, those who download the app early on are either innovators with high willingness to try new ideas or those who value what the app's initial version(s) has to offer (Rogers, 2003). What separates the remaining users on the market who have not yet downloaded the app from those who have, are their evaluations of the app's value proposition and their willingness to pay for that value. Converting these remaining users to potential adopters requires adjustments to the value proposition and, if the app is paid, the price. Introducing new and improved versions of the app by means of updates and lower regular prices can stimulate demand and speed up growth for new offerings (Ataman, Mela and Van Heerde, 2008). Temporary price reductions can further encourage app adoption by lowering the perceived risk of making the wrong purchase. Moreover, as perceived monetary risk is most strongly associated with functional risk among all perceived risk types (Jacoby and Kaplan, 1972), potential users of paid apps are likely to have higher expectations from the developer and place greater importance on the value the app offers compared to free apps.

Accordingly, we expect the effect of updates to increase over time, as they serve as a tool to expand the potential user base, and to be stronger for paid apps than free apps, as users have higher expectations of the app[11]. Moreover, consistent with the results in Simon (1979) and Bijmolt, Van Heerde, and Pieters (2005), we expect the magnitude of price elasticity to be larger in the early phases of an app's lifecycle. In the later phases, as fewer and more attentive users with higher willingness to pay would be on the market to find the app that satisfies their unique need, price may lose its importance. As for the over-time effects of discounts, we expect this positive association to start high and either increase over time or at least stay high, as discounts may serve as an encouragement for less enthusiastic adopters throughout an app's lifecycle.

3.3 Methodology

3.3.1 Data

For the purpose of studying the drivers of app downloads, we assembled a unique data set. The data set consists of a comprehensive list of variables acquired from one of the most prominent mobile analytics companies. The variables in this data set are downloads, revenues, updates, appearance in featured lists and position in top apps charts. We augment our transactional data set with publicly available data on app ratings and reviews. To that end, we developed a web crawler to collect ratings and reviews from the web page of the iTunes app store.

To be able to answer our research question, we needed to observe each app from its initial release date in the app store. Therefore, we took a stratified random sample of 1011 apps from 40,000 apps released in the Apple App Store during the first five months of 2012 (between January 1 and May 31) and obtained daily observations for all variables over a one-year time frame starting on the day each app was released. Thirty-two apps had less than 365 usable observations and were later discarded from the sample[12]. The stratification ensures that the distribution of the twenty-two app categories and business model types (i.e., free vs. paid app) in the app store is accurately represented in the sample. Because some categories, such as Food & Drinks or Education, did not have enough new

[11] When asked about why users have chosen to pay for apps over free alternatives, smartphone owners in the U.S. list app's content as the top reason (45%) and app's features/functionality as the second reason (35%) for paying for apps (Google, 2016).

[12] Eight of these applications were withdrawn before reaching the 1-year mark and 24 either had a name change or were withdrawn after the first year rendering access to publicly available data impossible.

apps launched in the sampling period, they are underrepresented. Moreover, we did not have any new Newsstand apps launched in the sampling period[13]. These differences are compensated with a slight overrepresentation in some other categories, such as Games. Yet, we believe our sample provides a sufficiently accurate representation of the situation in the app store at the time of data collection and helps us avoid the risk of producing results driven by category idiosyncrasies. Next, we present the model specification and detail the definition and operationalization of each variable in the model.

3.3.2 Model Specification and Estimation Strategy

As our goal is to explain which factors are related to downloads and how these relationships evolve over the first year of an app's life cycle, we specify a download response model with time varying parameters. The model explains downloads as a function of variables under the control of app platform owners, app users, app developers, and several control variables:

$$(1) \qquad \ln(D_{it}) = \alpha_i + \ln(D_{it-1}) + \sum_{m=1}^{M} \beta_{mt}^{PLT} X_{imt} + \sum_{n=1}^{N} \beta_{nt}^{USR} X_{int} + \sum_{p=1}^{P} \beta_{pt}^{DEV} X_{ipt} + \sum_{k=1}^{K} \gamma_k Z_{ikt} + u_{it}$$

where ln(Dit) is the natural logarithm of the number of times app i was downloaded on day t. Because there are a few days with no downloads (.55%), we add 1 to all observations before taking the logarithm. □i is an app-specific constant14. X_{imt}, X_{int}, X_{ipt} and Z_{ikt} are, respectively, platform-controlled ($m = 1, \dots, M$), user-side ($n = 1, \dots, N$), developer-controlled ($p = 1, \dots, P$), and control ($k = 1, \dots, K$) variables that explain daily downloads. Following Chevalier and Mayzlin (2006), we specify a log-log model, as there are scale effects emerging from higher views of popular apps compared to that of less popular apps. Because all our continuous independent variables are log-transformed, their coefficients can be interpreted as elasticities. The coefficients of the dummy variables, on the other

[13] The twenty-two application categories are Books, Education, Lifestyle, Magazines/Papers, News, Reference, Entertainment, Music, Photo/Video, Social Networking, Games, Food/Drink, Health/Fitness, Medical, Sports, Business, Finance, Navigation, Productivity, Travel, Utilities, and Weather (Source: Apple, 2018). Newsstand was later removed by Apple.

[14] We assessed whether fixed-effects or random-effects correction would be appropriate to control for time invariant differences across applications using the Hausmann test. The results of this test suggested that the fixed-effects model is appropriate in our case.

hand, are semi-elasticities.

To give the model the flexibility to capture the changing relationship between the explanatory variables and downloads during the first year of the app's life cycle, we specify the (semi-)elasticities as a function of linear and quadratic time trend:

(2a) $$\beta_{mt}^{PLT} = \beta_{m0}^{PLT} + \beta_{m1}^{PLT} t^* + \beta_{m2}^{PLT} t^{*2}$$

(2b) $$\beta_{nt}^{USR} = \beta_{n0}^{USR} + \beta_{n1}^{USR} t^* + \beta_{n2}^{USR} t^{*2}$$

(2c) $$\beta_{pt}^{DEV} = \beta_{p0}^{DEV} + \beta_{p1}^{DEV} t^* + \beta_{p2}^{DEV} t^{*2}$$

The quadratic time trend allows us to capture possible curvilinear relationships over time. Following Liechty, Fong, and DeSarbo (2005), we apply a transformation to time trend in the quadratic model for interpretation purposes: t* = (t/365 – 1/2).

Since the challenges faced by free and paid apps and the set of variables associated with downloads for these apps are different, we estimate the model separately for free and paid apps15. Moreover, as sensitivity checks, we explore whether there are any discrepancies in the results for different subsets of apps with respect to app categories (games vs. non-games), brands (new apps vs. apps by existing brands), and an app's ranking status (all apps vs. apps ranked at least 120 days) by estimating the model separately for these sub-samples.

3.3.3 Variable Definitions and Operationalization

The dependent variable in Equation (1) is the natural logarithm of the *daily number of unique downloads* of app i obtained from our data provider. They are first time downloads that are unique to the user and do not contain updates. Download numbers are estimated using transactional download data available to the mobile analytic company through their clients and public ranking charts. The mobile analytic company's access to transactional data from over 100,000 apps with over 1.5 billion downloads leverages a level of accuracy that is unmatched in the industry. In terms of iOS downloads in particular, the majority of apps are claimed to be estimated with a margin of error below 3% and 95% of apps with a margin of error below 10%.

[15] With the help of a Chow test, we assessed whether we can pool the coefficients. The test result suggests estimating separate coefficients for free and paid apps ($F_{77,357181} = 14.699$, $p < .01$).

The *platform-controlled variables* include appearance on featured lists and position in top app charts. Our data set contains information on (1) whether an app was on a "Featured List" and which list it was featured on and (2) the position of an app in a top apps chart and which chart it was in. We classify the "Featured List"s into two main categories, top featured lists and other featured lists, and code *appearance on top (other) featured lists* as a dummy variable[16]. We operationalized *appearance in top apps chart* considering only the "Top Free" and "Top Paid" charts, as they are the most important ones with the highest traffic. Inspired by the findings of Carrare (2012) and the design of the app store at the time of data collection, we acknowledge the natural break points in these charts and code appearance in a top apps chart using three dummy variables: above-the-fold (i.e., if an app was among the first five apps in the chart), below-the-fold (i.e., if an app was among the second five apps in the chart), and below-the-2nd-fold (i.e., if an app was among the apps listed between the 11th and 25th positions) [17].

The *user-side factors* associated with downloads include valence and volume of WoM. *Valence of WoM* is operationalized as the average rating score of the app's most recent version. Using the ratings and reviews data we crawled from the official web-page of iTunes, we calculated the average rating score for an app's most recent version by dividing the sum of all user ratings up to day t to the cumulative number of reviews up to day t, which is our measure for *volume of WoM*.

The *developer-controlled variables* associated with downloads include updates and regular price and discount depth (only for paid apps). We operationalize *updates* using the information in the three-digit number known as the version number (e.g., Version 2.3.1). We infer the nature of the changes made to the app from the digit changes between two consecutive versions: a change in the first digit indicates a major improvement; a

---

[16] 'Featured List' is a general term for all curated lists published by the platform. We observe 189 apps (out of 979) featured in 180 different lists. Given the scattered nature of these lists and the low number of featured apps, we decided to classify these lists under top featured lists and other featured lists. The reasoning behind this distinction is that top featured lists are the main lists that are the easiest for users to notice, while others are not. Users are exposed to the top featured lists on the landing page and need to actively search for the other lists. 'Top Overall', 'New and Noteworthy', or 'Editor's Choice' are examples of top featured lists. Other featured lists include category specific or curated lists for special days (e.g., Mother's Day Gift Guide, Apps for Graduates).

[17] At the time of data collection, Apple App Store top apps charts rolled on a continuous scrolling basis where each screen contained five apps. Therefore, we separated the effect of being visible on the first page (referred to as 'above-the-fold') from that of the second page (referred to as 'below-the-fold') and the following pages (referred to as 'below-the-2nd-fold') We think 5-page-views-by-scrolling corresponding to the natural breakpoint at 25 provides us with a comprehensive list of top apps .

change in the second digit indicates an intermediate improvement, while a change in the third digit indicates a minor improvement[18]. We code each update as a step dummy that is switched on for five days following an update.

In addition to daily downloads, our data set contains information on total revenues from downloads. We use these data to calculate the actual price of a paid app on a daily basis (in cents) and determine the *regular price* dynamically by checking the mode of actual prices in a fixed time window. Specifically, after setting the actual price on the first day equal to the regular price, we calculate the difference between the actual price on a given day and the regular price of the previous day. If this difference is zero (i.e., no price change), we set the regular price equal to the actual price. Otherwise, we look forward 30 days, calculate the mode of actual prices in this time window, and set the regular price to the mode if the mode is equal to the current price, if they are not equal the regular price is set to previous day's price[19]. This procedure allows us to separate temporary changes in prices from permanent changes. We define *discount depth* as the ratio of cents-off to the regular price of the app.

Finally, as *control variables* we include (1) previous day's downloads, which helps us to account for the unobserved effects of offline WOM, ads and other forms of publicity, (2) the number of days passed since an app has been updated, to capture the effect of the frequency of updates, (3) dummy variables for days of the week, special dates such as holidays (Christmas, New Year's Eve etc.) and special occasions (Mother's / Father's Day, Valentine's Day etc.), and (4) several step dummies to control for the introduction of new devices and new iOS software updates.

Table 12 summarizes the definition and operationalization of the variables in the model and Table 13 presents summary statistics per business model type.

[18] To illustrate the association between changes in version number digits and the nature of the updates consider an app with the following history: Version 2.3 "Added History option". Version 2.4 "Added a screenshot option. Now can save the picture in your iPad gallery any time you want. Find this option in game menu". Version 2.4.1 "Updated ABOUT and HISTORY views". Version 3 "Clear option for removing the packages and images, UI changes, New packages at the top of the list in selector, Ability to share packages to your friends (email, FB, twitter), Ability to create own packages". The update from Version 2.4.1 to Version 3 is a major update, from Version 2.3 to Version 2.4 is an intermediate update, and from Version 2.4 to Version 2.4.1 is a minor update.

[19] In a highly dynamic market where 5-day price drops have been claimed to have considerable effects on downloads, we choose 30 days as a long enough time window to outrun temporary price discounts and identify a new regular price level. Moreover, we checked the sensitivity of our findings by considering 15- and 45-day time windows and find that our results are robust. (https://techcrunch.com/2013/01/31/app-sales-work-five-day-iphone-app-price-drops-boost-downloads-by-1665-on-ipad-by-871-revenue-growth-by-day-3/, last accessed on 27/12/2019).

Table 12: Definition and Operationalization of Variables

Variable	Definition	Operationalization	Type/ Transformation (Range before trans.)	Source
Downloads	Daily downloads of an app	Number of times app i was downloaded on day t.	Continuous / Log (0 – 354,395)	Data Provider
Platform-controlled Variables				
Appearance on Featured Lists	Whether an app has been featured by the platform	Divided into two categories: Top and Other. “1” if the app exists on one of the featured lists under each category and “0” otherwise.	Dummy / N.A. (N.A.)	Data Provider
Appearance in Top App Charts	Whether and where an app has been placed in the top app charts	Divided into three categories: above-the-fold, below-the-fold, and below-the-2nd-fold. “1” if the app exists in one of these positions and “0” otherwise.	Dummy / N.A. (N.A.)	Data Provider
User-side Variables				
Valence of WOM	Average Rating Score	Average rating score of the current version of app i on day t calculated from the ratings of users who also wrote a review for the app up to day t	Continuous / Log (1 – 5)	iTunes Web page
Volume of WOM	Cumulative number of	Total number of reviews of app i up to day t.	Continuous / Log	iTunes Web

Variable	Definition	Operationalization	Type/ Transformation (Range before trans.)	Source
	reviews		(0 – 160,285)	page
Developer-controlled Variables				
Updates	Whether an app has been updated	Divided into 3 categories: minor, intermediate, and major. Dummy variable for each update category for five days following the release of a new version.	Dummy / N.A. (0 – 1)	Data Provider
Price	Regular price of an app in cents	Inferred from a dynamic search over daily actual prices.	Continuous / Log (0 – 49.99)	Data Provider
Discount	% cents-off	(Regular Price – Actual Price) / Regular Price	Continuous / None (0% – 100%)	Data Provider
Control Variables				
Day of the week	Control for day of the week	Monday is chosen as the baseline.	Categorical/NA (1-7)	NA
Days since last update	Counts days since last update	Number of days since last either of the update categories.	Continuous (0-365)	Data Provider

Notes: Before applying the log transformation, we add 1 to all downloads as we have a few days with no downloads (.55% of all observations). Exploratory analysis of average download numbers centered on each update and the observation that users give most feedback in the first few days after a new version release (Pagani and Maalej, 2013) supports our choice of 5-day time window. We check the sensitivity of our findings by considering a 4-day time window, the second likely candidate, and find that the results are robust.

Table 13: Summary Statistics

	Free Apps	Paid Apps
Number of Apps	602	377
Downloads	1350.337 (5857.519)	322.697 (2348.376)
Platform-controlled Variables		
Appearance on Top Featured List	.004 (.065)	.009 (.094)
Appearance on Other Featured List	.010 (.100)	.015 (.121)
Appearance Above-the-fold	.001 (.034)	.002 (.047)
Appearance Below-the-fold	.001 (.032)	.002 (.045)
Appearance Below-the-2nd-fold	.003 (.055)	.005 (.072)
User-side Variables		
Valence of WOM	2.963 (1.684)	3.453 (1.503)
Volume of WOM	143.052 (1231.176)	126.289 (545.603)
Developer-controlled Variables		
Minor Update	.028 (0.165)	.024 (0.153)
Intermediate Update	.032 (0.177)	.033 (0.179)
Major Update	.001 (.036)	.004 (.066)
Price	NA	2.621 (3.742)
Discount	NA	.009 (.083)
Control Variables		
Days since last update	81.615 (83.650)	92.594 (89.565)

Notes: Cell entries are means and standard deviations, in parentheses, across all apps and time periods.

3.4 Results

Table 14 displays the coefficient estimates of our main models (i.e., for free and paid apps) and of models we estimated for sensitivity checks. Because our model includes interactions among all regressors and first- and second-order time trend, discussing the results coefficient-by-coefficient is not fruitful. Instead, we calculated the marginal effect of each variable over time – starting on the day of the release and reaching 365 with increments of two weeks – and the 95% confidence interval around this estimate using the Delta method. Figure 14 displays the effects of platform-controlled variables, Figure 15 the effects of user-side variables, and Figure 16 the effects of developer-controlled variables.

In what follows, we first discuss the impact of each variable on downloads using the average of the marginal effects over time and, if available, compare the (semi-) elasticities to earlier findings. We then present our findings as to how these effects vary over the course of an app’s first year of existence. To facilitate comparison with our expectations, we summarize the key findings in Table 15. We conclude this section by discussing whether and how our main findings change under different sub-samples of apps.

Table 14: Parameter Estimates per App Type

	Main Models		Models for Sensitivity Checks					
Variable	**Free Apps**	**Paid Apps**	**Games**	**Non-Games**	**New Apps**	**Existing Apps**	**All Apps**	**Ranked Apps**
Constant	1.346***	1.503***	1.632***	1.348***	1.429***	1.372***	1.409***	1.910***
Time	-.324***	-.466***	-.349***	-.267***	-.283***	-.305***	-.289***	-.287***
Time^2	.775***	1.034***	.948***	.784***	.761***	.877***	.800***	2.036***
Top Featured Lists	.023	.117***	.063***	.116***	.093***	.097***	.087***	.110***
Top Featured Lists × Time	.038	-.138***	-.011	-.024	-.032	.018	-.017	.034
Top Featured Lists × Time^2	.172	.024	.208	-.253*	-.107	-.048	-.036	-.198
Other Featured Lists	-.045**	-.088***	-.045	-.067***	-.052***	-.077***	-.064***	-.034
Other Featured Lists × Time	.088***	.035	.321***	.090***	-.030	.158***	.027	-.017
Other Featured Lists × Time^2	-.240*	.491***	.909***	-.004	.165	.051	.148	-.383**
Above-the-fold	.662***	-.076	-.073	.536***	-.000	.617***	.296***	.578***
Above-the-fold × Time	-.217	-1.857***	-1.546***	-.073	-1.016***	-.100	-.220*	-.191
Above-the-fold × Time^2	-.859	-.764	-.104	-.054	.540	-.323	.874**	-.593
Below-the-fold	.424***	.102*	-.142**	.512***	.178***	.368***	.247***	.499***
Below-the-fold × Time	-.046	-.553***	.094	-.036	-.101	-.104	-.121	-.111
Below-the-fold × Time^2	.570	.690	3.512***	-.315	1.448***	.502	1.083***	-.627*
Below-the-2nd-fold	.393***	.141***	.206***	.236***	.218***	.247***	.230***	.320***
Below-the-2nd-fold × Time	.054	.021	.133**	.148***	.128***	-.043	.091**	.069
Below-the-2nd-fold × Time^2	.658***	1.086***	1.522***	1.066***	1.337***	.783***	1.175***	.030
ln(Valence)	-.003	.035***	-.034***	.018***	.007**	.011**	.009***	-.007
ln(Valence) × Time	.069***	.004	-.017	.059***	.042***	.045***	.045***	-.151***
ln(Valence) × Time^2	-.119***	-.130***	-.089**	-.131***	-.126***	-.077**	-.119***	-.099
ln(Volume)	.018***	.021***	.014***	.024***	.020***	.012***	.018***	.038***
ln(Volume) × Time	-.004**	-.005**	.005*	-.006***	-.004**	-.013***	-.007***	.017***
ln(Volume) × Time^2	-.051***	-.059***	-.073***	-.056***	-.046***	-.060***	-.049***	-.222***
Minor Update	.038***	.067***	.067***	.046***	.049***	.045***	.048***	.089***
Minor Update × Time	.046***	.077***	.035	.073***	.059***	.026	.049***	.117***
Minor Update × Time^2	-.312***	-.343***	-.398***	-.328***	-.308***	-.390***	-.331***	-.868***
Intermediate Update	.052***	.070***	.010	.074***	.055***	.061***	.058***	.105***
Intermediate Update × Time	.107***	.048**	.070**	.083***	.081***	.050*	.074***	.188***

	Main Models		Models for Sensitivity Checks					
Variable	**Free Apps**	**Paid Apps**	**Games**	**Non-Games**	**New Apps**	**Existing Apps**	**All Apps**	**Ranked Apps**
Intermediate Update × Time^2	-.506***	-.313***	-.083	-.520***	-.420***	-.375***	-.417***	-.795***
Major Update	.066	.132	.015	.067	-.000	.072	.021	.096
Major Update × Time	.736	.206	1.265**	.217	.326	.460	.334*	.756
Major Update × Time^2	1.161	.270	2.820***	.499	.921**	1.109	.905**	.753
ln(Price)	-	-.140***	-.185***	-.123***	-.144***	-.129***	-.140***	-.126***
ln(Price) × Time	-	.029***	-.026***	-.016***	-.021***	-.012***	-.019***	.035***
ln(Price) × Time^2	-	-.022**	.050***	-.015***	.007*	.007	.007*	-.069***
Discount Depth	-	1.394***	1.483***	1.291***	1.467***	.997***	1.355***	1.145***
Discount Depth × Time	-	-.389***	-.626***	-.177***	-.350***	-.482***	-.409***	-.348***
Discount Depth × Time^2	-	-1.694***	-2.272***	-1.124***	-1.938***	-.626*	-1.660***	-2.157***
ln(Downloads$_{t-1}$)	.737***	.723***	.720***	.736***	.735***	.728***	.734***	.723***
Tuesday	.038***	.030***	.043***	.031***	.035***	.034***	.035***	.049***
Wednesday	.034***	.030***	.051***	.024***	.031***	.037***	.032***	.053***
Thursday	.053***	.064***	.100***	.038***	.056***	.060***	.057***	.077***
Friday	.066***	.079***	.153***	.036***	.072***	.069***	.071***	.102***
Saturday	.142***	.152***	.257***	.099***	.144***	.150***	.146***	.186***
Sunday	.126***	.122***	.186***	.099***	.122***	.129***	.124***	.158***
Days Since Last Update	-.000***	-.001***	-.000***	-.000***	-.000***	-.000***	-.000***	-.001***
Number of apps	602	377	285	694	707	272	979	99
Number of observations	219730	137605	104025	253310	258055	99280	357335	36135
R-Square	.717	.752	.769	.718	.738	.723	.734	.781
Average VIF	8.76	8.74	9.26	7.13	7.68	7.71	7.40	11.65

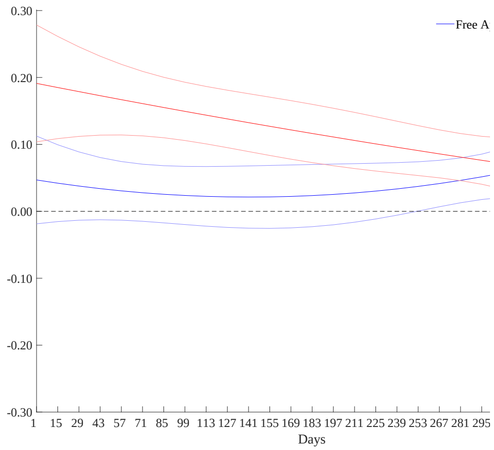
Notes: *indicates p < .1, ** indicates p < .05 and *** indicates p < .01. We use Monday as the baseline while dummy-coding days of the week variable. All models include other controls, which are not shown here to conserve space.

Table 15: Summary of Results for the Effects of External and Internal Factors on Downloads for Free vs. Paid Apps

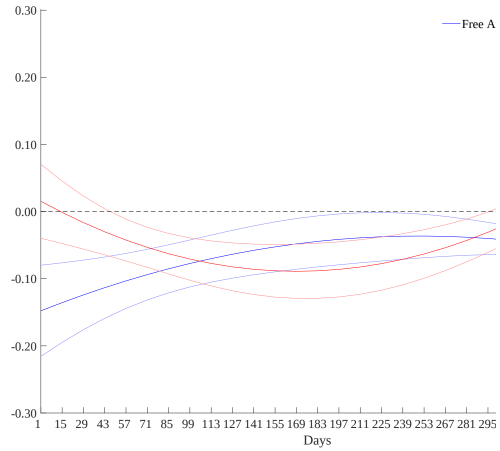
	Free Apps		Paid Apps	
Variable	**Direction**	**Evolution over time**	**Direction**	**Evolution over time**
Platform Controlled Variables				
Appearance on Top Featured Lists	+	Flat U shape	++	Decrease
Appearance on Other Featured Lists	-	Flat Inverse U shape	-	U shape
Appearance Above-the-fold	++	Flat Inverse U shape	-	Decrease
Appearance Below-the-fold	++	Flat U shape	+	Decrease
Appearance Below-the-2nd-fold	++	U shape	+	U shape
User-side Variables				
Valence of WOM	-	Decrease in magnitude	+	Inverse U shape
Volume of WOM	+	Inverse U shape	+	Inverse U shape
Developer Controlled Variables				
Minor Update	+	Inverse U shape	++	Inverse U shape
Intermediate Update	+	Inverse U shape	++	Inverse U shape
Major Update	+	Flat U shape	+	Flat U shape
Price	NA	NA	-	Decrease in magnitude
Discount	NA	NA	+	Inverse U shape

Notes: Directions are based on the sign of the average effect over time and does not necessarily imply that the effect stays in that region throughout. ++ indicates that the association between a variable and downloads is stronger for a specific app type compared to the other.

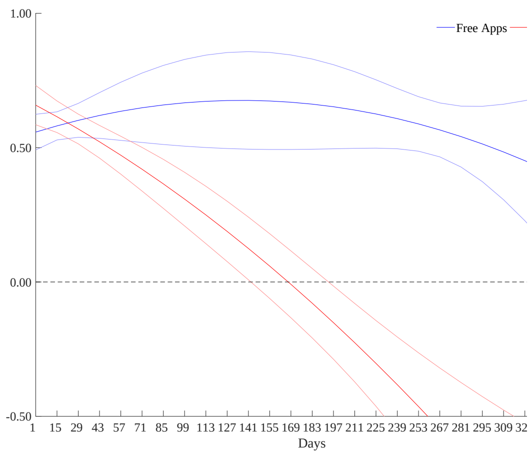
Figure 14: Effectiveness of Platform-controlled Variables over Time



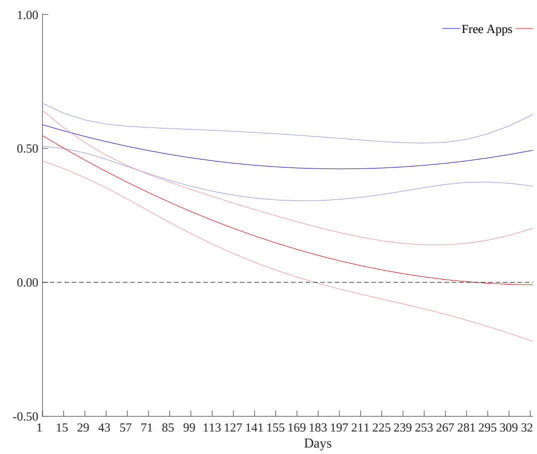
(A) Appearance on Top Featured Lists



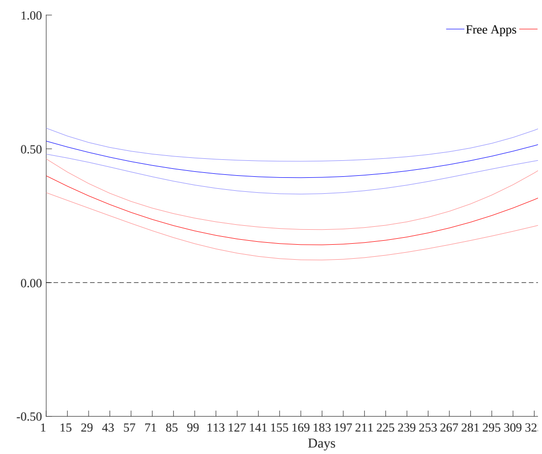
(B) Appearance on Other Featured Lists



(C) Appearance Above-the-fold



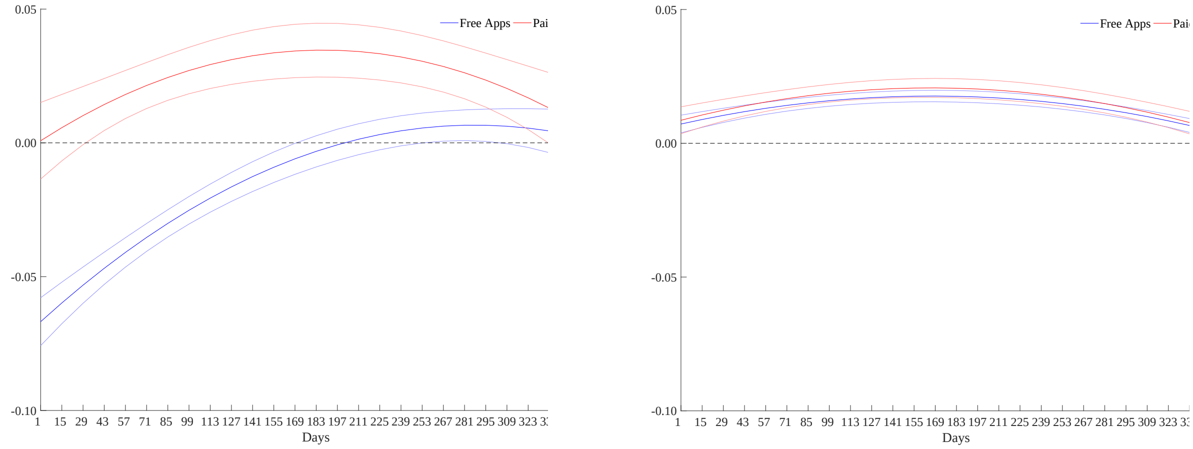
(D) Appearance Below-the-fold



(E) Appearance Below-the-2nd-fold

Notes: Blue represents free apps and red represents paid apps. The solid lines are average marginal effects and the shaded areas show 95% confidence interval.

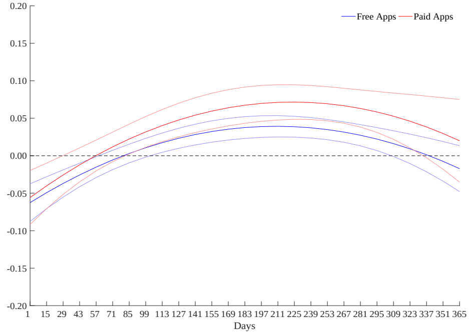
Figure 15: Effectiveness of User-side Variables over Time



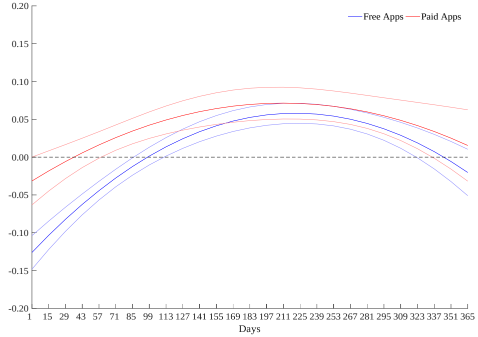
(A) WoM Valence (B) WoM Volume

Notes: Blue represents free apps and red represents paid apps. The solid lines are average marginal effects and the shaded areas show 95% confidence interval.

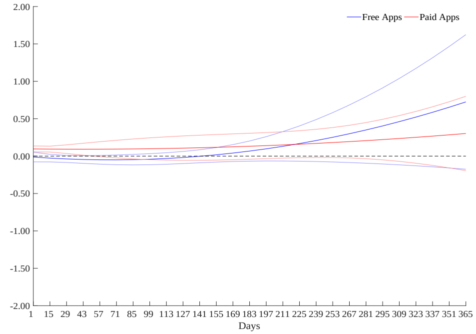
Figure 16: Effectiveness of Developer-controlled Variables over Time



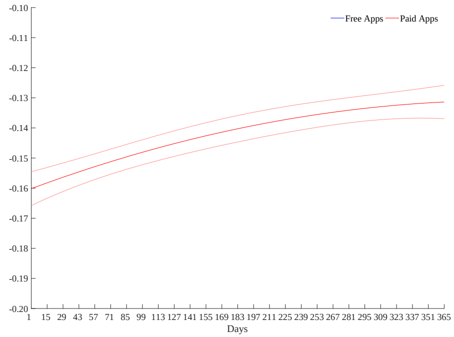
(A) Minor Update



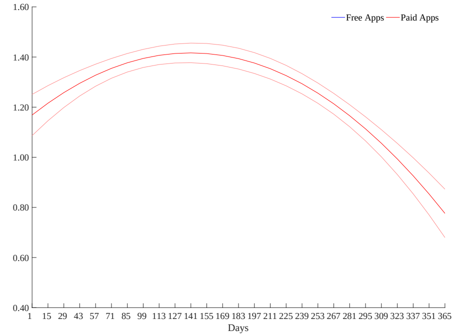
(B) Intermediate Update



(C) Major Update



(D) Price Elasticity



(E) Discount Depth

Notes: Blue represents free apps and red represents paid apps. The solid lines are average marginal effects and the shaded areas show 95% confidence interval.

3.4.1 Platform-controlled Variables

Being *featured in a top list* increases downloads of a free app by 3.93% and a paid app by 12.73% on average (Figure 14 Panel A). Contrary to our expectations, it benefits a paid app about three times as much. This result may suggest that appearance in the top curated lists (e.g., Top Overall, New and Noteworthy, or Editor's Choice) improves app discovery rates more in less-crowded app categories than it does in more-crowded categories. Alternatively, it may indicate that, potential adopters of paid apps consider these curated lists as a reliable source for a quality signal in their search for confirmation and uncertainty reduction before they commit to a transaction. As to the temporal variation of this factor's effectiveness, free apps enjoy a similar lift, in terms of magnitude, throughout the year. Appearance on a top featured list starts to boost downloads significantly only later in a free app's first year of existence. For paid apps, being featured in top lists has a substantial effect on downloads early on. The effectiveness of this tool gradually decreases over time and reaches a similar level of effectiveness observed for free apps.

In contrast, being *featured in other lists* fails to increase downloads: averaged over the entire year, downloads of free apps decline by 6.37% and paid apps by 4.24% (Figure 14, Panel B). Although contrary to our expectations, this result is not very surprising due to the very narrow and scattered nature of other featured lists. An obvious distinction between the top featured lists and others leaps out. Considering there are about 180 different lists, one may suggest that, instead of boosting downloads, appearing in these lists limits the general interest in the app and may even prevent users who normally would have downloaded the app to shy away. The magnitude of the deleterious effect declines over time but never completely disappears for free apps. Interestingly, being featured in other lists becomes effective for paid apps towards the end of the year.

In line with our expectations, merely *appearing in top apps charts* has a positive effect on downloads except for paid apps appearing above-the-fold later in their first year of existence (see Figure 14, Panels C-D)[20]. On average, getting into the list of apps presented above-the-fold increases downloads of free apps by 80.28%, below-the-fold by 60.95%,

[20] This unexpected result is due to a data peculiarity. We observe very few paid apps appearing above-the-fold in this sub-section of the time window. Accordingly, we are cautious about drawing strong conclusions about that particular data partition.

and below-the-2nd-fold by 57.36%. For paid apps, appearing above-the-fold has a negligibly small effect on average, whereas appearing below-the-fold increases downloads by 19.55% and below-the-2nd-fold by 27.35%. The effects are notably larger for free apps, as expected, and change sharply with each fold. Moreover, appearing in top apps charts has a much larger impact than (top) featured lists.

As to how the effects of appearing in top apps charts evolve over time, we observe that appearing above and below the fold has a relatively stable effect on free app downloads and a diminishing effect on paid app downloads. The effectiveness of appearing below-the-2nd-fold declines following the release of an app, for free and paid alike, and increases back to the initial level of effectiveness towards the end of the year. Collectively, these results suggest that appearing in top apps charts, anywhere above the 2nd fold, increases the speed with which paid app downloads reach their market potential and gradually lose their ability to bring in new users.

3.4.2 User-side Variables

Panel A and Panel B in Figure 15 display, respectively, *WoM valence* and *WoM volume* elasticities for free and paid apps. In line with Babić Rosario et al. (2016), we find that not all WOM metrics are positively associated with performance. Specifically, we find that a 10% increase in average rating score decreases free app downloads by .13% and increases paid app downloads by .23% on average. As expected, WoM valence has a higher impact on downloads in high risk situations (i.e., paid apps).

More interesting patterns emerge when the evolution of valence elasticities is considered. App download's sensitivity to changes in WoM valence early on is quite different for free and paid apps: an increase in average rating scores lowers the demand for free apps (by .42%, on average, in the first six months) but boosts download numbers for paid apps (by .22%, on average, in the first six months). The difference disappears as apps mature and valence elasticities of free and paid apps converge towards the end of the first year – approximately .02% and .05% increase for free and paid apps, respectively.

These findings raise concerns about the credibility of reviews for free apps written early on, where users may be less involved or the barrier to leave a review may be quite low – a particularly interesting issue considering the growing literature on fake reviews and their effects on sales (Dellarocas 2006; Streitfeld 2011; Mayzlin, Dover, and Chevalier 2014; Hu et al. 2012). Our finding suggests that users take the reviews of free apps written early on less seriously and even step back from downloading the app. However, as time passes and the average rating score of a free app stabilizes around a certain value, potential adopters start taking this information more seriously and into account.

As for paid apps, the results support the notion that potential adopters want to reduce perceived risks when purchasing apps by processing the information provided by current users. The experiences encoded in these reviews matter more in potential adopters' decisions in the first half of the year and increasingly less from then on.

WoM volume elasticities of downloads and their behaviors over time are quite similar across free and paid apps. On average, a 10% increase in WoM volume increases free app downloads by .13% and paid apps by .16%. This effect increases towards the mid-year of the app's release and declines at an increasing rate as apps mature.

3.4.3 Developer-controlled Variables

Panels A-C in Figure 16 display the relationships between *minor, intermediate, and major updates* and downloads of free and paid apps. As expected, updates benefit app demand in general. On average, downloads increase by 1.07% (minor), .83% (intermediate), and 22.30% (major) in response to free-app updates and by 3.78% (minor), 4.35% (intermediate), and 17.18% (major) for paid apps[21].

The evolution patterns of the update semi-elasticities are similar across update types and app business models, and the order of magnitude is mostly preserved. As expected, the effect of an update increases moving from minor to intermediate updates and this increase is larger for paid apps. Interestingly, minor updates released shortly after the launch of free/paid apps lower the demand (Figure 4, Panel A). We observe a similar pattern for intermediate updates of free apps. This result may suggest that having to offer a minor update (i.e., bug fixes and development tweaks) or an intermediate update (i.e., improvements to existing features of an app) shortly after an app's release signals low app

[21] Though major updates findings are consistent with expectations directionally and magnitude wise, there is substantial uncertainty around the estimates – due to the scarcity of major updates released in the last half of the data. Hence, we refrain from drawing strong conclusions about their effects.

quality (i.e., not ready for the market). However, approximately three months into an app's existence, the effects are reversed, and updates start to boost downloads as expected.

Panel D in Figure 16 displays the evolution of *price* elasticity over time. Consistent with the low-price elasticities reported for US Apple App Store (e.g., Ghose and Han 2014; Kübler et al. 2018), we find that a 10% increase in price lowers downloads by 1.41% on average. The magnitude of price elasticity declines with the passage of time: downloads become less sensitive to price changes as the app matures. As to the effect of *discounting* on downloads, displayed in Figure 16 Panel E, we find a 13.20% increase in app demand in response to a 10% temporary reduction in price. The increase in app demand in response to a discount is more than double what has been reported in other studies (e.g., Ghose and Han 2014), indicating that users are more discount sensitive shortly after the launch of an app and discounts lose their power to boost downloads with maturity. Supporting this conclusion, we observe that offering discounts increases downloads more and more as time passes, reaching peak effectiveness mid-year, declines from then on to a level lower than its initial effectiveness.

3.4.4 Sensitivity Checks

To explore the sensitivity of our findings, we re-estimate the models with different sub-groups of apps in our data. Specifically, we compared the results from (1) games (fun-oriented and hedonic) to non-games (task-oriented and utilitarian), (2) new apps (no history or customer base to rely on, mobile first) to apps by existing businesses (with a customer base that can readily be activated, not necessarily mobile first), and (3) all apps in the sample (current study's setting) to apps ranked at least 120 days (mimicking previous studies' settings). As the data exhibits a tendency to crumble, we refrain from further breaking these sub-samples down to free and paid apps. The coefficient estimates obtained from these sub-samples are presented in Table 14.

Noting that the over-time behavior of a given variable associated with downloads is fairly similar across different sub-samples within a grouping (e.g., games vs. non-games), unless otherwise mentioned, we observe the following structural differences. First, appearing on other featured lists, which had a deleterious effect on downloads, starts to work for games but only later in the first year of a game's existence. Second, the effectiveness of appearance in top app charts varies substantially across sub-samples. Appearing above (below) the fold is much more (more) strongly associated with downloads of games (vs. non-games), apps by existing businesses (vs. new apps), and apps ranked at least 120 days (vs. all apps).

Third, ratings and, more importantly, the number of reviews appear to have a stronger impact on downloads of non-games (vs. games) and new apps (vs. apps of existing businesses). Comparison of the user-side variables' effects of all apps vs. apps ranked at least 120 days shows that both over-time behavior and strength of associations exhibit substantial differences. Fourth, minor updates bring in slightly more users to games (vs. non-games). Intermediate updates, on the other hand, are more strongly associated with the downloads of non-games (vs. games). Though they follow a similar over-time pattern, the relationships between minor and intermediate updates and downloads observed in the apps ranked at least 120 days sub-sample (vs. all apps) are accentuated.

Finally, potential adopters of games (vs. non-games), new apps (vs. apps by existing businesses), and apps ranked at least 120 days (vs. all apps) are more sensitive to price changes independent of the direction of change. We also observe a change in the over-time behavior of price elasticity when comparing all apps to ranked apps.

3.5 Conclusions, Implications and Avenues for Future Research

In this paper, we explore factors that are related to app downloads and how these relationships may develop during the first year after an app's release. Our access to a rich database with download numbers enables us to include newly released apps in the sample independent of their ranking status and explore the effects of a broader set of variables to develop a more generalized understanding. *Time-varying* results from separate analyses for *free* and *paid* apps add interesting insights to the existing literature and suggest valuable implications for app developers.

Overall, our results suggest that the decisions and the actions of all three players in the app market – developers, users, and platform owners – seem critical for improving app performance at least at some point in the year following an app's release. The effects of platform-controlled variables, explored for the first time in this stream of the literature, dwarf those of variables shaping an app's relevance (i.e., developer-controlled factors) and variables reflecting current users' views about an app (i.e., user-side factors), highlighting the power app platform has on users' adoption decisions. Among these platform-controlled variables, the impact of appearance in top apps charts stands out, especially early on in a paid app's lifecycle and throughout a free app's. Featuring works when and where it benefits the platform owner the most: early on in the case of paid apps, which are featured almost twice as much, and only after gaining some traction with the users in the case of free apps, which experience a twofold increase in top feature placements over time. For an app platform that generates its revenues from paid app downloads and in-app purchases, most of which comes from free apps, our results have face validity.

The sheer size of platform-controlled variables' effects begs the question is this merely an awareness effect? Though it is without a doubt that the platform's decision to give apps a prominent position in the store aids app discovery, it is likely that potential adopters use this to infer additional information about apps. This is especially the case early on in an app's lifecycle, when relying on others' opinions is not an option either because the information is limited, or they think it is unreliable – evidenced by the deleterious effect of WoM valence on free app downloads shortly after release. Equipped with the common knowledge that an app's position in a top chart is determined by a combination of (i) a few unknown proprietary factors, (ii) previous updates, ratings, reviews, and downloads of the app – whose effects are controlled for in our analyses –, and (iii) user engagement, retention, and revenues from in-app purchases, one may argue that what this variable also captures is the effect current users' repeated interactions have on download decisions. This can be considered as a signal of app's quality based on others' actions. Likewise, a "feature" can also be considered as a signal of quality that reflects the platform's "seal of approval". Users looking to download an app may infer that the featured app must be of high quality because the platform owner has no incentive to feature an app with a low likelihood success. Independent of whether the actions of the platform owner merely aids app discovery or are used as quality signals that facilitate app evaluations or downloads, the app platform is powerful.

What can developers do given the influence app platforms have on users' adoption decisions? The pattern of results observed for free apps suggests that potential adopters are cautious early on. They are mainly swayed by the platform-controlled variable of appearance in top apps charts and the number of reviews the app has garnered (i.e., WoM volume), which signal how large and engaged the current user base is. Subjective evaluations of others (i.e., WoM valence) and developers' attempts to fix or improve apps (i.e., minor and intermediate updates) are either seen as signals that cannot be trusted or that the app is of inferior quality. As free apps mature, potential adopters start to rely more on what others say in addition to what others do. Yet, others' opinions never exceed the influence that (signals of) their actions have.

The only thing that is fully under the free-app developer's control is the app's value proposition; what unique need it satisfies and how effectively and efficiently it does so. The observation that intermediate updates appearing in the early days of a free app have a stronger deleterious effect on downloads than minor updates, which quickly recover, suggests that developers are better off releasing almost-ready-for-the-market apps. Though potential adopters may palate inefficiencies (i.e., bugs) early on, they are unforgiving when it comes to ineffectiveness (i.e., subpar content, functionality). This is especially important considering most free app developers launch minimum-viable-products and fix the issues along the way. As updates released later in a free app's lifecycle have a larger effect on downloads, especially when the changes between two consecutive versions of the app are more than minor, the developer can aim to increase the relevance of the app in the eyes of a larger pool of users and maintain or improve engagement of the current user base. This, in turn, may generate positive word-of-mouth on the platform and increase the chances that the free app gets a prominent position on the platform.

The pattern of results observed for paid apps suggests that potential adopters are even more cautious than those of free apps, especially early on. They combine signals from multiple sources (i.e., what others before them have said and done, whether the platform owner thinks the app is worthy of a prominent display in the store, how much they have to part with to acquire the app). However, as the paid app matures, the signals emanating from platform-controlled variables lose their relative power over those from app users and app developers.

Because getting the paid app in a top featured list as early as possible in the lifecycle helps with the discoverability problem and boosts downloads, the developer's actions that affect the curators' decisions to feature an app assumes great importance.

These decisions are based on, among other factors, the app’s content and functionalities (i.e., the value proposition) as well as user-experience and user-interface design (i.e., how effectively and efficiently the value proposition is delivered). Therefore, developers of paid apps should aim to launch a ready-for-the-market app that (better) satisfies a unique need and find ways of encouraging the users to rate and review the application. With the initial boost they can get from being featured in a top list and, possibly sometime later a prominent position in the top apps charts, they can attract more users who not only engage with the app but also generate the much needed positive word-of-mouth for even more downloads. As updates released later in the paid app’s lifecycle are capable of generating additional downloads, the developer can mine the reviews accumulated over time and decide in what direction to improve the app in the next version, ensuring longevity and a steady stream of revenues for the developer as well as the platform owner. Considering the recent changes in Apple’s revenue sharing model with developers of paid apps (i.e., a lower cut in the second year), survival has become more important than before.

Another decision variable at the disposal of a paid app developer is price. Developers should carefully determine their price points prior to release. As our results indicate that users are more price sensitive in the early phases of an app introduction and gradually become less concerned with price, penetration pricing seems to be the more meaningful choice. Yet, developers have room to set a slightly higher initial price and stimulate downloads and expand their user bases via promotions. Moreover, as discounting reaches its peak effectiveness several months into the app’s first year of existence, developers also have the flexibility to gradually increase the app’s price and encourage additional downloads occasionally by offering a discount.

Though our study adds interesting insights to the existing literature, there are several issues that may provide fruitful avenues for future research. First, given the nature of our data, we investigate the drivers of downloads at the aggregate level (i.e., number of downloads on a day). However, while conceptualizing, we rely on an individual’s decision journey on the app platform and identify factors that may facilitate users’ transitions from one journey stage to the next. Future research can enrich the insights by modeling at the individual level, provided these data exist and are accessible. Second, our findings on updates are particularly interesting, as this is the only variable that is completely under the app developer's control independent of the business model. In this paper, we inferred the nature of updates from the change in version numbers. Future research should consider the nature of these updates by analyzing the verbal descriptions of the improvements that accompany new version releases. Third, our analyses do not provide detailed insights into several systematic differences across apps. Although we provide initial insights on how the effects change across games vs. non-games or branded vs. non-branded developers, future research may contribute to an even more enriched understanding of these categorical differences. Finally, another growing area of research includes business model type as an important driver of app sales and performance. Especially for digital platforms, freemium business models are of increasing interest. Though extant work in this domain sheds some light on the effectiveness of freemium/paymium business model, our study could be extended to investigate the performance of apps following different business models.

Chapter 4

If It Ain’t Broke, Don’t Fix It: How Incorporating User Feedback In Product Development Affects Mobile Application Ratings

User insights are key to the development of successful products. Almost all successful companies by now have established their own ways to incorporate users in the process of product development, especially in the ideation and design stages. Although it required quite some effort on the companies’ side to reach out to users before, the balance has slid in favor of companies recently. The rapid advancements in technology and, the consequent emergence of platforms that publish customer comments (i.e., manufacturer and retailer websites, specialized customer review websites, online blogs, and social media) have enabled ubiquitous and easy access to valuable insights. This readily accessible and exponentially growing source of data has not gone unnoticed by scholars. Various aspects of user-generated content (e.g., volume, valence, and variance of ratings or topics/attributes mentioned in reviews) have been mined to study their effects on performance indicators such as sales (e.g., Godes and Mayzlin 2004; Dellarocas et al. 2007; Ghose and Han 2014), to infer the market structure (e.g., Lee and Bradlow 2011; Netzer et al. 2012), and to uncover latent user needs (e.g., Timoshenko and Hauser 2019). Yet, how companies can benefit further from these data, specifically in the context of continuous product development, remains a relevant question and a potentially fruitful avenue for research.

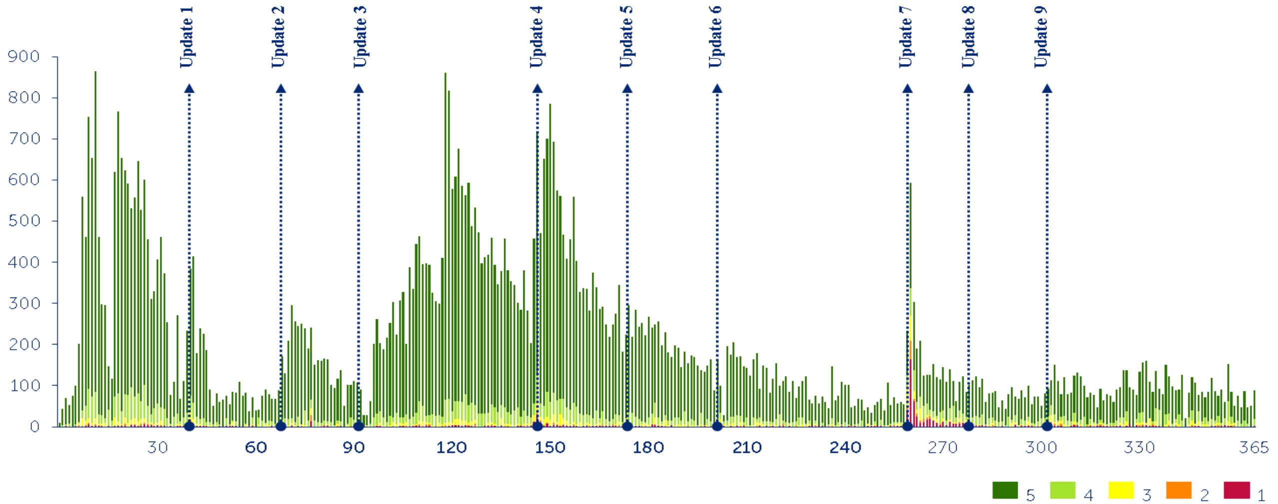
Consumers write reviews or generate content concerning products to communicate their personal experiences, hence their post-purchase evaluations of the product (Moe and Schweidel 2011). The potential and/or current customers of the product, in the process of forming their pre-purchase evaluations or adjusting their post-purchase evaluations of the product, are the natural audience for the reviews. However, the dynamic setting in the mobile applications market enables embedding feedback directed at the product supplier or manufacturer in these reviews. When writing the review, the consumers are motivated by the impact of their reviews on others (Wu and Huberman 2008)(direct impact). In a setting where companies can alter their value propositions of the product based on user generated content; a different dimension for 'the impact of the review' emerges: the prospect of contributing to the product development (indirect impact). In fact, companies can respond to the issues raised in user-generated content by merely replying to the comments, a passive form of response, or by taking direct action based on the information in the comments. The latter is an active form of response. Extant research has investigated the effects of the former (e.g., Proserpio and Zervas 2017; Chevalier, Dover and Mayzlin 2018; Wang and Chaudry 2018), leaving the latter a relatively unexplored area. Accordingly, we pose the following empirical questions in this study: How can firms utilize the information in user comments in the process of product development? What are the effects of incorporating user requests extracted from reviews in the development of successive generations of a product on user evaluations? To what extent do these effects vary depending on the nature of the requests and areas of improvement and as a function of time?

To explore how actively responding to user requests is reflected in product evaluations, we study the interlinked process of user reactions and successive releases of updated products in the mobile applications market. We focus on the early stages of mobile apps' lifecycles. The reason for choosing the mobile applications market and focusing on the period following an app's initial release is as follows. The idea of starting with a minimum viable product and pivoting has quickly taken root in the start-up world replacing the big design up front approach (Blank 2013). This trend has resonated most with none other than application developers; experimentation and continuous innovation have become the norm in their industry[22]. The mobile applications market provides us with a unique setting and a fertile ground to study whether firms can harness the opportunity of continuous interaction with their customers. First, constant rating and reviewing activity on the user side generates large amounts of data, from which one can extract customer feedback. Second, unlike traditional markets, where product improvement usually takes long and is associated with high costs, developers improve their products at relatively lower costs and in a shorter time frame. Frequent updating activity on the developer side provides many instances for analyzing the effects of (not) incorporating customer feedback in the product development process[23].

To illustrate it with an example, Figure 17 depicts the daily review star distribution and the updates for one of the games in our sample. The substantial changes in the star distribution of the application following the 7th and 8th Updates are particularly noteworthy. The investigation of the corresponding update descriptions reveals that Update 7 intends to add new features to the app. However, the investigation of consequent user comments shows that this is a failed attempt. The timely realization of this failed attempt and response of the developer to fix this issue in Update 8 results in users' praise in the reviews following Update 8 (See Figure 17 for update descriptions and examples of user reviews). In this example, Update 7 grows user expectations, which are then not met. This releases a sudden and strong tension, which is then relieved by Update 8.

[22] See https://medium.com/swlh/why-you-need-an-mvp-for-your-mobile-app-4f8046ac52e0.
[23] The investigation of the update descriptions evidences that developers actively monitor user reviews: "You asked for it, so we built it: a new review mode lets you polish up either individual lessons or else all of the content you've completed so far.", "You asked for it and we're thrilled to deliver. This latest version includes your recent orders in "The Usual" section. Plus, reorder your favorites with one click.", "Soundscapes/white noise, you asked for it and we added it :)", etc.

Figure 17: Daily Review Distribution of a Gaming App



Update 7 Description:
- 5 new animals to liven up your village
- New Items: Warm your heart with the Love Nest and Nursery.
- Max level has been raised even higher, with fun new quests for players level 60 and up!
- Compatibility with Facebook's Open Graph 2.0 to play more with your friends!

1.0	**Loved at first** Can't play after updating. Piece of crap.
1.0	**Sir** Crappy!!! I was at level 60 and had invested $60 in acorns. Put on the latest update and now the game crashes before it starts. No way to contact Gameloft for support! The support page says I have to uninstall and reinstall the app and lose everything.Not even worth one star now. Maybe 5 if it is fixed, before my babies run away.
1.0	**Pretty upset the new updated ruined my game** This stinks I can't open this anymore and I'm not starting over took me forever to get me where I was, so I guess I'm don't playing this game really bums me out :-/

Update 8 Description:
You can now enjoy the previously released content, especially the new animals and new items.
- 5 new animals to liven up your village
- Warm your heart with the Love Nest and Nursery.

4.0	**Latest version win!** With the new update they finally fixed the problem where it wouldn't open. (It took them forever) but now the game is great! It runs smoother than ever before!
5.0	**Thank you!** Thank you for getting our game up and running. We appreciate it. Seems as if everything is in order. Hope you had a wonderful vacation. Glad I was somewhat patient.
4.0	**Thanks for the fix** Great job on the update, finally can play again! Much faster gameplay. Would be 5 stars if you wouldn't break it every other update!

To address whether and how much it pays off to incorporate user feedback in development stages following a mobile app's initial release on the market, we deep dive into the detailed analysis of user reviews of mobile applications and verbal descriptions of application updates. For this purpose, we collected publicly available textual data on user reviews (approx. 1M reviews), the description of updates (approx. 3.2K updates listing 12.2K specific changes), and (quantitative) user ratings for 460 apps in the Apple App Store during the first year following the applications' initial releases. Content analysis of update descriptions reveals that updates can come in the form of fixing bugs, making the application compatible with new operating systems and devices, adding new features or content to the application, or improving existing features or content of an application – referred to as content hereafter. We extract user feedback corresponding to these four broad categories following a lexicon-based approach. As such lexica didn't previously exist, we created custom dictionaries. Using these data, we investigate the effects of (1) offering an update, (2) the intensity of the user feedback, (3) the time it takes the developer to address the requests, and (4) the interactions among these variables on the average rating score of an app's new version. We perform the analysis for different app business modes (i.e., free and paid) and types (i.e., games and non-games) and check the sensitivity of the results to an alternative operationalization of feedback intensity.

Our results indicate that mining user reviews and acting upon their requests can benefit developers in terms of product evaluations. For bug fixes, we observe that the developers are better off only when the users also request fixes and yet the rewards come with an expiry date as early as the first two versions following the complaints. Compatibility issues/updates behave differently. Being available to the user upfront is of crucial importance, as the negative effect of accumulated user requests for compatibility cannot be reversed by such updates. We observe that it is possible to delight users by adding new app content as long as such updates are released intermittently. Moreover, responding to user demands for new app content is beneficial. However, the developer has a limited time window to comply and enjoy the benefits. Finally, for updates wherein existing content is improved, we observe a deleterious effect, which can only be reversed when the response is prompt. Collectively, these findings suggest that mobile application developers should adopt a continuous product improvement strategy on some fronts while complying on others.

The remainder of the paper is organized as follows. We start by reviewing the related literature on user reviews, new product development, and mobile applications, which collectively create the conceptual foundation for our study. We then present an overview of the user-developer timelines that form the basis of our conceptual framework. Next, we describe the steps we followed when collecting and organizing the data. Specification of the empirical model and operationalizations of variables are followed by our results, conclusions, implications, and avenues for future research.

4.1 Research Background

Our research draws upon various streams in the literature, user reviews or online word-of-mouth, new product development, and mobile applications. We review the literature in each stream and summarize the key insights relevant to our research.

4.1.1 User Reviews: The Voice of the Customer

Online word-of-mouth has been a widely investigated topic for almost two decades, ever since the proliferation of user reviews due to the increasing number of available interfaces in digital platforms. As more customers rely on other customers’ opinions about a product in their purchase decisions, research in this domain initially focused on the effect of user reviews on sales and other performance measures in various industries such as books (Chevalier and Mayzlin 2006; Forman, Ghose and Wiesenfeld 2008), video games (Zhu and Zhang 2006), movies (Duan, Gu and Whinston 2011; Liu 2006), music (Dhar and Chang 2009), hotels (Vermeulen and Seegers 2009; Ye et al. 2011), and restaurants (Anderson and Magruder 2012; Luca 2016). Whereas earlier work mainly studied the relationship between valence, variance, and volume of online word of mouth and performance (Dellarocas and Narayan 2006), recent advancements in text mining and rapid diffusion of textual analysis software allowed for an in-depth analysis of the linguistic features of user reviews. Consequently, recent studies have sought to advance our understanding of how certain linguistic characteristics impact, for instance, the sentiment (Villarroel Ordenes et al. 2019) or persuasiveness (Packard and Berger 2017) of user reviews and, thereby, sales.

In addition to the relationship between online word-of-mouth and sales and how the linguistic characteristics of user reviews shape their impact, user reviews have also been studied to provide a better, or an alternative, understanding of the drivers of consumer choices, market structure, and competitive positioning of brands (e.g., Archak, Ghose and Ipeirotis 2011; Büschken and Allenby 2016; Lee and Bradlow 2011; Netzer et al. 2012; Tirunillai and Tellis 2014). Recently, Timoshenko and Hauser (2019) propose a method for selecting informative content within user reviews and extracting (latent) customer needs from the selected content. Collectively, these recent studies illustrate the presence of potentially useful information in reviews, in addition to the sentiment of reviews.

As to what managers can do with this information, one can make a distinction between passive and active forms of response. Managers' public responses to user reviews (i.e., mere replies) can be considered as a reactive form of response (i.e., passive). The literature on managers' public responses to user reviews provides interesting insights. For instance, Proserpio and Zervas (2017) find that management responses to user reviews lead to more positive subsequent reviews by increasing the potential cost of writing a negative review. On the contrary, Chevalier, Dover and Mayzlin (2018) find that manager responses to user reviews encourage customers to write about their complaints, which results in more negative reviews. Wang and Chaudry (2018) make a distinction between positive and negative reviews and find that responding to positive (negative) reviews publicly can result in more negative (positive) subsequent reviews in the case of hotels. The authors argue that responses to positive reviews can raise questions regarding the sincerity of the response and can be inferred as promotional, whereas users can observe and infer that management is adopting a strategy to address complaints from responses to negative reviews.

Although this stream of research provides an understanding of how the interactions between firms and customers affect the subsequent evaluation of a product, it is still unclear whether the proposed solutions or the promised changes are implemented – an active form of response – and, subsequently, can improve customer evaluations. For these insights, we turn to the new product development literature.

4.1.2 New Product Development: Bringing in the Voice of the Customer

The new product development (NPD) literature embraces the importance of acknowledging customer needs and incorporating the voice of the customer during various stages of the NPD process. Research in this domain spans studies on creating mechanisms for integrating customer requirements into the design stage (e.g., Bailetti and Litva 1995) and the effects of customizing products based on customers' expressed preferences on willingness to pay, purchase intentions, and attitudes toward the new product (e.g., Franke, Keinz and Steger et al. 2009) to meta-analyses on the determinants of new product success stating the significant effects of meeting customer needs (e.g., Henard and Szymanski, 2001). In a more recent meta-analysis, Chang and Taylor (2016) underline the importance of actively engaging customers in the early as well as the late stages of NPD. Consequently, crowdsourcing ideas for new and continuous product development has become a preferred strategy for many businesses in recent years.

Studying the effects of customer involvement on major innovation success, Coviello and Joseph (2012) suggest that prolonged co-creation with customers, who function as sources of latent needs, increases success. Early engagement and conversation as well as mindful trial and error with a sufficiently diverse customer mix are seen as building blocks of a successful new product co-development process. Viewing customers as co-innovators and firms as facilitators of information sharing and mutual learning, Coviello and Joseph (2012) define NPD for major innovations as socially constructed and generative processes and refer to an "almost ready, fire, do a bit more, refire" approach for its success.

This study is particularly important because the key points identified for major innovation success by the authors in the conventional NPD sense constitute the milestones of the setting in our study. These key points are (1) interaction with a sufficiently diverse user mix over time to understand their needs, and (2) seeing the NPD process as iterative and generative. These are also among critical unique properties of the mobile applications market; equipping us with an appropriate setting to re-study this traditional NPD problem through a new lens.

4.1.3 Mobile Applications: The Role of the Voice of the Customer

Because of the lucrative business opportunities mobile applications present, the market's rapid emergence, and its highly competitive nature, the mobile applications market has drawn considerable interest from scholars recently. Among many other factors, the roles user reviews and updates (i.e., the successive release of new versions of an application) play in mobile app success have been studied. Favorable product evaluations in the form of average user ratings increase an application's perceived utility (Hao et al. 2011) and ultimately its demand (Ghose and Han 2014). The literature has also reached a consensus on the positive association between updates and app performance: demand is higher for apps that are regularly updated (Aydin Gokgoz, Ataman and van Bruggen 2021; Carrare 2012; Ghose and Han 2014; Kübler et al. 2018). However, these studies investigate the effects of user reviews and updates on app performance independently, overlooking the interdependency between the two processes.

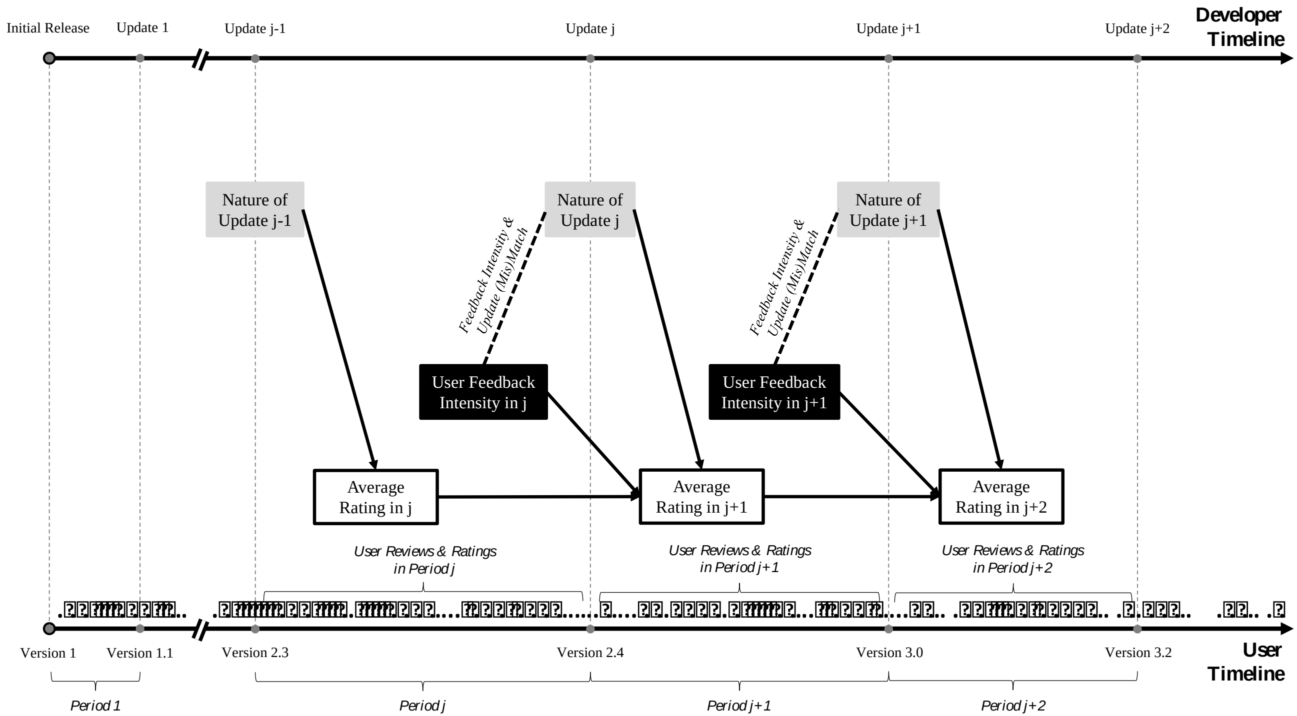
Jang and Chung (2015), who turn their attention to the relationship between updates and reviews, is a notable exception. Authors investigate the impact of different interaction activities (among customers (C2C interaction measured by the number of user reviews), from customers to firms (C2B interaction measured by the number of emails), and from firms to customers (B2C interaction measured by the number of online posts/emails and by the presence of a software update)) on app performance. Their results indicate that the quantity of C2C and C2B communication activities have a direct positive impact on app sales, but not on lifetime, and an indirect positive effect on both app sales and lifetime through an increase in R&D activity (i.e., updates).

Though Jang and Chung (2015) identify that this marketplace offers a dynamic setting to investigate the interaction activities between developers and users, the study ignores an important aspect of user reviews: its content. By processing and utilizing review content, developers can mold their applications to better satisfy user needs.

4.2 Reviews and Updates in a Mobile Application's Timeline

The timeline of a mobile application starts with its launch on the market. Following the initial release, the developer *updates* the application at specific, yet not necessarily regular, points in time. Each update is the result of a continuous product development effort, where the developer fixes, modifies, and/or enhances the application (e.g., makes several changes to the application at once). Running parallel to the sequence of updates is the continuous process of evaluation by the application's users. Users, depending on their arrival times, download the most up-to-date version of the application and, after interacting with the app for some time, express their overall satisfaction with a *star-rating*. These evaluations are often accompanied by a *review*, wherein the users justify their ratings for the benefit of other users and/or write feedback to the developer requesting certain changes to the application. Consequently, an application's timeline can be expressed as a repeated cycle of two continuous processes: updating (by the developer) and reviewing (by the user). Each cycle begins with an update that outsets a newer version of the application, which is then rated and reviewed by the users, and is completed with the release of the next version. Figure 18 displays these cycles in an application's timeline with the developer's timeline presented in the upper half and the users' in the lower half of the figure. Next, we discuss the interplay between user reviews and developer updates across these cycles and how this relationship influences users' overall evaluation of the application.

Figure 18: Conceptual Framework



Updating an application has the potential to improve its rating, as with each update the developer offers a new and improved version of its product to its current and potential future users. Existing research on the performance of mobile applications agrees that updates are beneficial – demand is found to be higher for apps that are regularly updated (Carrare 2012; Ghose and Han 2014) – and provides empirical evidence that the favorable impact of updating an application is likely to change depending on the nature of the update. For instance, Aydin Gokgoz, Ataman, and van Bruggen (2021) find that major updates generate more downloads than mid-level or minor updates. Moreover, they show that the effect of the updates changes over the life-cycle of the apps. Kübler et al. (2018) recommend localization of updates across countries for better performance. Yet, research to date is silent on how or why a developer updates an application in the way s/he does and how these decisions influence the application's performance. Coupled with insights from conventional NPD literature, we argue that the extent to which a developer brings in the voice-of-the-user to update decisions plays a critical role.

Following the release of an initial or a new-and-updated version of an application, the developer needs to decide when to offer the next update and what to change in this new version to maximize user satisfaction. As the developer is in the process of deciding what to do next, reviews of the most up-to-date version of the application keep accumulating. In these reviews, users voice their specific demands and request certain changes to the application. Some of these demands or requests will overlap and be voiced by many (e.g., see reviews following Update 7 in Figure 17), suggesting a specific route for the next set of development tasks whereas others will be scattered and voiced by only a few. The decisions pertaining to the next update (i.e., the timing and nature of the update) can be (1) contrary to users' feedback, either because specific requests have not been voiced by many in the reviews or the developer ignores the feedback, or (2) in line with user demands.We propose that the nature and the timing of the update along with the correspondence between what specific changes users demand and what the developer changes in the application will determine how favorably the new version is going to be evaluated. We rely on the Expectancy Confirmation Theory (referred to as ECT hereafter) (Oliver 1980) to develop the expectations.

Of the three possible and meaningful update scenarios, the first one, which we refer to as *compliance* corresponds to the situations wherein users request specific changes with one voice (i.e., feedback intensity is high) and the developer responds to these request[24]s in the update. Previous literature on NPD and confirmation cases in ECT would suggest that the new version of the application is going to be evaluated more favorably than the former version. Based on the learnings from the literature on customer complaints (Moore and Moore 2004; Istanbulluoglu 2017; Davidow 2003; Wang and Chaudry 2018), we expect that the associated rewards will be lower if the developer does not promptly update the application.

The second scenario is the reversal of the former situation and corresponds to cases wherein users almost unanimously complain about specific issues or explicitly state their requests regarding certain changes (i.e., feedback intensity is high); however, the developer chooses to ignore or fails to respond to these requests. We refer to this situation; when the developer prioritizes her/his agenda, as *non-compliance*. In ECT, non-compliance corresponds to negative disconfirmation as user expectations are not met. A non-compliant developer is likely to be penalized, and the application's new version will be rated lower than the previous version. Similarly, in line with previous literature on complaints, we expect the severity of the penalty to increase as the developer continues to ignore user requests.

In the final scenario, users do not request a specific change (i.e., feedback intensity is virtually non-existent), yet the developer proactively provides its users with an update. We refer to this situation as *user delight*, as the developer offers a superior application that meets the user needs in a prescient manner. Consequently, in line with ECT, the developer should enjoy higher ratings for the new version to reflect the awe factor stemming from offering a superior product beyond customers' expectations. User expectations will be raised following a delighting experience, making it harder for the developer to enjoy similar benefits. However, Rust and Oliver (2000) show that firms that delight their customers can benefit from forgetting so that the delighting experience can be repeated. Accordingly, we expect the rewards associated with user delight to increase with delay.

In sum, we argue that what the developer offers in an update (i.e., the nature of

[24] For simplicity, we consider the end cases of feedback intensity, boiling it down to an almost dichotomous scale.

the update) is going to be reflected in the new version's rating scores. More specifically, we suggest that the change in two consecutive version ratings is going to be related to the nature of the update that outsets the newer version and its correspondence – or lack thereof – to the user reviews preceding it. We expect an increase in new version rating scores in developer compliance and user delight cases and a decrease in developer non-compliance cases. Moreover, we expect compliance effects to diminish and non-compliance effects to intensify as developers take more iterations to respond (not-respond) to the users. Delays should benefit user delight. These expectations are summarized in Figure 19.

Figure 19: Summary of Expectations

		Developer Update	
		No	**Yes**
User Feedback	**Absent**	Base Case	Scenario: *Customer Delight* Expected Effect: *Positive* ECT Reason: *Beyond Expectations* Timing: *Intensify with Delay*
	Present	Scenario: *Non-Compliance* Expected Effect: *Negative* ECT Reason: *Negative disconfirmation* Timing: *Intensify with Delay*	Scenario: *Compliance* Expected Effect: *Positive* ECT Reason: *Confirmation* Timing: *Diminish with Delay*

4.3 Data

To investigate whether and to what extent responding to or ignoring user requests or delighting users influence how favorably the application's new version is evaluated, we have put together a unique data set on application updates and user reviews for a total of 1011 mobile applications – a stratified random sample taken from 40,000 newly released apps on the Apple App Store in 2012[25]. As experimentation and continuous innovation are more likely to be observed early on in an application's lifecycle, we focus on the first year of each application's existence. To accurately reflect the application business type (i.e., free or paid application) and application category (e.g., entertainment, lifestyle, social networking, games, etc.) distribution in the Apple App Store, we draw a random sample from each business type-category combination proportional to its share in the App Store. Table 21 and Figure 23 in Appendix show, respectively, the definitions and examples of application categories in the App Store and the distribution of applications across categories in the App Store and our sample.

For the sampled applications, we collected data on (1) textual definitions of updates provided by the developers and (2) reviews written by the users. These publicly available data were collected from the Apple App Store and App Annie, a leading mobile analytics company, with the help of a web crawler. The initial data set contained approximately 1.3 million user reviews and 6,200 developer updates with 16,000 lines, each indicating specific changes. We screened out applications that were never updated or updated only once, as we need at least two fully observed periods for analysis (i.e., two updates after the first version). We also screened out applications that had less than 50 reviews at the end of the first year to ensure that we have enough reviews per period for analysis. The final data set consists of 460 applications with a total number of 1,075,704 user reviews and 3,255 updates listing 12,268 specific changes. Next, we outline the procedures we follow in processing textual descriptions of updates and user reviews in detail.

4.3.1 Update Categories and Classification of Update Descriptions

An essential component in our study, are the actions of the developer; specifically, the changes a developer makes in the new version of the application. We infer the nature of an update by investigating and classifying the verbal update descriptions accompanying each update. These are concise and organized descriptions provided by the developers, mainly for the benefit of their current and potential users, listing the adjustments in the newly

[25] The list of new applications released in the first five months of 2012 was acquired from Distimo, one of the leading mobile analytics companies, now owned by App Annie, as part of a larger data set and complemented with publicly available data later.

released version of the application (i.e., What's new in Version #.#?). The first two columns of Table 16 display the update history of a randomly selected application in our sample and the list of changes made in each version. The last two columns of the table display the assigned update types of the specific changes. To determine the update types and where each entry in the update descriptions belongs, we followed the procedure outlined next.

Table 16: Example of An Application's Update History and Classification of Changes (Application: Highway Rider)

Version	Update Description	Update Subcategory	
		Primary	Secondary
1	N.A. (Initial release)	--	--
1.0.1	Minor bug fixes and tweaks	Bug fixes	
	Optimized for the iPad 3	OS/ Device Compatibility	
1.1	Added BOOSTS to get instant speed and higher top speeds!	Add Content	
	Sped up end sequence and made it skippable	Improve Content	Add Content
	Lots bug fixes and tweaks	Bug fixes	
1.1.1	Added pause button	Add Content	
	Now allows skipping of crash sequence	Add Content	
	Now allows skipping of intro scenes	Add Content	
	Bug fixes	Bug fixes	
1.2	Higher resolution models and textures for retina devices	OS/ Device Compatibility	
	Added fugitive mode with some angry cops!	Add Content	
	Now all hazards are score-able	Improve Content	
	Added experimental first person mode	Add Content	
	Multiplayer bug fixes and invite improvements	Bug fixes	Improve Content
	Many bug fixes and tweaks	Bug fixes	
1.3	Six brand new characters with unique handling and attitude!	Add Content	
	New scoring system based off how closely you score!	Add Content	
	Local leaderboards and new scoreboards	Add Content	
	Minor gameplay fixes and tweaks	Bug fixes	

	Optimized for the iPhone 5	OS/ Device Compatibility	
1.4.5	Updated highway visuals	UI improvements/ changes	
	Dramatically lowered prices of characters	In-App Purchase	
	Optimizations and bug fixes	Bug fixes	Performance improvement
1.4.6	Fixed a bug with crashes when a device is offline	Bug fixes	

First, we came up with an initial list of update types by content analyzing update descriptions and reviewing popular publications and/or blogs on the topic. Next, we fine-tuned this list through discussions with a user experience research and design expert. We provided the expert with the initial list of update types, the corresponding definitions, and a random sample of update descriptions extracted from another mobile application store and asked him/her to (1) group or split update categories, (2) propose new ones, and (3) evaluate the representativeness and coverage of his/her final proposal by applying it to the provided sample. Table 17 presents the final list of update types obtained after this iteration along with their definitions. The last column of the table contains some examples.

Table 17: Definition and Examples of Update Categories

Update Category	Update Type	Definition	Example
Bug Fix	Bug Fix	Bug fixes are minor updates that ensure that the application works, as it should	“Minor bug fixes and tweaks”, “Fixed a bug with crashes when a device is offline”
Compatibility	OS/ Device Compatibility	Developer updates the application to ensure that it works on different devices or functions properly in most up-to-date operating systems	“ios6 compatibility release”, “Compatible with more devices”
Add Content/ Feature	Personalization/ Customization	Allows the user to customize the application to her taste and remembers previous choices	“Your language selection is saved but can be changed again any time later”, “Remembers login”
	Offline Functionality	Allows users to access the application/use it without connecting to a network	“In the new tab “Other” you can now (even in the free version) download all mp3 audio files for all 100 lessons and in all language combinations”
	Location Sensitivity	The application is location sensitive (GPS enabled)	“GPS Track View, Play, and Record functions has been added. User could see GPS Track on the Map with Photos. GPS Track also can be played and saved (recorded)”
	Sharing/ Social Networking	Allows the user to connect with others in her social network	“You can now share with Facebook, Twitter or another social network!!”
	Feedback	Allows the user to connect with the developer directly	“You can now write us directly from the settings screen. We love your feedback!”
Add Content/ Feature	New Content	Offers the user content that was not present in the previous version of the application	“New levels”, “Helicopters, Shields and Weapons”
	Integration/ Synchronization	Allows the application to interact with other applications/web-sites	“Heyzap integration (The largest community of mobile gamers)”, “Share Link option for better integration w/ other Web Browsers”

Update Category	Update Type	Definition	Example
	Localization	Offer the users local features such as new languages, cities, states, geographies, etc.	"New localizations: Spanish, French and Italian are now supported", "English and Chinese languages are now supported"
Improve Content/ Feature	Personalization/Customization	See above.	"Optimize the Theme Customization process", "More customization supports"
	Offline Functionality	See above.	"Save, browse and load song files"
	Location Sensitivity	See above.	"Improved Current Location functionality by implementing the Google Maps My Location marker"
	Sharing/ Social Networking	See above.	"Made some Enhancements to sharing a story when posting it", "Changed login process to use new Facebook standard"
	Feedback	See above.	"Fine-grained feedback"
	Existing Content	See above.	"Improved libraries"
	User Interface	Includes enhancements in the user interface (i.e., design and/or placement of buttons, etc.)	"Images and colors can be used as backgrounds (16 custom wallpapers included)", "Hour and battery left on menu button"
Improve Content/ Feature	Gestures	Includes enhancements related to gestures (i.e., gestures needed to work and control the app).	"Paddle at the bottom of the screen to move the ball and fired to modify the area to be distinguished", "In this version you can enter your own currency rate by long press on currency in the list"
	Performance	Smaller file size, improved speed etc.	"Changed database access code to avoid locking on faster phones", "About 20% reduction in memory usage for most of themes!! More fluid now"
Remove Content/	Content/ Features	See above.	"Building underwater no longer possible"
	Advertisements	Removal of advertisements witihin the app	"New: No more ads!", "Banner ads removed so there

Update Category	Update Type	Definition	Example
Feature			will be more space for windows”
Sales/Offers	In-App Purchase	Enables In-App Purchase option for the application for the first time	“Add in app purchase function”, “Dietary Supplement - now you can shop right from our App to purchase D'Adamo Personalized Nutrition® supplements (see More, then Dietary Supplements)”
	Cross-selling	Ads of other applications by the developer	“Have you tried our other game in the series, Grandpa's Workshop?”
	Special Offers	Seasonal Promotions such as "Christmas" or "Valentine's day" or limited time offers	“4th July Sale 50% off Imperial Store items!”
Other	Feedback Requests	Asks the user to connect with the developer to rate the app, like app’s Facebook page, etc.	“Feel free to write us about any bugs or improvements to blueplopgames@gmail.com”
Other	News/ Information	Information about upcoming features of the app or any other news	“Coming soon:- App support for hands-free calling with Bluetooth™ compatible phones.”
	Tips	Guides the user through various features of the application	“TIP: You can always double tap any day to mark them as complete or to unmark them. ”
	“Thank you!” Notes	Includes thank you notes for users from developers	“Thanks for your awesome reviews and feedback!”
	Cryptic	The description does not allow the coder to classify the update	Empty Updates or Updates with version history only.

Because the number of update descriptions is not so high as to render human coding impossible, we decided to take this opportunity in the final coding. We recruited a research assistant with a background in computer engineering, who was undergoing a graduate-level training in marketing at the time of coding, provided him/her with the final list of update categories, definitions, and examples, and trained him/her in coding the entries in update descriptions to update categories. The assistant then coded the entire dataset, consulting the researchers for clarification questions when needed. S/he was allowed to assign an entry in the update description to multiple categories.

A careful examination of the content and the definitions of the update types reveals seven higher-order update categories: Bug Fix (i.e., indicates minor improvements that ensure the application works as intended), OS/Device Compatibility (i.e., ensures that the application works on different devices or functions properly in most up-to-date operating systems), Add Content/Feature (i.e., adds new content to the application or new features, such as allowing users to personalize, customize, work offline, work in harmony with other apps, etc.), Improve Content/Feature (i.e., improves the existing content or features of the application), Remove Content/Feature (i.e., disables undesirable content or features, such as intrusive ads), Sales/Offers (i.e., enables in-app purchases or encourages cross-selling) , and Other (i.e., update description entries that do not indicate an improvement, such as feedback requests, or that are not clear enough to be classified). In our empirical application, we focus on four higher-order update categories of "Bug Fix", "OS/Device Compatibility", "Add Content/Feature" and "Improve Content/Feature" that directly target current and/or future users of the application. We decided to ignore updates that fall under "Remove Content/Feature" because it had an insufficient number of observations, "Sales/Offers" because price changes would limit the analyses to a subset of the sample and they were not perfectly aligned with updates, and "Other" because they didn't indicate an improvement or an extension in the application. The frequency distribution of update categories for all applications and per application type (i.e., free vs. paid), as well as application category (i.e., games vs. non-games), is presented in Table 18.

Table 18: Data Descriptives

	All Apps		Free Apps		Paid Apps	
Number of Applications	460		276		184	
Number of Updates	3255		2015		1240	
Bug Fix	2118		1292		836	
OS/Device Compatibility	492		281		211	
Add Feature/ Content	1704		979		725	
Improve Feature/ Content	1542		937		605	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Average Rating	3.739	1.015	3.595	1.082	3.973	.845
Update						
Bug Fix	.654	.476	.641	.480	.674	.469
OS/Device Compatibility	.151	.358	.139	.347	.170	.376
Add Feature/ Content	.524	.500	.486	.500	.585	.493
Improve Feature/ Content	.474	.499	.465	.499	.488	.500
Versions Since Last…						
Bug Fix Update	.581	1.242	.648	1.375	.472	.980
OS/Device Compatibility Update	2.482	2.725	2.631	2.832	2.240	2.524
Add Content/Feature Update	.777	1.344	.886	1.438	.599	1.155
Improve Content/Feature Update	1.041	1.785	1.139	1.920	.882	1.530
	5-star Reviews		5-star Reviews		5-star Reviews	
	Included	Excluded	Included	Excluded	Included	Excluded
Number of Reviews	1,075,704	313,554	638,767	196,985	436,937	116,569

	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reviews per Version	330.48	3564.33	96.33	872.94	317.01	2287.60	97.76	546.35	352.37	4985.83	94.01	1231.30
Reviews per Application	2338.49	13146.58	681.64	3246.07	2314.37	11498.97	713.71	3022.59	2374.66	15323.03	633.53	3563.12
Feedback Intensity												
Bugs	.147	.180	.210	.226	.154	.189	.213	.228	.136	.165	.205	.224
OS/Device Compatibility Issues	.090	.137	.093	.154	.085	.135	.092	.157	.099	.140	.095	.149
New Content/Feature Requests	.103	.138	.118	.167	.102	.141	.119	.171	.104	.133	.117	.161
Improve Content/Feature Requests	.069	.102	.091	.131	.068	.100	.090	.128	.071	.104	.092	.135

	All Apps		**Games**		**Non-Games**	
Number of Applications	460		149		311	
Number of Updates	3255		1015		2240	
Bug Fix	2118		684		1444	
OS/Device Compatibility	492		117		375	
Add Feature/Content	1704		537		1167	
Improve Feature/Content	1542		398		1144	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Average Rating	3.739	1.015	4.087	.743	3.581	1.080
Update						
Bug Fix	.654	0.476	.674	.469	.645	.479
OS/Device Compatibility	.151	0.358	.115	.320	.167	.373
Add Feature/Content	.524	0.500	.529	.499	.521	.500

Improve Feature/Content	.474		0.499		.392		.488		.511		.500	
Versions Since Last…												
Bug Fix Update	.581		1.242		.546		1.353		.596		1.189	
OS/Device Compatibility Update	2.482		2.725		2.781		2.972		2.346		2.595	
Add Content/Feature Update	.777		1.344		.775		1.443		.777		1.297	
Improve Content/Feature Update	1.041		1.785		1.175		1.717		.980		1.812	
	5-star Reviews				5-star Reviews				5-star Reviews			
	Included		Excluded		Included		Excluded		Included		Excluded	
Number of Reviews	1075704		313554		801087		210226		274617		103328	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Reviews per Version	330.48	3564.33	96.33	872.94	789.25	6321.32	207.12	1543.60	122.60	477.84	46.13	142.53
Reviews per Application	2338.49	13146.58	681.64	3246.07	5376.423	22618.72	1410.91	5554.38	883.01	2256.51	332.24	703.19
Feedback Intensity												
Bugs	.147	.180	.210	.226	.115	.142	.197	.210	.162	.193	.216	.233
OS/Device Compatibility Issues	.090	.137	.093	.154	.050	.081	.053	.102	.109	.152	.111	.169
New Content/Feature Requests	.103	.138	.118	.167	.054	.076	.066	.094	.125	.153	.142	.187
Improve Content/Feature Requests	.069	.102	.091	.131	.051	.073	.078	.115	.078	.112	.097	.137

Further thinking of the nature of the updates reveals two underlying dimensions giving rise to the final four categories. Developers design an app with a value proposition in mind. Bug fixes and updates that improve the existing content of the application primarily help the developer to better deliver the envisioned value to its users. Compatibility updates and updates that add new content to the application, on the other hand, allow the developer to create new value for users. Accordingly, one of the underlying dimensions is the goal the developer wishes to achieve with an update: deliver envisioned value vs. create new value. Whereas the former would typically target an application's existing user base, the latter would also facilitate user base expansion. The nature of the implemented changes ties update-category pairs differently. Changes implemented both in bug fixes and compatibility updates can be characterized as source-code alterations. These source-code alterations either improve app efficiency or make the current app available and functional on different devices and operating systems. The remaining two updates involve content-related alterations that improve the effectiveness of an app. Consequently, the second underlying dimension emerges as the means with which a developer achieves the value goal: code vs. content as the main source of value.

Figure 20 displays the update-category classification based on a developer's value goal and the main source of value. Bug fixes (upper-left quadrant in Figure 19) and new content updates (lower-right quadrant in Figure 19) mark the two extremes of a continuum representing (1) the departure from the (former) value proposition and (2) the means to implement the changes. Compatibility updates and updates that improve the existing content (upper-right and lower-left quadrants in Figure 4, respectively) fall in between.

Figure 20: Update Classification based on Developer's Value Goal and Source of Value

Source of Value	Developer's Value Goal →	Deliver Envisioned Value	Create New Value
	Code	Bug Fixes	OS/Device Compatibility
	Content	Improve Content	Add Content

4.3.2 The Effects of Updates, Feedback Intensity, and Update Timing

We find that the coefficients of all *update dummies* are insignificant (.003, n.s. for bug fix, -.069, n.s. for OS/device compatibility, .029, n.s. for add new content, -.049, n.s. for improve existing content). This suggests that offering an update of a certain kind regularly (i.e., in all versions) when users do not explicitly request these changes fails to *delight* the users. Though insignificant, the presence of negative coefficient estimates may indicate that regularly updating an application can be considered by the users as a signal of the application's subpar quality and/or functioning in the first place.

We observe that all but one of the *feedback intensity* variables have negative and significant coefficient estimates (-.714, $p < .10$ for bug fix, -.568, $p < .10$ for OS/device compatibility, -.712, $p < .10$ for add content, -.391, n.s. for improve content). This result not only evidences our custom feedback dictionaries' ability to detect requests and complaints expressed in user reviews but also confirms our prediction that unmet user requests drive down application ratings. For example, holding all else constant, if 25% of the reviews contain language asking the developer to add new content to the application and the developer fails to respond immediately in the next version, the application's average rating score will decline .18 points (the decline is .18 points for bug fixes, .14 points for OS/device compatibility and .10 points for improve content). Considering the 5-

point scale of ratings, developer *non-compliance* effects are rather substantial.

The signs of the parameter estimates for the *update dummy* and *feedback intensity* interaction terms and their significance levels suggest that developer *compliance* occasionally pays off. Responding immediately to the mentions of bugs in the application and adding new content to the application following user requests counteract the deleterious impacts of such feedback on application ratings (.616, $p < .10$ and .802, $p < .10$, respectively). However, the negative effects of user requests or complaints on the existing content of the application or its compatibility with ever-changing operating systems and new devices may not easily be reversed (respectively, .269, n.s. and -.417, n.s.).

As to the *timing of the updates*, we find that the results differ across update categories as well as delight, non-compliance, and compliance scenarios. Some of the noteworthy findings are as follows.

First, though surprising the users with new content in every version does not improve average rating scores (.029, n.s.), our results suggest that failing to do so lowers the ratings in the long run (-.056, $p < .10$). However, the positive and significant interaction between add content update and the number of versions since last add content update (.059, $p < .05$) suggests that the developer can potentially make up for the deleterious effect of not offering an update for some time. In contrast, neither improving nor failure to improve the existing content of the application in every version influence application ratings significantly (respectively, -.049, n.s. and .005, n.s.). However, we find that the users penalize the developer for delaying an update of this nature (-.049, $p < .10$).

Second, the positive and significant coefficient estimates of feedback intensity and versions since last update interaction terms in the "add new content" or "improve existing content" classes (respectively, .288, $p < .10$ and .260, $p < .10$), suggest that the deleterious effect of non-compliance diminishes as time passes (i.e., some forgetting takes place).

Finally, the negative and significant 3-way interaction between the update dummy, feedback intensity, and versions since the last update observed only in the "add new content" class (-.528, $p < .10$) indicates that the desired effect of compliance on application ratings (.802, $p < .10$) diminishes over time and highlights the importance of being prompt in responding to user requests.

4.3.3 Extracting User Feedback from User Reviews

The feedback users provide to the developers is the other essential component in our conceptual model. Each time a user writes a review, s/he explains what s/he (dis)likes in the application in as much detail as s/he pleases. Though these reviews are mainly written for the benefit of potential users of the application, the review-writers may also use this platform to communicate with the developer. They are either internally motivated to do so or encouraged by the developer[26]. Independent of why these reviews are written, their content is filled with complaints and/or specific requests directed at or at least informative for the developer (Pagano and Maalej 2013).

To decide how best to approach the task of feedback extraction, we started by exploring the reviews to understand common user-requests and the way they were expressed. This exploration step revealed that the content of the reviews uses a daily and informal language with plenty of abbreviations and content-specific words rendering a human-driven investigation more suitable than machine learning techniques. Therefore, we decided to adopt a lexicon-based approach to feedback extraction. As dictionaries to extract user feedback corresponding to our specific update categories do not exist, we need to develop our *feedback-category dictionaries* manually. To develop these dictionaries, we followed the steps outlined below (see Berger et al. 2019; Humphreys and Wang 2018 for more details).

Creating Initial Feedback-Category Dictionaries from Language in Update Descriptions. The updates, assigned to categories in the previous section, are possible responses to specific user requests; therefore, we expect similar feedback categories to emerge from user reviews. To explore this, we selected a sample of user reviews and examined their content to identify common words and phrases used to complain or comment about an issue or request a specific feature in the reviews. Observing that the voiced concerns in user reviews map on to the categories that developers offer in their

[26] Developers sometimes dedicate a sentence in the update descriptions to requesting users to provide feedback on the application (i.e., ‘‘We are already working on version 1.2 iTuner Radio. Please send us suggestions of new features..’’; ‘‘Please review this latest app version! Sharing your feedback helps us improve the app with the new features you want.’’)

updates, we formed the initial feedback-category dictionaries using the words/phrases that commonly appear in the coded update description data.

Expanding Feedback-Category Dictionaries from Language in User Reviews. Next, we populated our feedback-category dictionaries by integrating the complementary information contained in the user reviews in two steps.

In the first step, we drew a *1% stratified random sample from user reviews* that contained text other than a mere title (i.e., full reviews). The stratification ensured that the distribution of games vs. other applications crossed with star-ratings in the full-reviews data is represented in the sample. We then asked two judges to tag the 7315 reviews in this sample. The judges assigned each user review to one or more of the four feedback/update categories: (1) reporting or complaining about a bug, (2) requesting new content, (3) requesting an improvement on existing content, and (4) requesting or complaining about OS/device compatibility. The judges initially worked independently and compared their tags after they completed tagging the sampled reviews. Multiple rounds of discussions were held until they reached an agreement on the final set of tags for each review. We then investigated the tagged user reviews thoroughly to identify words and phrases that were regularly used to refer to a specific issue and included the missing ones to the initial dictionary. This step substantially enlarged our feedback-category dictionaries.

In the second step, as an additional measure, we extracted the list of unigrams (i.e., single words), bigrams (i.e., a contiguous sequence of two words), and trigrams (i.e., a contiguous sequence of three words) from *all user reviews* and calculated their frequencies. We first went over the unigrams observed more than 50 times, to check whether there are missing words that can be added to our feedback-category dictionaries. Next, we investigated the bigrams observed more than 90 times, to identify two-word phrases that may be related to the feedback categories. We checked the contexts of these potentially relevant bigrams via trigrams and included the relevant ones. Finally, we perused the list of trigrams observed more than 50 times to identify and include three-word phrases that were relevant but not captured by the bigrams.

Expanding Feedback-Category Dictionaries with Related Words. We took an extra step to identify words that may be used in user feedback, yet still missing from the dictionaries. Specifically, we visited 'relatedwords.org' for each word in the feedback-category dictionaries and added missing words or phrases that are relevant to our feedback categories.

Fine-tuning Feedback-Category Dictionaries. Considering our goal of understanding the impact of developer (non-)compliance to user requests on their evaluation of an application, we need to extract user feedback that developers can act upon. This necessitates further customization of feedback-category dictionaries. For this purpose, we removed all positive or neutral words and phrases from the dictionaries. Specifically, we checked the context of each unigram (bigram) in the dictionaries by studying the bigrams and trigrams (trigrams) that contained the unigram (bigram) and deleted the words and phrases that are used in both positive and negative or neutral contexts. Instead, we added negative word combinations. For example, we removed the unigram "read" from the dictionary – a word almost exclusively used to refer to user interface related issues under 'improve content'– and added phrases such as "hard to read", "difficult to read", "can't read", "doesn't read", etc. instead. If a word or a phrase occurs only in positive contexts (e.g., "easy to use", also used to refer to user interface related issues), then that word is removed from the dictionary. This final step resulted in an increased number of phrases in the dictionaries that help us rule out positive, neutral, or out-of-context usages of generic words in the dictionaries.

Table 19 displays a sample of words and phrases in the final dictionaries. The complete feedback-category dictionaries can be found in Tables 22, 23, 24 and 25 in Appendix.

Table 19: Sample of Feedback-category Dictionaries

Bugs	OS/ Device Compatibility	Add Content/ feature	Improve Content/ feature
accident	iPad	add	could better
crash	device	could use more	need better
fall apart	tab	if it had	accident press
freeze	idevices	make episode	cleaner interface
kick out	iOS	need content	enlarge
never work	platform	new content	less intuitive
scratchy	i touch	not enough	poor design
stop work	iPhone	repetitive	hard see
tweak	iPod	there should be	bad sound
wont work	phone	wish more	lag
black screen	ios	bit short	could use
debug	retina display	end quick	need work
fault	compatible	kinda short	bad design
glitch	OS	make longer	confusing navig
lose progress	IO6	need episode	hit wrong button
nothing works	tablet	new mission	make easier navig
shaky		old news	sketchy
stuck		save camera	make easier use
unresponsive		want level	bit quicker
work anymore		wish there were	quality terrible
buggy		bring back	get better
defect		expansion	typo
flaw		lack content	bare usable
goes black		make skin	control annoy
maintenance		need mission	horrible control
please correct		new room	make usable
shut down		over quick	terrible control
stutter		short though	difficult read
unstable		want more	flow better
wrong		wish you put	screen resolution
cant open		change back	improve
doesnt work		finish too soon	use work
force close		lengthen	better control
incorrect		maxed	difficult to use
malfunction		need more	ill follow
problem		next chapter	need effect
skippy		please make	ui need
trouble		should have	make easier find
unsteady		way short	frame rate
keep close		would love	turbulent
choppy		could longer	make better
error		get old	could change
force quit		like to see more	big thumb
interrupt		monotone	disappoint control
mistake		need new	interface better
repair		next part	need type
sloppy		pretti short	unreadable
turbulent		should make	aggravate

Bugs	**OS/ Device Compatibility**	**Add Content/ feature**	**Improve Content/ feature**
unsuccessful random close collapse failure forever load issue need correct resolve snap turn black white screen wont work		widen bring back could use challenge give more limited more levels need option nice to have really short should put wish longer short beat	higher quality unstable misspell long time deliver cant read easier type layout could not user friendly hard read bad quality higher resolution use quality

Using the custom feedback-category dictionaries, we extracted the information related to specific requests or demand in all 1,075,704 user reviews in the sample. Each user review was normalized and parsed before extraction. Specifically, we tokenized all reviews, removed all non-alphanumeric and non-Ascii characters, and converted all letters to lowercase. We then stemmed all words to their roots using Snowball Stemmer (i.e., Porter2 Stemmer). The same stemming was applied to feedback-category dictionaries. Then, following Fu et al. (2013), who analyzed a similarly sized sample, we removed uncommon words (i.e., words that occur less than 10 times in the sample) to obtain 127,613 unique word stems with a total word stem count of 7,849,239 where words appearing at least 10 times in the sample make up to 8,7% (11,138 unique stems) of our sample with a 7,666,561 total count (97,7% of our sample).

Finally, we removed stop words using a context-specific list. For customization of the standard stop words list, we added context-specific common and uninformative words (e.g., game, app, application) and removed all "negation words" from the standard list, as they can be used while expressing a complaint or a malfunction (e.g., doesn't work, cannot open, etc.). We then analyzed each token that occurred at least 50 times. Words that are irrelevant for either of the feedback categories are marked as stop words regardless of their form (e.g., verbs, adjectives, nouns, prepositions etc.). For a word, whose relevance is hard to distinguish, we consulted the bigram list to infer the context in which it is used and decided whether to include it in the stop word list. Also, abbreviations and daily language slangs were checked via the web. We decided not to include (1) any country, state, or city name in the stop word list, as they may tap into the localization requests, (2) words referring to time units as they may indicate performance issues or special offers, and (3) numbers that may indicate prices.[27]

Our feedback-category extraction algorithm simply matches the words and phrases extracted from the reviews to the set of words and phrases in each of the four feedback-category dictionaries. Specifically, a review is assigned to contain user feedback on a specific topic (e.g., bug fix or add new content) if it contains one or more of the dictionary entries of that feedback-category. Alternatively, one can "score" user feedback by counting the number of words and phrases in a review matching the entries in the feedback-category dictionary. However, we refrain from scoring for two reasons. First, we do not want to place undue weights to verbose review-writers. Second, it is the absence or presence of feedback on a specific topic that matters more for the developer, not the length of the feedback.

Aggregating the extracted feedback over all reviews posted before the release of a new version, yields user feedback in each category in a given period. We assess the impact of an update that (mis)matches this feedback on user evaluations as discussed subsequently.

4.4 Model Specification

To test the effect of (mis)match between user feedback and developer updates on the evaluation of a mobile application, we specify a model built on the idea that the rating of an application's current version is an update-dependent adjustment of its older version's rating:

[27] Our context-specific stop word list can be provided upon request.

$$
\begin{aligned}
\mathrm{ARS}_{i,v} = \alpha_i + \beta_0 \mathrm{ARS}_{i,v-1} \\
&+ \sum_{j=1}^{4} \Big(\beta_{1j} U_{i,v}^{j} + \beta_{2j} \mathrm{FI}_{i,v-1}^{j} + \beta_{3j} \big(U_{i,v}^{j} \times \mathrm{FI}_{i,v-1}^{j} \big) + \beta_{4j} \mathrm{VSLU}_{i,v}^{j} \\
&+ \beta_{5j} \big(U_{i,v}^{j} \times \mathrm{VSLU}_{i,v}^{j} \big) + \beta_{6j} \big(\mathrm{FI}_{i,v-1}^{j} \times \mathrm{TSLU}_{i,v}^{j} \big) \\
&+ \beta_{7j} \big(U_{i,v}^{j} \times \mathrm{FI}_{i,v-1}^{j} \times \mathrm{VSLU}_{i,v}^{j} \big) \Big) + \varepsilon_{i,v}
\end{aligned}
$$

where $\mathrm{ARS}_{i,v}$ is the *average rating score* of application i's version v and calculated as the average of all ratings the application receives in a time window starting with the launch of a new version until next version. α_i is an application-specific constant capturing systematic differences across ratings of apps, controlling for the effects of the potentially omitted time-invariant unobservables[28]. β_0 captures the carryover in ratings across versions. Moreover, the presence of lagged rating scores helps us control for the effects of omitted unobservable time-varying factors.

$U_{i,v}^{j}$ is a dummy variable indicating whether the improvements made in version v of application i belongs to the *update category* j (j = 1 for bug fixes, j = 2 for updates that add new content, j = 3 updates that improve existing content, and j = 4 for OS/device compatibility updates). $\mathrm{FI}_{i,v-1}^{j}$ is the *intensity of user feedback* in jth feedback category of application i's former version, $v-1$. The operationalization of feedback intensity is discussed subsequently. Finally, $\mathrm{VSLU}_{i,v}^{j}$ is *versions since the last update* and counts the number of versions released since the last improvements belonging to the update category j.

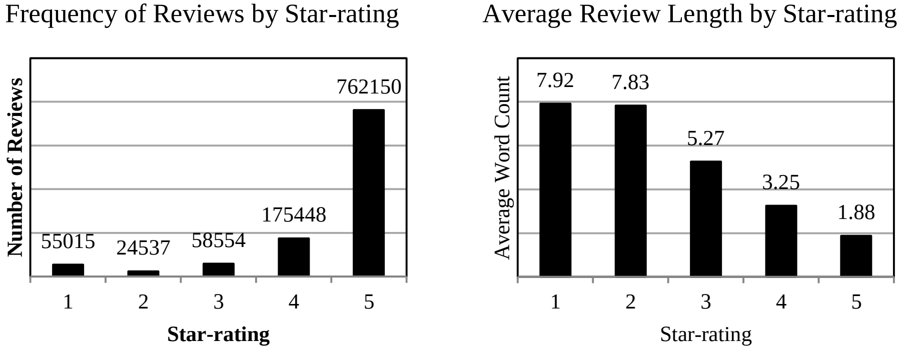
Dropping the update/feedback-category identifier j for ease of exposition, β_1 captures the effect of a regular update on a new version's ratings in the absence of user feedback (i.e., rewards due to user delight), β_2 captures the potentially deleterious effect of not responding to user requests (i.e., penalties due to developer non-compliance), and β_3 captures whether and to what extent an update that addresses user requests offsets the undesirable effects of non-compliance (i.e., countervailing rewards due to developer compliance). β_4 is the effect of not offering a particular update for a while. Finally, the coefficients β_5, β_6, and β_7 capture the effects of the passage of time on rewards due to user

[28] Hausmann test favors random application effects over fixed application effects.

delight, penalties due to developer non-compliance, and countervailing rewards due to developer compliance, respectively.

We calculate feedback intensity, $\mathrm{FI}^{j}_{i,v-1}$, as the ratio of the number of reviews referencing an issue or request about a specific feedback category to the total number of reviews written on the former version of the application. However, as Aralikatte et al. (2018) points, a 5-star rating can be assigned to an entirely complimentary review and one that doesn't report any problems. One may argue that these short and non-informative texts that accompany 5-star reviews, which make up a considerable portion of the data (see Figure 21), may not help the developer decide what to improve in the next version of the application. Therefore, we decided to calculate two versions of the feedback intensity variable, one including all reviews and one excluding 5-star reviews, and estimate the model separately using both versions.

Figure 21: Frequency and Length of Reviews per Star-rating



Moreover, to assess whether the same pattern of results would be found across different application types and categories, we estimate the model separately for (1) free vs. paid applications and (2) games vs. non-games. Table 18 displays the descriptive statistics of our data with a breakdown of feedback intensity variable alternatives, application type, and application category.

4.5 Results

Table 20 displays the parameter estimates of the estimated models using data from (1) all applications, (2) free applications, (3) paid applications, (4) games, and (5) non-games with and without 5-star reviews in the calculation of feedback intensity. In what follows, we discuss the findings of the model including all applications and all reviews – the first column in Table 20. We then discuss whether and how these findings change depending on application type, application category, and feedback intensity calculation.

Table 20: Parameter Estimates

	5-star Reviews Included					5-star Reviews Excluded				
	All	**Free**	**Paid**	**Games**	**Non-Games**	**All**	**Free**	**Paid**	**Games**	**Non-Games**
Constant	1.720*	1.907*	2.118*	1.844*	1.765*	1.580*	1.764*	1.915*	1.768*	1.642*
Average Rating (Lag)	.580*	.517*	.500*	.564*	.560*	.613*	.558*	.526*	.583*	.588*
Update Category: Bug Fix										
Update	.003	.032	-.062	-.063	.002	-.016	.003	-.039	-.086	-.009
Intensity	-.714*	-.674*	-.717*	-1.056*	-.644*	-.366**	-.502*	-.101	-.658*	-.311*
Update x Intensity	.616*	.418**	.721**	1.153*	.449**	.486*	.482*	.268	.812*	.346*
Versions Since Last Update	.009	.019	-.027	-.023	.012	.008	.018	-.032	-.029	.018
Update x Versions Since Last Update	.002	-.017	.041	.055	-.005	.020	.012	.051	.072	.006
Intensity x Versions Since Last Update	-.035	-.035	-.032	.515*	-.152	-.026	-.013	.078	.345*	-.157
Update x Intensity x Versions Since Last Update	-.054	.002	-.120	-.496**	.061	-.102	-.103	-.196	-.401**	.028
Update Category: OS/Device Compatibility										
Update	-.069	-.123	.032	.147	-.114	-.075	-.091	-.012	.094	-.105
Intensity	-.568*	-.812*	.030	.001	-.589*	-.130	-.260	-.375	.182	-.096
Update x Intensity	-.417	-.071	-1.223*	-1.852*	-.154	-.379	-.100	-1.115*	-1.817*	-.193
Versions Since Last Update	.011	.011	.014	.003	.015	.012**	.015	.012	.003	.017
Update x Versions Since Last Update	-.000	.009	-.027	-.031	.008	.001	-.002	-.017	-.051**	.008
Intensity x Versions Since Last Update	-.030	-.060	-.051	-.099	-.018	-.041	-.071	-.060	-.081	-.036
Update x Intensity x Versions Since Last Update	.027	.027	.135	.186	-.018	.026	.041	.110	.901*	-.001

	5-star Reviews Included					5-star Reviews Excluded				
	All	**Free**	**Paid**	**Games**	**Non-Games**	**All**	**Free**	**Paid**	**Games**	**Non-Games**
Update Category: Add Content/Feature										
Update	.029	.015	.025	.032	-.014	-.025	+.000	.052	.037	.001
Intensity	-.712*	-.840*	-.617*	-.174	-.645*	-.763*	-.995*	-.269	-.281	-.766*
Update x Intensity	.802*	1.096*	.224	.760	.811*	.779*	1.144*	.083	.653	.843*
Versions Since Last Update	-.056*	-.069*	-.013	-.014	-.088*	-.075*	-.096*	-.006	-.021	-.115*
Update x Versions Since Last Update	.059**	.088*	-.012	.026	.097*	.074*	.115*	-.023	.048	.117*
Intensity x Versions Since Last Update	.288*	.375*	.195	.237	.317*	.457*	.588*	.145	.247	.526*
Update x Intensity x Versions Since Last Update	-.528*	-.665*	-.212	-1.029**	-.540*	-.617*	-.857*	-.189	-1.229*	-.657*
Update Category: Improve Content/Feature										
Update	-.049	-.027	-.062	.026	-.070	-.083*	-.075	-.065	.024	-.103**
Intensity	-.391	-.605**	-.155	-.255	-.433	-.639*	-.841*	-.422	-.121	-.745*
Update x Intensity	.269	-.030	.488	-.190	.409	.467**	.477	.373	-.179	.612*
Versions Since Last Update	.005	.012	.006	.008	.011	.006	.011	.004	.016	.009
Update x Versions Since Last Update	-.049*	-.093*	.009	-.030	-.063*	-.044*	-.074*	.014	-.044	-.048**
Intensity x Versions Since Last Update	.260**	.326*	.561	-.036	.308*	.156	.183**	.602*	-.134	.220**
Update x Intensity x Versions Since Last Update	-.115	.180	-.871**	.053	-.193	-.080	.004	-.937	.227	-.308
n apps	460	276	184	149	311	460	276	184	149	311
n observations	2795	1739	1056	866	1929	2795	1739	1056	866	1929
R-squared overall	.439	.485	.296	.381	.423	.432	.481	.287	.381	.417

Notes. ** $p < 0.1$, * $p < 0.05$

4.5.1 The Effects of Updates, Feedback Intensity, and Update Timing

The coefficients of all update dummies are insignificant (.003, n.s. for bug fix, -.069, n.s. for OS/device compatibility, .029, n.s. for add new content, -.049, n.s. for improve existing content). This suggests that offering an update of a certain kind regularly (i.e., in all versions) when users do not explicitly request these changes fails to delight the users. Though insignificant, the presence of negative coefficient estimates may indicate that regularly updating an application can be considered by the users as a signal of the application's subpar quality and/or functioning in the first place.

We observe that all but one of the feedback intensity variables have negative and significant coefficient estimates (-.714, $p < .10$ for bug fix, -.568, $p < .10$ for OS/device compatibility, -.712, $p < .10$ for add content, -.391, n.s. for improve content). This result not only evidences our custom feedback dictionaries' ability to detect requests and complaints expressed in user reviews but also confirms our prediction that unmet user requests drive down application ratings. For example, holding all else constant, if 25% of the reviews contain language asking the developer to add new content to the application and the developer fails to respond immediately in the next version, the application's average rating score will decline .18 points (the decline is .18 points for bug fixes, .14 points for OS/device compatibility and .10 points for improve content). Considering the 5-point scale of ratings, developer non-compliance effects are rather substantial.

The signs of the parameter estimates for the update dummy and feedback intensity interaction terms and their significance levels suggest that developer compliance occasionally pays off. Responding immediately to the mentions of bugs in the application and adding new content to the application following user requests counteract the deleterious impacts of such feedback on application ratings (.616, $p < .10$ and .802, $p < .10$, respectively). However, the negative effects of user requests or complaints on improving the existing content of the application or its compatibility with ever-changing operating systems and new devices may not easily be reversed (respectively, .269, n.s. and -.417, n.s.).

The results for the timing of the updates, differ across update categories as well as delight, non-compliance, and compliance scenarios. Some of the noteworthy findings are as follows.

First, though surprising the users with new content in every version does not improve average rating scores (.029, n.s.), our results suggest that failing to do so lowers the ratings in the long run (-.056, $p < .10$). However, the positive and significant interaction between add content update and the number of versions since last add content update (.059, $p < .05$) suggests that the developer can potentially make up for the deleterious effect of not offering an update for some time. In contrast, neither improving nor failure to improve the existing content of the application in every version influence application ratings significantly (respectively, -.049, n.s. and .005, n.s.). However, we find that the users penalize the developer for delaying an update of this nature (-.049, $p < .10$).

Second, the positive and significant coefficient estimates of feedback intensity and versions since last update interaction terms in the "add new content" or "improve existing content" classes (respectively, .288, $p < .10$ and .260, $p < .10$), suggest that the deleterious effect of non-compliance diminishes as time passes (i.e., some forgetting takes place).

Finally, the negative and significant 3-way interaction between the update dummy, feedback intensity, and versions since the last update observed only in the "add new content" category (-.528, $p < .10$) indicates that the desired effect of compliance on application ratings (.802, $p < .10$) diminishes over time and highlights the importance of being prompt in responding to user requests.

4.5.2 Robustness Checks

A comparison of coefficient estimates across models with and without 5-star reviews in feedback intensity calculation reveals that the results are consistent. Though the significance levels of six coefficients change when 5-star reviews are excluded, two turning insignificant and four turning significant, the estimates are directionally the same. Moreover, we observe that four out of the six changes pertain to requests and/or updates to improve the existing content of an application. Suggesting or requesting improvements to the existing content does not necessarily indicate that the users are dissatisfied with the application. Rating an application with five stars and listing possible improvements is quite common among users[29]. Excluding 5-star reviews from the calculation of feedback intensity implies neither the developer nor the users, who have yet to rate the application, pays attention to this feedback. We believe this is a rather stringent assumption. Therefore, we decided to focus on results obtained from models that use 5-star reviews in feedback intensity calculation hereafter.

Comparisons of coefficient estimates in the 2nd, 3rd, and 4th columns of Table 20, to assess how the results differ across application types, reveal that the pattern of findings discussed above mainly holds for free applications. For paid applications, we find that (1) application ratings take a hit as soon as users start requesting new content; and (2) responding late to improve existing content requests and responding, even promptly, to operating system and/or device compatibility requests hurt application ratings. These findings collectively suggest that developers of paid applications are better off offering a ready-for-the-market, high-quality applications that work on all most up-to-date operating systems and a wide range of devices upfront. Launching a (minimally) viable paid application and improving it on the way based on user feedback appears to backfire in terms of ratings.

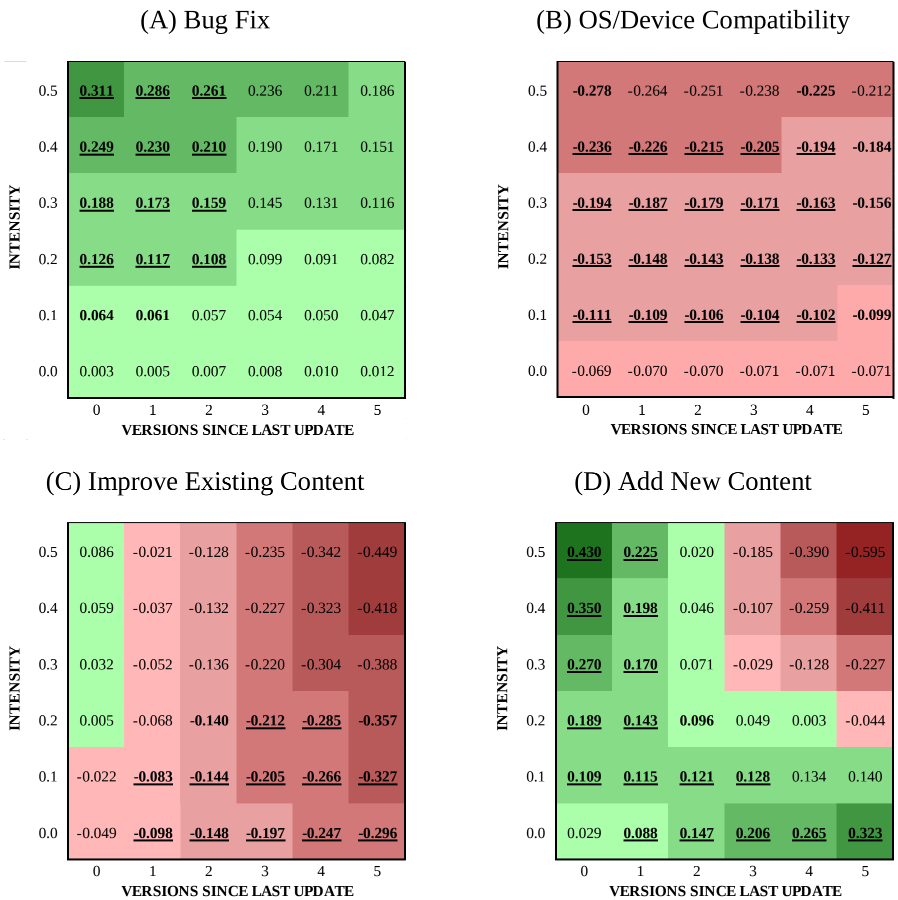
Finally, comparisons of coefficient estimates in the 2nd, 5th, and 6th columns of Table 20 reveal that the pattern of results discussed above exactly matches those of non-games. We observe that bug-related feedback and bug fix updates seem to be particularly important for user's evaluations of games. Though users' complaints about bugs in the app lower the game's average rating score, the deleterious impact of the feedback diminishes over time. The results also suggest that releasing a bug-free version of the game counteracts the deleterious impact of the feedback. However, the beneficial effect of developer compliance diminishes with time. Finally, worthy of note, is the rather substantial and deleterious OS/device compatibility compliance effects in games. Like our observations pertaining to paid applications, if users have to bring up an issue before it is dealt with, the game's average rating score suffers substantially.

[29] This type of rating-reviewing behavior is observed quite frequently. A sample of review texts of 5-star reviews are as follows: Let's keep on making it better. Lots of fun but time table is slow. Love this app even though it needs some improvement it is very helpful. Can't wait to see new improvements to the app.

4.5.3 The Interplay among Update, Feedback Intensity, and Update Timing

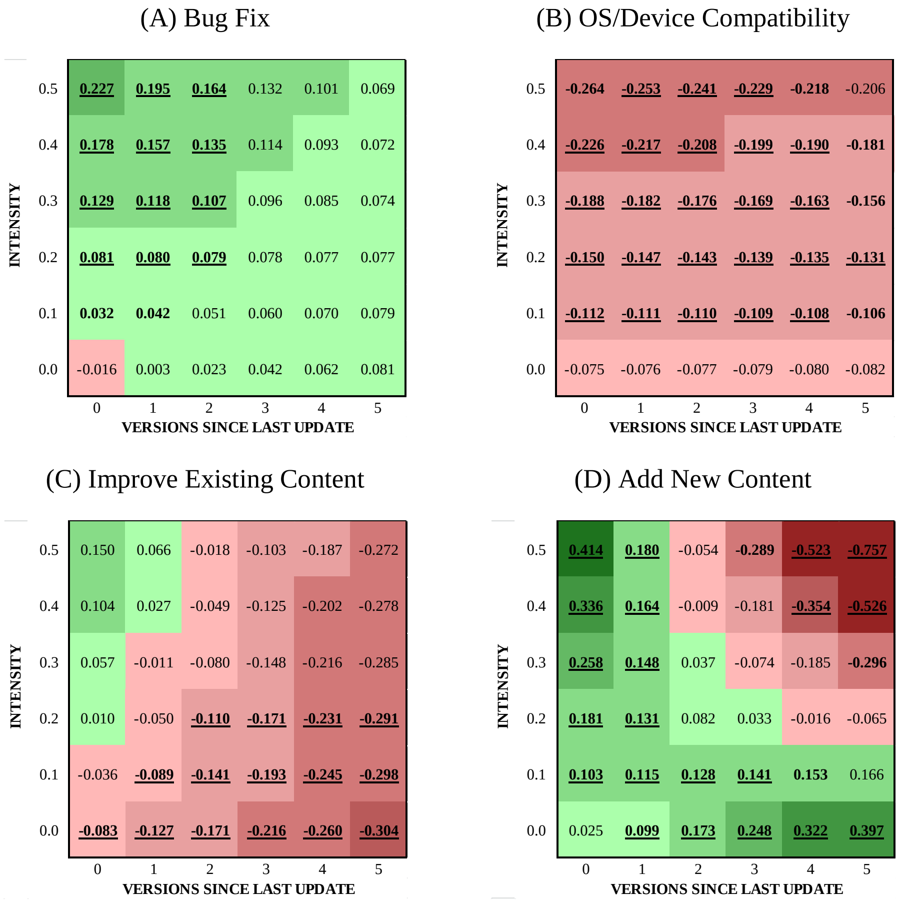
The discussion above reveals that user requests and updates in certain categories as well as their timing influence an application's average rating score; however their combined effect is hard to judge. Accordingly, using the parameter estimates for all applications, we calculated the average marginal effect of providing an update on the average rating score of an application at different values of feedback intensity and versions since the application was last updated, separately for each update category. In these calculations, we restricted the ranges of feedback intensity (between 0 and .5 with increments of .1) and versions since last update (between 0 and 5 with increments of 1) wherein more than 90% of the data lies. The average marginal effects represent the incremental gains due to user delight over time, when feedback intensity is at 0, and the incremental gains due to developer compliance over time, for all non-zero values of feedback intensity. Figure 22 and 23 display incremental gains in ratings from an update as a function of feedback intensity and update timing; the former one is plotted for all reviews and the latter one excluding 5-star reviews in feedback intensity calculations. Bold and underlined (bold) entries in these plots denote significance at 5% (10%) level.

Figure 22: Incremental Gains in Ratings due to Updating as a Function of Feedback Intensity and Update Timing[30]



[30] Green and red cells denote positive and negative entries respectively. Bold and underlined entries denote significance at p<0.05; bold entries denote significance at p<0.10 levels.

Figure 23: Incremental Gains in Ratings due to Updating as a Function of Feedback Intensity and Update Timing [31]



[31] Green and red cells denote positive and negative entries respectively. Bold and underlined entries denote significance at p<0.05; bold entries denote significance at p<0.10 levels.

Fixing Bugs. Panel A in Figure 22 shows the incremental gains from an update containing a bug fix at different levels of feedback intensity and versions since the release of a similar update. Inspection of the figure's lowest slice (i.e., feedback intensity is zero) reveals that a developer cannot delight the users by fixing bugs no matter how long it has been since s/he last fixed the application's bugs. However, a developer who responds to user complaints about bugs enjoys significantly higher application ratings than a developer who ignores these complaints. The higher the number of reviews mentioning bugs is, the greater the reward due to compliance is. These rewards appear to diminish if the developer takes time to respond (i.e., the developer releases versions that don't address the bugs in between); however these timing differences are not statistically significant.

OS/Device Compatibility. Similar to bug fixes, a developer can't delight users with a compatibility update (see Panel B in Figure 22). Moreover, updating the application after users start talking about these issues appears to be futile, the developer is penalized no matter what.

Adding New Content. Panel D in Figure 22 suggests that developers who just released new content don't enjoy significant improvements in application ratings from the release of another version with even newer content compared to developers who don't. In other words, rewards due to user delight are negligible if it is done in every single version. However, if a developer has not released a new version of the application with new content for a while, s/he experiences a positive and significant improvement in application ratings when s/he does. This result is consistent with the (1) notion that the surprise element can only resurface with forgetting and (2) novelty effect resulting from the developer taking the time to offer additional benefits that are well-thought through and well-developed.

If user feedback contains new content requests, addressing them can be rewarding. Yet, the magnitude of compliance rewards change depending on the intensity of the feedback and the timing of the update. At low levels of intensity, forgetting counterbalances the deleterious impact of delayed response and developers who respond to these requests enjoy greater rating scores than developers who don't; no matter how long they take to respond. However, if a large group of users voices such requests, delayed response fails to improve version ratings.

Improving Existing Content. Panel C in Figure 22 shows the incremental gains from improving existing content as a function of feedback intensity and over time. The figure reveals that a developer may not delight the users of its application by improving existing content in every version but will certainly be penalized if s/he skips versions. Moreover, having to offer such improvements at the behest of users fails to improve and may even hurt application ratings if not addressed immediately.

4.6 Conclusion

Based on an automated text analysis of about 1Muser reviews and content analysis of about 3K mobile app updates observed over a wide range of application categories and business models, this paper assesses the impact of the correspondence between the feedback in user reviews and the nature of changes in app updates on users' evaluations of an application's new version. Specifically, we quantify the rewards (penalties) developers enjoy (incur) after releasing an updated version of an application as a function of their attentiveness to (disregard of) users' voiced complaints or requests in deciding the specifics and the timing of the update. To provide fine-grained insights into the issue, we distinguish among four broad topics of feedback corresponding to four areas of improvement that emerged from the content analysis of update descriptions.

Our results indicate that actively responding to user requests can benefit mobile product developers/suppliers. Ignoring them during re-development is associated with penalties and reflected in the evaluations of subsequent versions of the product. However, the rewards and penalties appear sensitive to the nature of the feedback/improvement and the timing of the update.

We make the following contributions to the three streams of literature we build upon. First, we add to the literature on user-generated content by showing that user comments contain valuable user insights, which can be extracted through simple, custom-built dictionaries and proactively utilized by firms. Second, we contribute to the literature on new product development that acknowledges the important role of engaging with the customers. We demonstrate that insights obtained from social listening – a less costly alternative to direct engagement with the users – can guide firms in their product re-development decisions. Finally, and more importantly, we add to the growing body of literature on mobile applications, which recognizes the role of developer updates and user ratings/reviews in generating app demand but often overlooks the interdependence between the two.

By examining numerous scenarios along different levels of feedback intensity, the existence, and the promptness of the response per update category, our study provides mobile product owners guidance on the challenge of prioritizing possible development paths. Although particularly important for the mobile applications market, the implications of our findings may extend to domains where experimentation is natural and firms may adopt a minimum viable product strategy. Examples of domains with similar dynamics include the development of web-pages or software, the growing market of smart products that enable continuous development via updates, and (digital) services that allow for quick customization.

The findings of this study imply that mobile product owners should allocate their resources between compliance and continuous improvement. First, while attempts at fixing problems that users don't reckon are unavailing, timely attending to issues about the essential functioning of the application is necessary. Prompt response to user complaints regarding bugs is necessary for developers to restore their app's average rating score.

Second, developers should adopt a continuous improvement approach to maintain their apps' average rating scores on two fronts: (i) improving the existing content of the application and (ii) ensuring optimal performance on various operating systems and availability for a wide range of devices. However, the need for continuous improvement in these two intermediate levels of departure from the value proposition is for different reasons. Being optimized for various operating systems and available for a wide range of devices is of crucial importance, as the deleterious effects of incompatibility are irreversible once users start complaining. Continuously improving the existing content of the application is critical because users are expectant of these developments and penalize the developer for delivering these updates intermittently.

Third, whenever users request new content, the developer's priority should be to deliver these requests promptly. These updates extend the value proposition of a mobile application and help the developers improve their apps' average rating scores and get ahead of their competitors.

Finally, prioritizing compliance may drain the resources for continuous improvement and lead to delays for certain types of updates. To counter-balance the deleterious effects arising from the inferiority of the mobile product or insufficient coverage of operating systems and devices, the developer may try to deflect or bundle late updates with additional benefits. The rewards associated with updates that add new content increase with time; hence, the developer may try to anticipate users' needs and offer new value (alongside other changes) before their request.

Though our work paves the way for optimizing organically generated feedback implementation in the process of product development, it can be improved upon in several directions. First, a prevalent observation that surfaces from the analysis of user reviews is that users often discuss issues related to price and in-app purchases. Whether and how developers respond to these requests, which are not necessarily aligned with updates and therefore cannot be tracked by studying update descriptions, and the rewards (penalties) they enjoy (incur) due to compliance (non-compliance) presents an interesting avenue for future research. Moreover, app performance indicators other than average rating scores (e.g., downloads, revenues, in-app purchases) might be more appropriate to track for price-related requests. Finally, future research can examine how these findings relate to the existing processes in continuous innovation settings in digital products such as smart products, software, and PC or console games. In the broader sense, our categories speak to the development of the traditional products as well and, conditional on data availability, future research can investigate whether our results can be replicated in different product and market settings.

Appendix

Table 21: Apple App Store Categories for Mobile Applications

Category	Definition	Examples
Books	Apps that provide extensive interactivity for content that is traditionally offered in printed form.	Stories, comics, eReaders, coffee table books, graphic novels.
Education	Apps that provide an interactive learning experience on a specific skill or subject.	Arithmetic, alphabet, writing, early learning and special education, solar system, vocabulary, colors, language learning, standardized test prep, geography, school portals, pet training, astronomy, crafts.
Lifestyle	Apps relating to a general-interest subject matter or service.	Real estate, crafts, hobbies, parenting, fashion, home improvement.
Magazines & Papers	Apps that offer auto-renewing subscriptions to magazine or newspaper content.	Newspapers, magazines, other recurring periodicals.
News	Apps that provide information about current events or developments in areas of interest such as politics, entertainment, business, science, technology, and so on.	Television, video, radio, or online news outlets or programs, RSS readers.
Reference	Apps that assist the user in accessing or retrieving information.	Atlas, dictionary, thesaurus, quotations, encyclopedia, general research, animals, law, religious, how-tos, politics.
Entertainment	Apps that are interactive and designed to entertain and inform the user, and which contain audio, visual, or other content.	Television, movies, second screens, fan clubs, theatre, ringtones, voice manipulation, ticketing services, art creation.
Music	Apps that are for discovering, listening to, recording, performing, or composing music, and that are interactive in nature.	Music creation, radio, education, sound editing, music discovery, composition, lyric writing, band and recording artists, music videos and concerts, concert ticketing.
Photo & Video	Apps that assist in capturing, editing, managing, storing, or sharing photos and videos.	Capture, editing, special effects, sharing, imaging, printing, greeting card creation, manuals.

Category	**Definition**	**Examples**
Social Networking	Apps that connect people by means of text, voice, photo, or video. Apps that contribute to community development.	Interpersonal connections, text messaging, voice messaging, video communication, photo & video sharing, dating, blogs, special interest communities, companion apps for traditional social networking services.
Games	Apps that provide single or multiplayer interactive activities for entertainment purposes.	Action, adventure, arcade, board, card, family, music, puzzle, racing, role playing, simulation, sports, strategy.

Table 22: Bug Feedback-category Dictionary

accident	derail	forever load	need correct	stuck
address	doesnt allow	freeze	never load	stutter
back home screen	doesnt let	get rid of	never work	terminate
black out	doesnt load	glitch	nonworking	trouble
black screen	doesnt save progress	goes black	nothing works	turbulent
blank screen	doesnt open	goes home screen	oversight	turn black
blowout	doesnt play	gripe	past load screen	turn off
blunder	doesnt start	hap	please correct	tweak
botch	doesnt work	hasnt worked	problem	unable
break	dont show	hung up	rectify	uncommunicative
bug	dont work	inaccurate	redress	unresponsive
buggy	drop dead	incapable	repair	unstable
cant access	erratic	incorrect	resolve	unsteady
cant load	erroneous	instable	restore	unsuccessful
cant log	error	interrupt	restore purchase	white screen
cant login	exit	issue	rework	wobbly
cant move	fail	kick off	scratchy	wont allow
cant open	failure	kick out	shaky	wont download
cant play	fall apart	kink	shut down	wont go
cant start	fallible	lapse	shut off	wont let
cant turn	fault	let play	skip	wont load
casualty	faulty	lock up	skippy	wont open
choppy	fix	lose progress	slip	wont start
collapse	flaw	lost progress	sloppy	wont turn on
collide	force close	maintenance	snap	wont work
concern	force exit	malfunction	squish	work anymore
crash	force quit	mend	stick	wouldnt let log
cut off	force restart	misconception	stop dead	wouldnt load
debug	force start	misfunction	stop load	would't work
defect	force stop	mishap	stop play	wrong
deficient	forceclose	mistake	stop work	keep close
				random close

Table 23: OS/Device Compatibility Feedback-category Dictionary

iPad	support	OS	ios	iPhone
iOS	device	tablet	IO6	retina display
iPod	platform	tab	itouch	
compatible	phone	i touch	idevices	

Table 24: Add Feature/Content Feedback-category Dictionary

ad new	more to come	should make	appletv	uverse
add	need another	should put	at&t	Verizon
addition	need challenge	should try	authentication	website
bit short	need content	some more	Bluetooth	work minecraft
bring back	need episode	subsequent	cable	wont let connect
cant wait	need item	there sould be	cloud support	wont let sign
cant save	need level	trade system	Cloudon	wish it would
change back	need longer	undo button	comcast	wish longer
continue make	need mission	wait next version	connect itunes	wish more
continue to develop	need more	want episode	connect with	wish sound
could interact	need new	want level	directv	wish there was
could longer	need option	want more	dropbox	wish there were
could use challenge	need paus button	want there to be	email support	wish there were more
could use more	need save	way short	exchange support	wish to have
could use sound	need sound	widen	Facebook	wish you put
do more	need weapon	wish could	flash	wishing for
end quick	needs to be longer	wish episod	full site	would be
expansion	new content	wish it could	game center	would be amazing if
finish too soon	new episode	wish it has	google docs	would be nice
forthcoming	new level	wish it was	hbo	would better sound
get old	new mission	wish it were	icad	would like to see
give more	new room	wish it were longer	icloud	would love
have more	new weapon	wish it would	instagram	bring back
if it had	next chapter	wish longer	integrate	look forward
keep come	next episode	wish more	integration	wait new level
keep going	next level	wish sound	internet	easi beat
keep them coming	next part	wish there was	iphoto	short beat

keep update	next update	wish there were	klout	beat whole
kind short	nice to have	wish there were more	log	minute beat
kinda short	not enough	wish to have	login	alreadi beat
lack content	not long	wish you put	mac	beat app
lengthen	not long enough	wishing for	MacBook	app beat
like to c more	old news	would be	merge	access site
like to see more	outplay	would be amazing if	message friend	add friend
limited	over quick	would be nice	minecraft pc	airplay support
littl short	please make	would better sound	minecraft pe	appletv
look forward	plz make	would like to see	minecraft pocket	at&t
make another	pretti short	would love	mobile site	authentication
make episode	really short	bring back	nook	Bluetooth
make longer	renew	look forward	online	cable
make more	repetitive	wait new level	outlook	cloud support
make skin	replay value	easi beat	passbook	Cloudon
make text	run out	short beat	PC	comcast
maxed	save camera	beat whole	pcmac	connect itunes
missing	save photo	minute beat	pe minecraft	
monotone	save picture	alreadi beat	share	
monotonous	scant	beat app	support site	
more everything	sequel	app beat	sync	
more food	short though	access site	tell friend	
more levels	should have	add friend	text friend	
more please	should have been longer	airplay support	twitter	

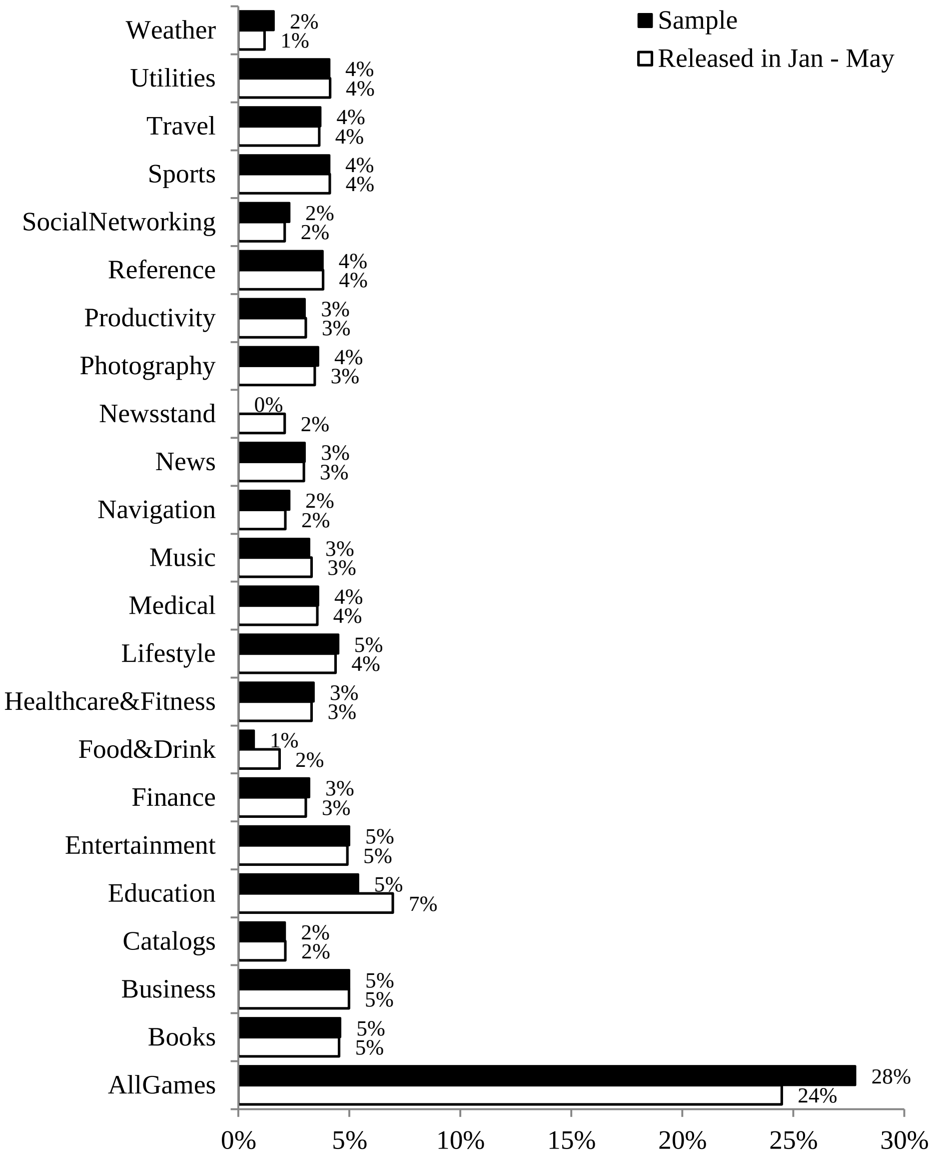
Table 25: Improve Feature/Content Feedback-category Dictionary

advance	background	difficult to play	landscape	tilt
bigger	bad control	difficult to use	larger	tocuh sensitive
can not make	bad design	disappoint control	layout better	top left
confusing	bad graphic	right corner	layout could	top right
could be	bare usable	doesnt display	left corner	touch button
could better	better control	doubl tap	left right	touch cant
could move	better effect	easier control	left side	touch control
could use	better graphic	easier type	less intuitive	touch respons
dont make sense	better interface	effect cant	less user friendly	touch screen
get better	better layout	effect could	lower right	track pad
grammar	better read	effect dont	make easier navig	turn left
improve	better tap	effect little	make effect	turn right
little easier	better type	effect need	make playable	ui could
make better	better ui	effect wish	make ui	ui need
make it better	better user friendly	enlarge	make usable	unreadable
misspell	better user interfac	far user friendly	make user friendly	upper left
need better	better user interface	finger	move left	upper right
need bigger	big thumb	finger movement	move right	usable need
need change	bottom left	finger tap	need effect	use effect
need work	bottom right	flip back	need sound effect	user firend wish
needs to be	button	flip page	need type	user friendly need
pale	button left	flip phone	need user friendly	wish effect
should be	button right	flip picture	not user friendly	wish keyboard
should be able to	cannot read	flip screen	old layout	wish sound effect
spelling	cant press	flip side	one tap	zoom
typo	cant read	front flip	one touch	font size
use better	cant tap	gesture	option type	hard read
wish easier level	cant touch	graphic could better	palm hand	hard see
wish would	cant turn	hard control	palm reject	make easier use
would be better	cant type	hard navig	palm rest	difficult read

would better	change layout	hard read	pinch	make easier find
use work	cleaner interface	hard steer	poor control	3g
make work better	click	hard to follow	poor design	aggravate
could change	confusing navig	hard to learn	respond touch	also delay
would better could	control annoy	hard to play	right fingertip	annoy wait
make better would	control awkward	right finger	right hand	bad quality
long time build	control better	hard to use	right left	bad sound
take forever deliver	control easier	hard use	right side	battery
long time deliver	control frustrat	harder navig	right top	battery drain
could make better	control improve	harder read	rotate	better performance
take forever build	control interface	hit wrong button	screen flip	better quality
take long arrive	control lack	horrible control	screen tap	better resolution
wait long deliver	control left	ill follow	scroll	better sound
long deliver item	control movement	ill read	scroll left	bit quicker
take time build	control panel	impossible read	scroll read	choppy
hate wait delivery	control poor	improve control	sketchy	connectivity
delivery time long	control stick	interface better	slide left	CPU
long item deliver	control terrrible	interface cant	small read	delay game
able type	could type	interface could	steer control	delay time
accident press	could use effect	interface doesnt	step right	detain
right click	could use type	interface dont	swipe left	disk
accident tap	could user friendly	interface improve	swipe right	drag
accident touch	couldnt read	interface lack	tap button	drain battery
accidental hit	cursor	interface little	tap finger	drain phone
allow type	difficult control	interface need	tap screen	even wifi
back flip	difficult navig	joystick	terrible control	faster load
back left	difficult read	keyboard wont	though	faster pace

			control	
flow better	load time	perform better	start take forever	unstable
frame rate	long download	poor quality	start take long	unsteady
higher quality	long load	processor	still load	use quality
higher resolution	long wait	quality bad	still wait	wait forever
hold off	longer load	quality better	storage	wait long
huge delay	lot wait	quality could	take long repair	wait start
improv performance	low quality	quality horrible	take long start	wait time
improve quality	low resolution	quality terrible	time delay	wifi cant
lag	lower quality	response time	time download	wlan
little delay	lower resolution	responsiveness	time load	would better faster
little faster	memory	screen resolution	time response	take forever load
little quicker	need faster	server	time start	take long load
load faster	need make faster	shouldnt take long	time wait	long time load
load proper	need quicker	signal	tire wait	take forever download
load screen	not work well	slow	time work	take long download
load slow	notice delay	sometimes delay	turbulent	take time load
load speed	perform	space		

Figure 24: Distribution of Mobile Application Categories in Apple App Store vs. Sample



Chapter 5

Conclusion

This dissertation brings a fresh perspective to mobile marketing by focusing on mobile application markets that have established their presence in the last decade. Chapter 2 offers a detailed review of the literature and an integrated framework for mobile marketing research in the last decade. Chapter 3 discusses the user's journey to mobile application adoption and investigates drivers of mobile app downloads from platforms', users' and developers' perspectives. Chapter 4 investigates whether, how, and when the dynamic relationship between developers and users can benefit in the process of product development. In this final chapter, in Sections 5.1, 5.2 and 5.3, I summarize findings derived from each research project debated in the previous chapters, outline their contributions to the existing literature; in Section 5.4, I present a general discussion of the field, in Section 5.5, I discuss practical implications of the previous chapters. Finally, in Section 5.6, I offer avenues for future research.

5.1 Rise of Mobile: A Decade of Research in Review

Seamless integration of mobile technology into the daily routine of todays' consumers has unfolded new avenues for research. A growing number of studies originating from the rapid change in the lifestyle of consumers accumulated in recent years. Early on, Shankar and Balasubramanian (2009) have defined mobile marketing and offered integrative frameworks. Researchers have then acknowledged its importance within the larger ecosystems such as interactive marketing (Ratchford, 2015) or digital marketing (Kannan and Li, 2017). Recently, Lamberton and Stephen (2016) provide a thematic exploration of digital, social, and mobile marketing spanning the time period 2000-2015. The review presented in Chapter 2 builds on their insights by (1) offering an integrated framework for mobile marketing by exclusively focusing on the broad set of articles on the subject; and (2) considering research published since 2015 - corresponding to the higher share of articles due to the increasing growth in number of studies over time.

For this purpose, I analyze studies related to mobile marketing published in STAR or P marked journals in the ERIM journals list (Erasmus Research Institute of Management) between the years 2009-2019. The analysis of 178 articles, directly relevant to mobile marketing, in our data base illustrates the changing landscape of the field in the last decade. Based on this set of articles, I re-formulate a framework that reflects (1) the irreversible transformation in consumer behavior originating from the changing lifestyle of users, (2) the digital and *mobile-first* transformation of existing businesses and emergence of new ones due to mobile opportunities; and (3) the interaction and integration of mobile with other channels.

The overview of our data provides us with several valuable observations. *First,* the exponential growth of number of studies over the last decade reveals that mobile continues to provide new research opportunities emanating from the changing lifestyle of its users. This increased interest in mobile marketing is also reflected in the publication outlets. In the beginning, more specialized journals have published articles in this emerging field, whereas over time, the coverage has spread to top journals (appearing in FT 50 rankings). *Second*, although the cumulative distribution of conceptual vs. empirical studies is even, the share of empirical studies increases over time. This suggests that the early work in the field initially discusses the opportunities and threats of the emerging channel, offers concepts and frameworks, and builds theories to be tested. When coupled with the observation that the shares of experimental and secondary data collection methods also increase over time, it is possible to infer that the later era in the review period mostly engages in causal and behavioral identification of the theories proposed early on. *Third*, (1) mobile applications as a form of mobile communication with users, (2) the deployment and integration of mobile with other channels and (3) mobile advertising and promotions including location based targeting are the most prominent themes within research on the mobile channel. Investigation of the themes over time in the three eras reveals what each era entails. The first era (2009 – 2012) is mainly concerned with the exploration of mobile technologies, and its impact on retailing landscape in general. The second era (2013 – 2016) highlights the increased interest in mobile advertising practices. Finally, the third era (2017 – 2019) includes a high number of specialized topics such as mobile apps, customer engagement or mobile data in addition to the renewed interest in retailing and advertising. *Fourth*, the examination of dependent variables shows the early interest in consumer acceptance of mobile while the interest in user engagement is quite stable; and the performance-based measures grow substantially over time. For independent variables, mobile application/ channel/ service related variables are studied both with product and brand performances. Mobile promotion/ advertising/ message related variables are studied heavily with consumer acceptance highlighting user permission and acceptance of advertising.

Since its emergence over a decade ago, mobile marketing has rapidly established itself as an integral part of marketing strategies. In the center of a digital, data-rich and open to development space (Sridhar and Fang, 2019), mobile marketing will continue to attract attention of scholars in the future.

5.2 There's an App for That: Understanding the Drivers of Mobile Application Downloads

Among the prevalent themes identified in Chapter 2, the mobile application space has gathered attention from scholars since its emergence due to the overcrowded nature of the market. Previous research has established the impact of user characteristics (Kim et al., 2017), app characteristics (Schulze, Schöler, and Skiera, 2014), app pricing (Arora, Hofstede, and Mahajan, 2017; Carrare 2012; Ghose and Han 2014; Kübler et al., 2018), app updates (Ghose and Han 2014; Kübler et al., 2018), other users' experiences (Ghose and Han 2014; Kübler et al., 2018), and, in the broader mobile eco-system, integration, ownership, and novelty of the apps (Van den Ende, Jaspers and Rijsdijk, 2013) on mobile app adoption. In Chapter 3, I bring in a new lens to the mobile app adoption decision of the user by considering the path to adoption. Specifically, I lay out a user's decision journey in the app store leading to adoption, and consider which factors may have an effect during progression through each step. Through this new lens, I investigate the effects of a comprehensive set of variables on mobile application downloads. The contributions to the extant literature are threefold: (1) the unique data set that I put together for the purpose of the study allows bringing in *platform-side variables* into the picture that are vital in the discovery phase, (2) *the composition of the apps* under investigation are selected on the basis of their release date on the market and does not impose any ranking restriction, allowing for including unsuccessful apps (lying in the long tail of the crowded market) in our analyses (3) and more importantly the focus of the study is to study how the effects of these variables *vary over time* since the app's release on the market. Moreover, I investigate how these effects vary with respect to the business model (i.e. free vs. paid) of the apps.

The results display substantial effects of *platform-controlled variables*, investigated for the first time in the literature to our knowledge. The effects of appearing in top charts are the highest, surpassing the effects of appearing in top featured lists. Appearing in top charts benefit free apps more compared to the paid apps, whereas the reverse holds for appearing in top featured lists. For the temporal variation of the effects, although relatively stable for free apps, the effects of appearing in featured lists and appearing in above and below the fold decrease over time for paid apps.

The results for *user-side variables* support the recent notion that not all WOM metrics are positively associated with performance (Babić Rosario et al., 2016). When investigated over time and with respect to the break-down of free/paid apps; an interesting pattern emerges. The effect of WOM valence for free apps is negative on average in the first six-months following an app's release and becomes positive afterwards – as WOM volume also stabilizes-; whereas it stays positive for paid apps. This pattern is particularly interesting given the growing literature on the effects of fake reviews, a phenomenon mostly occurring in the early stages of a product's lifecycle to signal credibility to the potential users, on sales (Dellarocas 2006; Streitfeld 2011; Mayzlin, Dover, and Chevalier 2014; Hu et al. 2012).

Finally, the tools readily at disposal of developers, *developer-controlled variables,* assume great importance. In line with previous literature (Ghose and Han 2014; Kübler et al., 2018), the results show that the updates benefit app demand. In addition, distinguishing between minor, middle and major updates shows that the effects of updates increase proportional to the degree of improvement. This increase when moving from minor to major updates is larger for paid apps. The overtime evolution of the effects shows that updates that are not minor and middle (only for free apps) released shortly after an app's release lower demand, reversed around the third month on the market.

For paid apps, price and discounting decisions can also help in reaching potential users. Consistent with the previous literature (e.g., Ghose and Han 2014; Kübler et al. 2018), we find that a 10% increase in price lowers downloads by 1.41% on average. The effect of discount is higher compared to what has been reported in Ghose and Han (2014); indicating that users are more discount sensitive in the early phases.

Last but not least, the comparison of different sub-groups of data reveals interesting insights and can guide future research to investigate these categories in greater detail.

In sum, by putting together a unique data set rendering (1) observing both successful and unsuccessful apps since their first day in the market, (2) including platform-controlled variables, (3) investigating over time effects for free and paid apps possible, Chapter 3 contributes to the growing literature on mobile applications by offering novel insights.

5.3 If It Ain't Broke, Don't Fix It: How Incorporating User Feedback in Product Development Affects Mobile Application Ratings

Results of Chapter 3 hint updates to be a valuable tool for mobile application developers to mold their products in a relatively less costly and timely manner. The unique organic formation in the mobile application market offers an appropriate setting to investigate user comments as an input for developers, and specifically to investigate whether and how firms can utilize the information readily accessible in user comments in the process of product development through updates.

In Chapter 4, I zoom into this unique relationship between the users and developers facilitated through reviews on the user side and updates on the developer side. Specifically, I look into the effects of (1) offering an update, (2) the intensity of the user feedback, (3) the time it takes the developer to address the requests, and (4) the interactions among these variables on the average rating score of an app's new version. I perform the analysis, on a large data set spanning 3K app updates and 1M user reviews, and check the robustness of our findings for different app business modes (i.e., free and paid), types (i.e., games and non-games) and an alternative operationalization of feedback intensity. The results show that the rewards associated with responding to user requests and the penalties due to ignoring these requests can be substantial but also that the topic of the feedbacks and the timing of the response matters.

I contribute to the three streams of literature Chapter 4 builds on: user-generated content, new product development and the mobile applications. Different dimensions of user generated such as volume, valence or variance of reviews have been studied to measure their effects on performance (e.g., Godes and Mayzlin 2004; Dellarocas et al. 2007; Ghose and Han 2014), to infer the market structure (e.g., Lee and Bradlow 2011; Netzer et al. 2012), or to uncover latent user needs (e.g., Timoshenko and Hauser 2019). I contribute to this user generated content literature by showing that the valuable information contained in the user reviews can be extracted through simple, custom-built dictionaries and utilized by firms in a proactive manner. Secondly, I contribute to the NPD literature by showing the crucial role of engaging with the customers in all stages of product development in addition to the new product development. Specifically, I demonstrate that insights obtained from social listening – a less costly alternative to direct engagement with the users – can guide product re-development decisions to the benefit of the firms. Finally, I contribute to the growing body of literature on mobile applications detailed in the previous chapter, which acknowledges the role of developer updates and user ratings/reviews in generating app demand but often overlooks the interdependence between the two. I show that this interdependence is a novel setting that can be utilized in the process of product development which in turn works in benefit of both developers and users.

5.4 General Discussion

This dissertation puts mobile marketing under the scope. Ubiquity of mobile, enabled by the outstanding advancements in technological infrastructures, fueled the irreversible transformation in consumer behavior, and the consequent transformation of businesses.

This mobile shift coupled with the spread of social media also changed the way consumers and businesses interact. Consequently, the landscapes of retailing, advertising, and promotions have embraced this impact and evolved into new and more complex systems. The distinctive features of mobile paving the way for this chain of transformations make it fundamentally different from other communication technologies/channels in marketing, leading to its own theory development. Recently, the existing research frameworks and theories of marketing are being updated by marketing scholars to include mobile marketing and its impact. In addition to the revision of the existing theories, the emergence of new platforms such as mobile applications with unique dynamics brings in a new angle to theory development within the marketing domain.

Although mobile marketing has now secured its space within marketing research, it is evident from Chapter 2 that the top journals in the field are relatively late to give coverage to the then innovative subject of mobile marketing. This is understandable to a degree given that there are numerous new subjects competing for the limited space in these journals. However, given the emphasis on theoretical and managerial relevance, stepping up to lead the way can benefit the field greatly by triggering the exchange of these theory and concept developments to reach a wider audience base earlier; which in turn can light the way for practice.

Mobile space also creates new types of data that did not previously exist (i.e. location history, content generated on mobile). This in turn, creates a need to utilize new methods to thoroughly understand these new forms of data mobile have to offer. For instance, most of the consumer-to-consumer communication frequently takes place on mobile. Despite the similarities between the mobile and other interactive channels, content generated on mobile has been shown to be different in many dimensions compared to non-mobile content (Grewal and Stephen, 2019; Liu et al., 2019b; Melumad et al., 2019; Ransbotham et al., 2019). This discrepancy alone hints to the transformation of the consumer behavior, resulting in non-existing forms of self-expressions. This increase in the available textual information is paralleled in the advancements in text mining, sentiment analysis, automated learning systems techniques. For instance, in Chapter 4, I analyze a big data set spanning about 1 million mobile user reviews using a lexicon-based approach to attain a high level of accuracy. To that end, I tediously develop custom dictionaries for user request and corresponding update categories, as dictionaries for these categories do not previously exist. Moreover, depending on the structure of the data, the advancements in machine learning techniques offer a promising tool to remove the human-coding barrier bottleneck to analyze big data sets. Location data, another previously nonexistent form of data now accessible due to mobile, has also given rise to new methods combining field data with analytical models (Chen et al., 2017; Dube et al., 2017) or with network analysis (Zubcsek et al., 2017). Chapter 2 reveals that the data collection methods rely on surveys in the earlier years, whereas experiments take over in the later years. Without a doubt, relying on experiments when uncovering causal relations is the safe way to go; however, the evolving and the original nature of the mobile field calls for new and innovative methods to analyze these new forms of data.

5.5 Practical Implications

The review provided in Chapter 2 shows that mobile marketing is a field that continues to grow at an increasing pace within which various sub-streams of research emerge. Among these, the stream of mobile applications is particularly prevalent as it stays relevant with its digital base allowing for integration of new technologies. The following chapters (Chapter 3 and Chapter 4) execute the presented studies in the mobile applications domain. Therefore, practical and managerial implications of the results from both chapters collectively offer valuable insights for all parties involved in this attractive market ranging from individual users or developers to well-known brands.

In Chapter 3, I adopt a holistic view at the mobile applications market and consider the adoption challenge that the app developers face by considering multiple players (i.e. platforms, developers and users). In this highly competitive market with low barriers to entry, the results display the substantial role the platform effects play. Hence, developer controlled variables assume great importance to survive from the view point of developers. Updates that gradually determine the value proposition of the app are one strong tool developers can utilize. In addition to the positive effects of these updates, by distinguishing between the types of updates, I find that this positive effect increases proportional to the degree of improvement (i.e., magnitude of the update). The over-time investigation of the effects of updates draw attention to potential adopters being intolerant especially for minor and middle updates early after an app's release. Counterintuitive to the common starting-off with a minimum viable product approach, the results suggest that offering a well-prepared application upfront and offering major developments later on can benefit app adoption the greatest.

The now-rule-of-thumb of starting off with a minimum viable product extends beyond app features to the app pricing strategies due to the market's ability to integrate price changes in a fast and effortless way. The platform facilitates this by allowing the developer to schedule price changes directly. Therefore, developers, who have full control over their pricing, can choose to settle at a price after some experimentation. To this end, I show that users become less sensitive to price as apps mature whereas the effects of discounts reach its peak a few months after the release and then start to decline. Interpreted together, the developers can adopt a penetrative pricing approach from the beginning. Alternatively, they can offer discounts along the way to boost their download numbers.

Chapter 4 builds on the findings of Chapter 3 and further investigates how developers can utilize updates – one of the few decision variables they can control – by thoroughly investigating their content and by considering their interdependence with reviews arriving from the users. I provide developers with detailed recipes on how to prioritize and formulate their product development strategies. The results indicate that careful and timely monitoring of the user reviews and responding to the voiced requests in terms of product evaluations can benefit developers in terms of subsequent product evaluations. Moreover, the nature and the timing of the response vary greatly among update categories. Whereas the developers are penalized when they do not comply to the user requests for some categories (i.e., improving existing content, compatibility), they are rewarded when they comply to these requests for some other (i.e., adding new content, fixing bugs). Developers need to *resolve bugs* in a timely manner, only when the users explicitly ask for these fixes to enjoy rewards. The developers on the other hand can be rewarded either by taking advantage of the element of surprise or by promptly responding to the requests when offering *new content* in their updates. On the other hand being *compatible* with as many devices and operating systems upfront is of crucial importance, as the negative effect of compatibility requests cannot be reversed. Interestingly, the deleterious effect of *improving existing content* can only be reversed when the response is prompt. Taken together, given enough resources, the developers are advised to adopt a continuous improvement approach to avoid the penalties from offering a not-ready-for-the-market application and to ensure compatibility with most recent operating systems and wide range of devices. In the absence of enough resources, bundling with new content can counter-balance these penalties when ensuring prompt responding to reported bugs and new content requests.

Collectively, I demonstrate that survival in a highly competitive market passes through careful elaboration of the mobile application's value proposition and its efficiency (i.e., how well it delivers what it intends to). Implications discussed herein not only provide potential app developers with valuable insights but also offer existing developers remedies to resuscitate their applications along the way, following their release on the market. Moreover, the categories I identify when studying updates in Chapter 4 in the broad sense can relate to digital products such as smart products, software, and PC or console games (i.e., continuous innovation settings).

5.6 Future Research Avenues

The studies executed in the mobile applications market offer a fertile ground for research with high managerial relevance and also pave the way for further research. To elaborate, the user's adoption journey presented in Chapter 3 continues with the user's first interaction with the app, followed by repeated interactions. These interaction opportunities are particularly important for brands. As mobile apps can be thought as experience goods, users base their quality assessments on their experiences. Starting from the first exposure, users continuously revise their evaluations based on certain characteristics of the app. Most evaluations are already complete after the first exposure when we consider that 21% of the MAs downloaded in 2018 were used only once (Localytics, 2018). This observation suggests two things. First, creating a positive user experience in this very first exposure is the key to keep the app's space in the user's mobile phone. Brands and app developers have the chance to create customer retention only if they can pass through this phase. Secondly, and rather disturbingly, the first engagement with the application may be the only chance that the company has to connect with its customers, thereby increasing the importance of this first exposure. Creating a branded app, seems like an obvious move toward engaging potential customers either in the form of utility or branded entertainment (Hudson and Hudson, 2006). Big brands are heavily investing in this new medium and the increasing demand indicates that consumers are responding accordingly. Given that a user has moved to the second step by downloading an app, the user experience created during the first exposure will determine whether or not the brand will be able to stay on the user's mobile phone. Completion of this phase by generating a positive user experience will provide the brand with the opportunity to communicate with the user on a regular basis. Therefore, future research can build on the insights from Chapter 3 by modeling the individual's journey within the app at the individual level to guide app developers to sustain app retention and referral.

Secondly, business models in the digital economy have created a growing research interest among scholars in the last decade, especially with the emergence of "freemium" business models; the discussion on the free and paid bussiness models in Chapter 3 can be extended to include the freemium business models. The primary source of revenue generation in the mobile app space depends on the business model apps utilize. Free apps can be downloaded and used at zero cost by their users. Revenues can be generated through in-app advertisements and in-app purchases. Paid apps can be downloaded at a cost for the user, while these paid apps often also offer additional features that mostly come at low costs (mostly < $5). Finally, app developers can use the freemium business model and launch both free and paid versions of the app. The freemium business model, commonly used in digital products, is defined as having both a perpetually free but limited version and a premium version with enhanced features that requires a fee on the market (Lee et al. 2017). The free app is available at zero-cost to encourage trial and promote the paid version of the app, which will in most cases come with extended functionalities. So far, research investigating freemium business models in app stores yields diverse findings. Liu et al. (2014) find that higher ranks and rating scores of the freemium version positively affect the sales rank of paid apps. However, only high ratings of the free version affect paid version *revenues*. The effect of ratings disappears when the free version is on the market and for hedonic apps. On the contrary, Arora et al. (2017) find that offering freemium versions of an app is negatively associated with the paid app's adoption speed and that this effect is stronger for hedonic apps and in the later life stages of paid apps. Rietveld (2017) also finds that freemium games are played less and generate fewer revenues than premium games. In sum, different business models driving the pricing strategy of the developers impose different characteristics on free vs. paid applications. Although few observations offering both free and paid versions in our sample prevent us from exploring the effects of freemium business models on app performance, this is a promising area for further research.

Finally, in the larger mobile marketing domain, researchers have identified future research avenues as in-store technologies in retailing (Grewal et al., 2019; Dekimpe, 2019); mobile as an enabler of AR configurations (Heller et al., 2019); and its sensory communication ability (Petit et al., 2019; Hadi and Valenzuela, 2019; Appel et al., 2019). From where I stand, although the field of mobile marketing seems to be maturing, its digital base allows for continuous developments to integrate these evolving new technologies in the future. With the increased use of mobile, cost-and-benefit perspectives of users when understanding the permission grants (Krafft et al., 2017) assume great importance. Developers need to thoroughly understand how much users are willing to share at which costs. Transparency and consent when processing personal data might increasingly become a differentiating factor for developers. Consequently, privacy concerns need careful revisiting with the irreversible transformation in consumer behavior.

References

Acquisti, A., & Spiekermann, S. (2011). Do Interruptions Pay off? Effects of Interruptive Ads on Consumers' Willingness to Pay. *Journal of Interactive Marketing*. 25(4), 226-240. doi: 10.1016/j.intmar.2011.04.003.

Anderson, M. & Magruder, J. (2012). Learning from the Crowd: Regression Discontinuity Estimates of the Effects of an Online Review Database*. *The Economic Journal*. 122, 957-989. doi: 10.1111/j.1468-0297.2012.02512.x.

Andrews, M., Goehring, J., Hui, S., Pancras, J., & Thornswood, L. (2016a). Mobile Promotions: A Framework and Research Priorities. *Journal of Interactive Marketing*. 34, 15-24. doi: 10.1016/j.intmar.2016.03.004.

Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2016b). Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness. *Marketing Science*. 35(2), 201-340. doi: 10.1287/mksc.2015.0905.

AppAnnie. (2018). The 2017-2022 App Economy Forecast: 6 Billion Devices, $157 Billion in Spend & More. < https://www.appannie.com/en/insights/market-data/app-annie-2017-2022-forecast/> Retrieved 9 July 2020.

AppAnnie. (2019). The State of Mobile 2019. Downloaded on 5 December 2019.

AppBrain. (2019). Number of Android Apps on Google Play. <https://www.appbrain.com/stats/number-of-android-apps> Retrieved 9 July 2020.

Appel, G., Grewal, L., Hadi, R., & Stephen, A. (2019a). The Future of Social Media in Marketing. *Journal of the Academy of Marketing Science*. 48, 79-95. doi: 10.1007/s11747-019-00695-1.

Appel, G., Libai, B., Muller, E., & Shachar, R. (2019b). On the Monetization of Mobile Apps. *International Journal of Research in Marketing.* 37(1), 93-107. doi: 10.1016/j.ijresmar.2019.07.007.

Apple Insider. (2018). The Revolution Steve Jobs Resisted: Apple's App Store Marks 10 years of Third-party Innovation. <https://appleinsider.com/articles/18/07/10/the-revolution-steve-jobs-resisted-apples-app-store-marks-10-years-of-third-party-innovation> Retrieved 9 July 2020.

Apple. (2020). < https://searchads.apple.com/> Retrieved 9 July 2020.

Aralikatte, R., Sridhara, G., Gantayat, N., & Mani, S. (2018). Fault in Your Stars: An Analysis of Android App Reviews. *CoDS-COMAD '18: Proceedings of the ACM India Joint International Conference on Data Science and Management of Data*, 57-66.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the Pricing Power of Product Features by Mining Consumer Reviews. *Management Science*. 57 (8), 1485-1509. doi: 10.1287/mnsc.1110.1370.

Arora, S., ter Hofstede, F., & Mahajan, V. (2017). The Implications of Offering Free Versions for the Performance of Paid Mobile Apps. *Journal of Marketing*. 81, 62-78. doi: 10.1509/jm.15.0205.

Ataman, M.B., Van Heerde, H. & Mela, C. (2008). Building Brands. *Marketing Science*. 27. 1036-1054. doi: 10.1287/mksc.1080.0358.

Aydin Gokgoz, Z., Ataman, M.B. & Van Bruggen, G. (2020). If It Ain't Broke, Don't Fix It: How Incorporating User Feedback in Product Development Affects Mobile Application Ratings. *Working Paper, Rotterdam School of Management, Erasmus University*.

Aydin Gokgoz, Z., Ataman, M.B., & Van Bruggen, G. (2021). There's an App for that! Understanding the Drivers of Mobile Application Downloads. *Journal of Business Research.* 123, 423-437. doi: 10.1016/j.jbusres.2020.10.006.

Babić Rosario, A., Sotgiu, F., De Valck, K. & Bijmolt, T. H. A. (2016). The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors. *Journal of Marketing Research*, 53(3), 297-318. doi: 10.1509/jmr.14.0380.

Bacile, T., Ye, C., & Swilley, E. (2014). From Firm-Controlled to Consumer-Contributed: Consumer Co-Production of Personal Media Marketing Communication. *Journal of Interactive Marketing.* 28(2), 117-133. doi: 10.1016/j.intmar.2013.12.001.

Baek, T. H., & Yoo, C. (2018). Branded App Usability: Conceptualization, Measurement, and Prediction of Consumer Loyalty. *Journal of Advertising*. 47, 70-82. doi: 10.1080/00913367.2017.1405755.

Bailetti, A.J., & Litva, P. F. (1995). Integrating Customer Requirements into Product Designs. *Journal of Product Innovation Management*. 12 (1), 3-15. doi: 10.1016/0737-6782(94)00021-7.

Banerjee, M. (2014). Misalignment and Its Influence on Integration Quality in Multichannel Services. *Journal of Service Research*. 17(4), 460-474. doi: 10.1177/1094670514539395.

Bart, Y., Stephen, A. & Sarvary, M. (2014). Which Products Are Best Suited to Mobile Advertising? A Field Study of Mobile Display Advertising Effects on Consumer Attitudes and Intentions. *Journal of Marketing Research*. 51, 270- 285. doi: 10.1509/jmr.13.0503.

Basoglu, N., Daim, T., & Polat, E. (2014). Exploring Adaptivity in Service Development: The Case of Mobile Platforms. *Journal of Product Innovation Management*. 31(3), 501-515. doi: 10.1111/jpim.12110.

Batra, R., & Keller, K. (2016). Integrating Marketing Communications: New Findings, New Lessons and New Ideas. *Journal of Marketing*. 80(6), 122-145. doi: 10.1509/jm.15.0419.

Belk, R. (2013). Extended Self in a Digital World. *Journal of Consumer Research*. 40(3), 477-500. doi: 10.1086/671052.

Bellman, S., Potter, R., Treleaven-Hassard, S., Robinson, J., & Varan, D. (2011). The Effectiveness of Branded Mobile Phone Apps. *Journal of Interactive Marketing*. 25(4), 191-200. doi: 10.1016/j.intmar.2011.06.001.

Berger, A., Schlager, T., Sprott, D., & Herrmann, A. (2018). Gamified Interactions: Whether, When, and How Games Facilitate Self–brand Connections. *Journal of the Academy of Marketing Science*. 46, 652-673. doi: 10.1007/s11747-017-0530-0.

Berger, J., Humphreys, A., Ludwig, S., Moe, W.W., Netzer, O. & Schweidel, D. A. (2019). Uniting the Tribes: Using Text for Marketing Insight. *Journal of Marketing*. 84 (1), 1-25. doi: 10.1177/0022242919873106.

Bettman, J., Luce, M. F. & Payne, J. W. (1998). Constructive Consumer Choice Processes. *Journal of Consumer Research*, 25 (3), 187-217. doi: 10.1086/209535.

Bijmolt, T., van Heerde, H. & Pieters, R. (2005). New Empirical Generalizations on the Determinants of Price Elasticity. *Journal of Marketing Research*. 42, 141-156. doi: 10.1509/jmkr.42.2.141.62296.

Blank, S. (2013). Why the Lean Start-up Changes Everything. *Harvard Business Review*. 91, 63-72.

Blattberg, R. C., Briesch, R. & Fox, E. J. (1995). How Promotions Work. *Marketing Science*. 14 (3), 122-132. doi: 10.1287/mksc.14.3.G122.

Blut, M., Wang, C., & Schoefer, K. (2016). Factors Influencing the Acceptance of Self-Service Technologies: A Meta-Analysis. *Journal of Service Research*. 19(4), 396-416. doi: 10.1177/1094670516662352.

Bond, S., He, S., & Wen, W. (2019). Speaking for "Free": Word of Mouth in Free-and Paid-Product Settings. *Journal of Marketing Research*. 56(2), 276-290. doi: 10.1177/0022243718821957.

Boyd, D., Kannan, P. K., & Slotegraaf, R. (2019). Branded Apps and Their Impact on Firm Value: A Design Perspective. *Journal of Marketing Research*. 56(1), 76-88. doi: 10.1177/0022243718820588.

Bradlow, E., Gangwar, M. & Kopalle, P., & Voleti, S. (2017). The Role of Big Data and Predictive Analytics in Retailing. *Journal of Retailing*. 93(1), 79-95. doi: 10.1016/j.jretai.2016.12.004.

Breugelmans, E., Bijmolt, T., Zhang, J., Basso, L., Dorotic, M., Kopalle, P., Minnema, A., Mijnlieff, W., & Wünderlich, N. (2015). Advancing Research on Loyalty Programs: A Future Research Agenda. *Marketing Letters*. 26, 127-139. doi: 10.1007/s11002-014-9311-4.

Business Insider. Mobile App Users are Key to Amazon’s Success. <https://www.businessinsider.com/mobile-app-users-amazon-2019-3#:~:targetText=Amazon's%20app%20users%20spent%2012.8,billion%20minutes%20on%20the%20site> Retrieved 7 December 2019.

Büschken, J., & Allenby, G. (2016). Sentence-Based Text Analysis for Customer Reviews. *Marketing Science*. 35 (6), 831-998. doi: 10.1287/mksc.2016.0993.

Cao, L., & Li, L. (2015). The Impact of Cross-Channel Integration on Retailers’ Sales Growth. *Journal of Retailing*. 91(2), 198-216. doi: 10.1016/j.jretai.2014.12.005.

Cao, L., & Li, L. (2018). Determinants of Retailers’ Cross-channel Integration: An Innovation Diffusion Perspective on Omni-channel Retailing. *Journal of Interactive Marketing*. 44, 1-16. doi: 10.1016/j.intmar.2018.04.003.

Cao, L., Liu, X., & Cao, W. (2018). The Effects of Search-Related and Purchase-Related Mobile App Additions on Retailers' Shareholder Wealth: The Roles of Firm Size, Product Category, and Customer Segment. *Journal of Retailing*. 94(4), 343-351. doi: 10.1016/j.jretai.2018.08.003.

Carrare, O. (2012). The Impact of Bestseller Rank on Demand: Evidence from the App Market. *International Economic Review*. 53, 717-742. doi: 10.1111/j.1468-2354.2012.00698.x.

Chang, C., Lee, W. & Liu-Thompkins, Y. (2019). Advertising in Asia: Theories and Implications for Practice. *Journal of Advertising*. 48(5), 417-436. doi: 10.1080/00913367.2019.1675103.

Chang, W., & Taylor, S. A. (2016). The Effectiveness of Customer Participation in New Product Development: A Meta-Analysis. *Journal of Marketing*. 80 (1), 47-64. doi: 10.1509/jm.14.0057.

Chen, A. (2018). New Data Shows Losing 80% of Mobile Users is Normal, and Why the Best Apps Do Better. < https://andrewchen.co/new-data-shows-why-losing-80-of-your-mobile-users-is-normal-and-that-the-best-apps-do-much-better/> Retrieved 9 July 2019.

Chen, Y., Li, X., & Sun, M. (2017). Competitive Mobile Geo Targeting. *Marketing Science*. 36(5), 645-812. doi: 10.1287/mksc.2017.1030.

Chevalier, J.A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*. 43 (3), 345-354. doi: 10.1509/jmkr.43.3.345.

Chevalier, J.A., Dover, Y., & Mayzlin, D. (2018). Channels of Impact: User Reviews When Quality Is Dynamic and Managers Respond. *Marketing Science*. 37 (5), 688-709. doi: 10.1287/mksc.2018.1090.

Colicev, A., Malshe, A., Pauwels, K., & O'Connor, P. (2018). Improving Consumer Mindset Metrics and Shareholder Value Through Social Media: The Different Roles of Owned and Earned Media. *Journal of Marketing*. 82 (1), 37-56. doi: 10.1509/jm.16.0055.

Consiglio, I., Deangelis, M., & Costabile, M. (2018). The Effect of Social Density on Word of Mouth. *Journal of Consumer Research*. 45(3), 511-528. doi: 10.1093/jcr/ucy009.

Coviello, N.E., & Joseph, R. M. (2012). Creating Major Innovations with Customers: Insights from Small and Young Technology Firms. *Journal of Marketing*. 76 (6), 87-104. doi: doi.org/10.1509/jm.10.0418.

Danaher, P., Smith, M., Ranasinghe, K., & Danaher, T. (2015). Where, When, and How Long: Factors That Influence the Redemption of Mobile Phone Coupons. *Journal of Marketing Research*. 52(5), 710-725. doi: 10.1509/jmr.13.0341.

Davidow, M. (2003). Organizational Responses to Customer Complaints: What Works and What Doesn't. *Journal of Service Research*. 5 (3), 225-50. doi: 10.1177/1094670502238917.

De Haan, E., Kannan, P. K., Verhoef, P., & Wiesel, T. (2018). Device Switching in Online Purchasing: Examining the Strategic Contingencies. *Journal of Marketing*. 82.(5), 1-19. doi: 10.1509/jm.17.0113.

De Vany, A. & Walls, W. (1996). Bose-Einstein Dynamics and Adaptive Contracting in the Motion Picture Industry, *Economic Journal*. 106 (439), 1493-1514. doi: 10.2307/2235197.

Deighton, J., & Kornfeld, L. (2009). Interactivity's Unanticipated Consequences for Marketers and Marketing. *Journal of Interactive Marketing*. 23(1), 4-10. doi: 10.1016/j.intmar.2008.10.001.

Dekimpe, M. (2019). Retailing and Retailing Research in the Age of Big Data Analytics. *International Journal of Research in Marketing*. 37(1), 3-14. doi: 10.1016/j.ijresmar.2019.09.001.

Dellarocas, C. (2003). The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science*. 49 (10), 1407-1424. doi: 10.1287/mnsc.49.10.1407.17308.

Dellarocas, C. (2006). Strategic Manipulation of Internet Opinion Forums: Implications for Consumers and Firms. *Management Science*. 52 (20), 157-1593. doi: 10.1287/mnsc.1060.0567.

Dellarocas, C., & Narayan, R. (2006). A Statistical Measure of a Population's Propensity to Engage in Post-Purchase Online Word-of-Mouth. *Statistical Science*. 21, 277-285. doi: 10.1214/088342306000000169.

Dellarocas, C., Zhang, X. M., & Awad, N. F. (2007). Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. *Journal of Interactive Marketing*. 21 (4), 23-45. doi: 10.1002/dir.20087.

Dhar, V., & Chang, E. A. (2009). Does Chatter Matter? The Impact of User-Generated Content on Music Sales. *Journal of Interactive Marketing*. 23 (4), 300-307. doi: 10.1016/j.intmar.2009.07.004.

Duan, W., Gu, B. & Whinston, A. B. (2011). The Dynamics of Online Word-of-Mouth and Product Sales: An Empirical Investigation of the Movie Industry. *Journal of Retailing*. 84, 233-242. doi: 10.1016/j.jretai.2008.04.005.

Dube, J.P., Fang, Z., Fong, N., & Luo, X. (2017). Competitive Price Targeting with Smartphone Coupons. *Marketing Science*. 36(6), 813-1017. doi: 10.1287/mksc.2017.1042.

Eigenraam, A., Eelen, J., Lin, A., & Verlegh, P. (2018). A Consumer-based Taxonomy of Digital Customer Engagement Practices. *Journal of Interactive Marketing*. 44, 102-121. doi: 10.1016/j.intmar.2018.07.002.

Eisingerich, A., Marchand, A., Fritze, M., & Dong, L. (2019). Hook vs. Hope: How to Enhance Customer Engagement through Gamification. *International Journal of Research in Marketing*. 36(2), 200-214. doi: 10.1016/j.ijresmar.2019.02.003.

Ende, J., Jaspers, F., & Rijsdijk, S. (2013). Should System Firms Develop Complementary Products? A Dynamic Model and an Empirical Test. *Journal of Product Innovation Management.* 30(6), 1178-1198. doi: 10.1111/jpim.12053.

Engström, P. & Forsell, E. (2018). Demand Effects of Consumers' Stated and Revealed Preferences. *Journal of Economic Behavior & Organization*. 150, 43-61. doi: 10.1016/j.jebo.2018.04.009.

Facebook. 10-K SEC Filing. (2019). <https://investor.fb.com/financials/default.aspx> Retrieved 6 December 2019.

Feit, E., Wang, P., Bradlow, E. & Fader, P. (2013). Fusing Aggregate and Disaggregate Data with an Application to Multi-Platform Media Consumption. *Journal of Marketing Research*. 50(3), 348-364. doi: 10.1509/jmr.11.0431.

Ferrell, O. (2017). Broadening Marketing's Contribution to Data Privacy. *Journal of the Academy of Marketing Science.* 45, 160-163. doi: 10.1007/s11747-016-0502-9.

Fong, N., Fang, Z., & Luo, X. (2015). GEO-Conquesting: Competitive Locational Targeting of Mobile Promotions. *Journal of Marketing Research*. 52(5), 726-735. doi: 10.1509/jmr.14.0229.

Fong, N., Zhang, Y., Luo, X., & Wang, X. (2019). Targeted Promotions on an E-Book Platform: Crowding Out, Heterogeneity, and Opportunity Costs. *Journal of Marketing Research*. 56(2), 310-323. doi: 10.1177/0022243718817513.

Forman, C., Ghose, A. & Wiesenfeld, B. (2008). Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*. 19 (3), 243-396. doi: 10.1287/isre.1080.0193.

Franke, N., Keinz, P. & Steger, C. J. (2009). Testing the Value of Customization: When Do Customers Really Prefer Products Tailored to Their Preferences?. *Journal of Marketing*. 73 (5), 103-121. doi: 10.1509/jmkg.73.5.103.

Fu, B., Lin, J., Li, L., Faloutsos, C., Hong, J.I., & Sadeh, N.M. (2013). Why People Hate Your App: Making Sense of User Feedback in a Mobile App Store. *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*.

Garg, R. & Telang, R. (2013). Inferring App Demand from Publicly Available Data. *MIS Quarterly*. 37 (4), 1253-1264. doi: 10.25300/MISQ/2013/37.4.12.

Ghose, A., & Han, S. P. (2014). Estimating Demand for Mobile Applications in the New Economy. *Management Science*. 60 (6), 1470-1488. doi: 10.1287/mnsc.2014.1945.

Ghose, A., Goldfarb, A., & Han, S. (2013). How is the Mobile Internet Different? Search Costs and Local Activities. *Information Systems Research*. 24 (3), 613-631. doi: 10.1287/isre.1120.0453.

Gill, M., Sridhar, S., & Grewal, R. (2017). Return on Engagement Initiatives: A Study of a Business-to-Business Mobile App. *Journal of Marketing*. 81(4), 45-66. doi: 10.1509/jm.16.0149.

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*. 23 (4), 545-560. doi: 10.1287/mksc.1040.0071.

Goh, K.Y., Chu, J., & Wu, J. (2015). Mobile Advertising: An Empirical Study of Temporal and Spatial Differences in Search Behavior and Advertising Response. *Journal of Interactive Marketing.* 30, 34-45. doi: 10.1016/j.intmar.2014.12.002.

Google. (2016). How People Discover, Use, and Stay Engaged with Apps. < https://www.thinkwithgoogle.com/_qs/documents/331/how-users-discover-use-apps-google-research.pdf> Downloaded on 9 July 2019.

Grewal, D., Ahlbom, C.P., Beitelspacher, L., Noble, S., & Nordfält, J. (2018). In-Store Mobile Phone Use and Customer Shopping Behavior: Evidence from the Field. *Journal of Marketing*. 82(4), 102-126. doi: 10.1509/jm.17.0277.

Grewal, D., Ailawadi, K., Gauri, D., Hall, K., Kopalle, P., & Robertson, J. (2011). Innovations in Retail Pricing and Promotions. *Journal of Retailing*. 87(1), 43-52. doi: 10.1016/j.jretai.2011.04.008.

Grewal, D., Bart, Y., Spann, M., & Zubcsek, P. (2016). Mobile Advertising: A Framework and Research Agenda. *Journal of Interactive Marketing*. 34, 3-14. doi: 10.1016/j.intmar.2016.03.003.

Grewal, D., Hulland, J., Kopalle, P., & Karahanna, E. (2019). The Future of Technology and Marketing: A Multidisciplinary Perspective. *Journal of the Academy of Marketing Science*. 48, 1-8. doi: 10.1007/s11747-019-00711-4.

Grewal, D., Noble, S., Roggeveen, A., & Nordfält, J. (2020). The Future of In-store Technology. *Journal of the Academy of Marketing Science*. 48, 96-113. doi: 10.1007/s11747-019-00697-z.

Grewal, D., Roggeveen, A., Compeau, L., & Levy, M. (2012). Retail Value–Based Pricing Strategies: New Times, New Technologies, New Consumers. *Journal of Retailing*. 88(1), 1-6. doi: 10.1016/j.jretai.2011.12.001.

Grewal, L., & Stephen, A. T. (2019). In Mobile We Trust: The Effects of Mobile Versus Nonmobile Reviews on Consumer Purchase Intentions. *Journal of Marketing Research*. 56(5), 791–808. doi: 10.1177/0022243719834514.

Gu, X., Kannan, P. K., & Ma, L. (2018). Selling the Premium in Freemium. *Journal of Marketing*. 82(6), 10-27. doi: 10.1177/0022242918807170.

Hadi, R., & Valenzuela, A. (2019). Good Vibrations: Consumer Responses to Technology-Mediated Haptic Feedback. *Journal of Consumer Research*. 47(2), 256–271. doi: 10.1093/jcr/ucz039.

Hao, L., Li, X., Tan, Y. & Xu, J. (2011). The Economic Value of Ratings in App Market. *SSRN Electronic Journal*. doi: 10.2139/ssrn.1892584.

Helkkula, A., Kowalkowski, C., & Tronvoll, B. (2018). Archetypes of Service Innovation: Implications for Value Cocreation. *Journal of Service Research*. 21(3), 284-301. doi: 10.1177/1094670517746776.

Heller, J., Chylinski, M., De Ruyter, K., Mahr, D., & Keeling, D. (2019b). Touching the Untouchable: Exploring Multi-Sensory Augmented Reality in the Context of Online Retailing. *Journal of Retailing*. 95(4), 219-234. doi: 10.1016/j.jretai.2019.10.008.

Henard, D. H., & Szymanski, D. M. (2001). Why Some New Products are More Successful than Others. *Journal of Marketing Research*. 38 (3), 362–375. doi: 10.1509/jmkr.38.3.362.18861.

Hennig-Thurau, T., Malthouse, E., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The Impact of New Media on Customer Relationships. *Journal of Service Research*. 13(3), 311-330. doi: 10.1177/1094670510375460.

Herhausen, D., Kleinkercher, K., Verhoef, P.C., Emrich, O., & Rudolph, T. (2019). Loyalty Formation for Different Customer Journey Segments. *Journal of Retailing*. 95(3), 9-29. doi: 10.1016/j.jretai.2019.05.001.

Hofacker, C., De Ruyter, K., Lurie, N., Manchanda, P., & Donaldson, Je. (2016). Gamification and Mobile Marketing Effectiveness. *Journal of Interactive Marketing*. 34, 25-36. doi: 10.1016/j.intmar.2016.03.001.

Hu, N., Bose, I., Koh, N. & Liu, L. (2012). Manipulation of Online Reviews: An Analysis of Ratings, Readability, and Sentiments. *Decision Support Systems*. 52 (3), 674-684. doi: 10.1016/j.dss.2011.11.002.

Huang, N., Burtch, G., Hong, Y., & Polman, E. (2016). Effects of Multiple Psychological Distances on Construal and Consumer Evaluation: A Field Study of Online Reviews. *Journal of Consumer Psychology*. 26(4), 474-482. doi: 10.1016/j.jcps.2016.03.001.

Hui, S. (2017). Understanding Repeat Playing Behavior in Casual Games Using a Bayesian Data Augmentation Approach. *Quantitative Marketing and Economics*. 15, 29-55. doi: 10.1007/s11129-017-9180-2.

Humphreys, A., & Wang, R. (2018). Automated Text Analysis for Consumer Research. *Journal of Consumer Research*. 44(6), 1274-1306. doi: 10.1093/jcr/ucx104.

Inman, J., & Nikolova, H. (2017). Shopper-Facing Retail Technology: A Retailer Adoption Decision Framework Incorporating Shopper Attitudes and Privacy Concerns. *Journal of Retailing.* 93(1), 7-28. doi: 10.1016/j.jretai.2016.12.006.

Istanbulluoglu, D. (2017). Complaint Handling on Social Media: The impact of multiple Response Times on Consumer Satisfaction. *Computers in Human Behavior*. 74, 72-82. doi: 10.1016/j.chb.2017.04.016.

Jacoby, J. and Kaplan, L.B. (1972). The Components of Perceived Risk. *Proceedings of the Annual Conference of the Association for Consumer Research*. 10, 382-393.

Jang, S., & Chung, J. (2015). How Do Interaction Activities among Customers and between Customers and Firms Influence Market Performance and Continuous Product Innovation? An Empirical Investigation of the Mobile Application Market. *Journal of Product Innovation Management.* 32(2), 183-191. doi: 10.1111/jpim.12170.

Johar, G. (2016). Mistaken Inferences from Advertising Conversations: A Modest Research Agenda. *Journal of Advertising*. 45(3), 318-325. doi: 10.1080/00913367.2016.1217810.

Kakatkar, C., & Spann, M. (2019). Marketing Analytics Using Anonymized and Fragmented Tracking Data. 36(1), 117-136. *International Journal of Research in Marketing*. doi: 10.1016/j.ijresmar.2018.10.001.

Kannan, P. K., & Li, A. (2017). Digital Marketing: A Framework, Review And Research Agenda. *International Journal of Research in Marketing*. 34(1), 22- 45. doi: 10.1016/j.ijresmar.2016.11.006.

Kannan, P. K., Reinartz, W., & Verhoef, P. (2016). The Path to Purchase and Attribution Modeling: Introduction to Special Section. *International Journal of Research in Marketing*. 33(3), 449-456. doi: 10.1016/j.ijresmar.2016.07.001.

Katsikeas, C., Morgan, N., Leonidou, L., & Hult, G. T. M. (2016). Assessing Performance Outcomes in Marketing. *Journal of Marketing*. 80(2), 1-20. doi: 10.1509/jm.15.0287.

Kawaf, F. (2019). Capturing Digital Experience: The Method of Screencast Videography. *International Journal of Research in Marketing*. 36(2), 169-184. doi: 10.1016/j.ijresmar.2018.11.002.

Keller, K. (2010). Brand Equity Management in a Multichannel, Multimedia Retail Environment. *Journal of Interactive Marketing*. 24(2), 58-70. doi: 10.1016/j.intmar.2010.03.001.

Kerckhove, A., & Pandelaere, M. (2018). Why Are You Swiping Right? The Impact of Product Orientation on Swiping Responses. *Journal of Consumer Research*. 45(3), 633-647. doi: 10.1093/jcr/ucy013.

Kim, M., Kim, J., Choi, J., & Trivedi, M. (2017). Mobile Shopping Through Applications: Understanding Application Possession and Mobile Purchase. *Journal of Interactive Marketing*. 39, 55-68. doi: 10.1016/j.intmar.2017.02.001.

Kim, S. J., Wang, R., & Malthouse, E. (2015). The Effects of Adopting and Using a Brand's Mobile Application on Customers' Subsequent Purchase Behavior. Journal of Interactive Marketing. 31, 28-41. doi: 10.1016/j.intmar.2015.05.004.

Kleijnen, M., Lievens, A., De Ruyter, K., & Wetzels, M. (2009). Knowledge Creation Through Mobile Social Networks and Its Impact on Intentions to Use Innovative Mobile Services. *Journal of Service Research*. 12(1), 15-35. doi: 10.1177/1094670509333238.

Klostermann, J., Plumeyer, A., Böger, D., & Decker, R. (2018). Extracting Brand Information From Social Networks: Integrating Image, Text, And Social Tagging Data. *International Journal of Research in Marketing*. 35(4), 538-556. doi: 10.1016/j.ijresmar.2018.08.002.

Koenigstorfer, J., & Groeppel-Klein, A. (2012). Consumer Acceptance of the Mobile Internet. *Marketing Letters*. 23, 917-928. doi: 10.1007/s11002-012-9206-1.

Kozinets, R. V. (2019). Consuming Technocultures: An Extended JCR Curation. *Journal of Consumer Research*. 46(3), 620–627. doi: 10.1093/jcr/ucz034.

Krafft, M., Arden, C., & Verhoef, P. (2017). Permission Marketing and Privacy Concerns - Why Do Customers (Not) Grant Permissions?. *Journal of Interactive Marketing*. 39, 39-54 doi: 10.1016/j.intmar.2017.03.001.

Kumar, V. (2015). Evolution of Marketing as a Discipline: What Has Happened and What to Look Out For. *Journal of Marketing*. 79(1), 1-9. doi: 10.1509/jm.79.1.1.

Kumar, V. (2018). Transformative Marketing: The Next 20 Years. *Journal of Marketing*. 82(4), 1-12. doi: 10.1509/jm.82.41.

Kumar, V., & Gupta, S. (2016). Conceptualizing the Evolution and Future of Advertising. Journal of Advertising. 45(3), 302-317. doi: 10.1080/00913367.2016.1199335.

Kumar, V., Anand, A., & Song, H. (2017). Future of Retailer Profitability: An Organizing Framework. *Journal of Retailing*. 93(1), 96-119. doi: 10.1016/j.jretai.2016.11.003.

Kumar, V., Nim, N., & Sharma, A. (2019). Driving Growth of Mwallets in Emerging Markets: a Retailer’s Perspective. *Journal of the Academy of Marketing Science*. 47, 747–769. doi: 10.1007/s11747-018-0613-6.

Kübler, R., Pauwels, K., Yildirim, G., & Fandrich, T. (2018). App Popularity: Where in the World Are Consumers Most Sensitive to Price and User Ratings?. *Journal of Marketing*. 82(5), 20-44. doi: 10.1509/jm.16.0140.

Lamberton, C., & Stephen, A. (2016). A Thematic Exploration of Digital, Social Media, and Mobile Marketing Research's Evolution from 2000 to 2015 and an Agenda for Future Research. *Journal of Marketing*. 80(6), 146-172. doi: 10.1509/jm.15.0415.

Lambrecht, A., Goldfarb, A., Bonatti, A., Ghose, A., Goldstein, D., Lewis, R., Rao, A., Sahni, N., & Yao, S. (2014). How Do Firms Make Money Selling Digital Goods Online?. *Marketing Letters*. 25, 331-341. doi: 10.1007/s11002-014-9310-5.

Lavidge, R., & Steiner, G. (1961). A Model for Predictive Measurements of Advertising Effectiveness. *Journal of Marketing*. 25 (6), 59-62. doi: 10.2307/1248516.

Lee, C., Kumar, V. & Gupta, S. (2017), Designing Freemium: Strategic Balancing Growth and Monetization. Available at SSRN: https://ssrn.com/abstract=2767135.

Lee, G. & Raghu, T.S. (2014) Determinants of Mobile Apps' Success: Evidence from the App Store Market. *Journal of Management Information Systems*. 31 (2), 133-170. doi: 10.2753/MIS0742-1222310206.

Lee, T. Y., & Bradlow, E. T. (2011). Automated Marketing Research Using Online Customer Reviews. *Journal of Marketing Research*. 48 (5), 881–894. doi: 10.1509/jmkr.48.5.881.

Lemon, K., & Verhoef, P. (2016). Understanding Customer Experience throughout the Customer Journey. *Journal of Marketing*. 80(6), 69-96. doi: 10.1509/jm.15.0420.

Li, A., Jain, S., & Kannan, P. K. (2019). Optimal Design of Free Samples for Digital Products and Services. *Journal of Marketing Research*. 56(3), 419-438. doi: 10.1177/0022243718823169.

Li, C., Luo, X., Zhang, C., & Wang, X. (2017). Sunny, Rainy, and Cloudy with a Chance of Mobile Promotion Effectiveness. *Marketing Science*. 36(5), 645-812. doi: 10.1287/mksc.2017.1044.

Libai, B., Bolton, R., Bügel, M., De Ruyter, K., Götz, O., Risselada, H., & Stephen, A. (2010). Customer-to-Customer Interactions: Broadening the Scope of Word of Mouth Research. *Journal of Service Research*. 13(3), 267-282. doi: 10.1177/1094670510375600.

Liechty, J. C., Fong, D. K. H. & DeSarbo, W.S. (2005). Dynamic Models Incorporating Individual Heterogeneity: Utility Evolution in Conjoint Analysis. *Marketing Science*. 24 (2), 285-293. doi: 10.1287/mksc.1040.0088.

Liu, C., Sinkovics, R., Sinkovics, N., & Haghirian, P. (2012). Determinants of Consumer Perceptions toward Mobile Advertising - A Comparison between Japan and Austria. *Journal of Interactive Marketing*. 26(1), 21-32. doi: 10.1016/j.intmar.2011.07.002.

Liu, H., Lobschat, L., Verhoef, P., & Zhao, H. (2019a). App Adoption: The Effect on Purchasing of Customers Who Have Used a Mobile Website Previously. *Journal of Interactive Marketing*. 47, 16-34. doi: 10.1016/j.intmar.2018.12.001.

Liu, X., Lee, D., & Srinivasan, K. (2019b). Large-Scale Cross-Category Analysis of Consumer Review Content on Sales Conversion Leveraging Deep Learning. *Journal of Marketing Research*. 56(6), 918-943. doi: 10.1177/0022243719866690.

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing*. 70 (3), 74-89. doi: 10.1509/jmkg.70.3.074.

Liu, C. Z., Yoris, A. Au, & Hoon, S. C. (2014). Effects of Freemium Strategy in the Mobile App Market: An Empirical Study of Google Play. *Journal of Management Information Systems*. 31(3), 326–354.

Liu-Thompkins, Y. (2019). A Decade of Online Advertising Research: What We Learned and What We Need to Know. *Journal of Advertising*. 48(1), 1-13. doi: 10.1080/00913367.2018.1556138.

Liu-Thompkins, Y., & Malthouse, E. (2017). A Primer on Using Behavioral Data for Testing Theories in Advertising Research. *Journal of Advertising*. 46(1), 213-225. doi: 10.1080/00913367.2016.1252289.

Lovett, M. J., & Peres, R. (2018). Mobile Diaries – Benchmark Against Metered Measurements: An Empirical Investigation. *International Journal of Research in Marketing*. 35(2), 224-241. doi: 10.1016/j.ijresmar.2018.01.002.

Luca, M. (2016). Reviews, Reputation, and Revenue: The Case of Yelp.com. *Harvard Business School NOM Unit Working Paper*. No. 12-016 doi: 10.2139/ssrn.1928601.

Malthouse, E., Haenlein, M., Skiera, B., Wege, E., & Zhang, M. (2013). Managing Customer Relationships in the Social Media Era: Introducing the Social CRM House. *Journal of Interactive Marketing*. 27(4), 270-280. doi: 10.1016/j.intmar.2013.09.008.

Malthouse, E., & Li, H. (2017). Opportunities for and Pitfalls of Using Big Data in Advertising Research. *Journal of Advertising*. 46(2), 227-235. doi: 10.1080/00913367.2017.1299653.

Martin, K., & Hill, R. (2015). Saving and Well-Being at the Base of the Pyramid. *Journal of Service Research*. 18(3), 405-421. doi: 10.1177/1094670514563496.

Martin, K., & Murphy, P. (2016). The Role of Data Privacy in Marketing. *Journal of the Academy of Marketing Science*. 45, 135-155. doi: 10.1007/s11747-016-0495-4.

Mayzlin, D., Dover, Y. & Chevalier, J. (2014). Promotional Reviews: An Empirical Investigation of Online Review Manipulation. *The American Economic Review*. 104 (8), 2421-2455. doi: 10.1257/aer.104.8.2421.

Mclean, G., Osei-Frimpong, K., Khalid, A. & Marriott, H. (2020). Examining Consumer Attitudes towards Retailers' M-commerce Mobile Applications – An Initial Adoption vs. Continuous Use Perspective. *Journal of Business Research*. 106, 139-157. doi: 10.1016/j.jbusres.2019.08.032.

Meeker, Mary. (2019). Internet Trends Report.

Melumad, S., Inman, J., & Pham, M. (2019). Selectively Emotional: How Smartphone Use Changes User-Generated Content. *Journal of Marketing Research*. 56(2), 259-275. doi: 10.1177/0022243718815429.

Meyer, R. (2018). Reflections on “Transformative Marketing: The Next 20 Years”. *Journal of Marketing*. 82(4), 13-14. doi: 10.1509/jm.82.42.

Mills, P., & Zamudio, C. (2018). Scanning For Discounts: Examining The Redemption Of Competing Mobile Coupons. *Journal of the Academy of Marketing Science*. 46(5), 964-982. doi: 10.1007/s11747-018-0592-7.

Moore, R., & Moore, M. (2004). Customer Inquiries and Complaints: The Impact of Firm Response Time to Email Communications. *Marketing Management Journal*. 14 (2), 1-12.

Muller, E. (2019). Delimiting Disruption: Why Uber Is Disruptive, But Airbnb Is Not. *International Journal of Research in Marketing*. 37(1), 43-55. doi: 10.1016/j.ijresmar.2019.10.004.

Narang, U., & Shankar, V. (2019). Mobile App Introduction and Online and Offline Purchases and Product Returns. *Marketing Science*. 38(5), 733-912. doi: 10.1287/mksc.2019.1169.

Neslin, S., Jerath, K., Bodapati, A., Bradlow, E., Deighton, J., Gensler, S., Lee, L., Montaguti, E., Telang, R., Venkatesan, R., Verhoef, P., & Zhang, Z. (2014). The Interrelationships Between Brand and Channel Choice. *Marketing Letters*. 25, 319-330. doi: 10.1007/s11002-014-9305-2.

Netzer, O., Feldman, R., Goldenberg, J. & Fresko, M. (2012). Mine Your Own Business: Market-Structure Surveillance Through Text Mining. *Marketing Science*. 31 (3), 521-543. doi: 10.1287/mksc.1120.0713.

Noort, G., & Reijmersdal, E. (2019). Branded Apps: Explaining Effects of Brands' Mobile Phone Applications on Brand Responses. *Journal of Interactive Marketing*. 45, 16-26. doi: 10.1016/j.intmar.2018.05.003.

Nysveen, H., Pedersen, P. E. & Thorbjørnsen, H. (2005). Intentions to Use Mobile Services: Antecedents and Cross-Service Comparisons. *Journal of the Academy of Marketing Science*. 33 (3), 330-346. doi: 10.1177/0092070305276149.

Okazaki, S., & Mendez, F. (2013). Perceived Ubiquity in Mobile Services. *Journal of Interactive Marketing.* 27(2), 98-111. doi: 10.1016/j.intmar.2012.10.001.

Okazaki, S., Li, H., & Hirose, M. (2009). Consumer Privacy Concerns and Preference for Degree of Regulatory Control. *Journal of Advertising*. 38(4), 63-77. doi: 10.2753/JOA0091-3367380405.

Oliver, R. L. (1980). A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*. 17(4), 460-469. doi: 10.2307/3150499.

Osinga, E., Zevenbergen, M., & Zuijlen, M. (2019). Do Mobile Banner Ads Increase Sales? Yes, in the Offline Channel. *International Journal of Research in Marketing*. 36(3), 439-453. doi: 10.1016/j.ijresmar.2019.02.001.

Ostrom, A., Parasuraman, A. P., Bowen, D., Patrício, L., & Voss, C. (2015). Service Research Priorities in a Rapidly Changing Context. *Journal of Service Research*. 18(2), 127-159. doi: 10.1177/1094670515576315.

Packard, G., & Berger, J. (2017). How Language Shapes Word of Mouth's Impact. *Journal of Marketing Research*. 54 (4), 572–588. doi: 10.1509/jmr.15.0248.

Pagani, M., & Malacarne, G. (2017). Experiential Engagement and Active vs. Passive Behavior in Mobile Location-based Social Networks: The Moderating Role of Privacy. *Journal of Interactive Marketing*. 37, 133-148. doi: 10.1016/j.intmar.2016.10.001.

Pagano, D., & Maalej, W. (2013). User Feedback in the Appstore: An Empirical Study. *21st IEEE International Requirements Engineering Conference (RE), Rio de Janeiro*. 125-134.

Park, C. H., Park, Y.H., & Schweidel, D. (2018). The Effects of Mobile Promotions on Customer Purchase Dynamics. *International Journal of Research in Marketing*. 35(3), 453-470. doi: 10.1016/j.ijresmar.2018.05.001.

Payne, J., Bettman, J., & Johnson, E. (1993). The adaptive decision maker. *New York: Cambridge University Press.*

Peltier, J., Milne, G., & Phelps, J. (2009). Information Privacy Research: Framework for Integrating Multiple Publics, Information Channels, and Responses. *Journal of Interactive Marketing*. 23(2), 191-205. doi: 10.1016/j.intmar.2009.02.007.

Pescher, C., Reichhart, P., & Spann, M. (2014). Consumer Decision-making Processes in Mobile Viral Marketing Campaigns. *Journal of Interactive Marketing*. 28(1), 43-54. doi: 10.1016/j.intmar.2013.08.001.

Petit, O., Velasco, C., & Spence, C. (2019). Digital Sensory Marketing: Integrating New Technologies Into Multisensory Online Experience. *Journal of Interactive Marketing*. 45, 42-61. doi: 10.1016/j.intmar.2018.07.004.

Proserpio, D., & Zervas, G. (2017). Online Reputation Management: Estimating the Impact of Management Responses on Consumer Reviews. *Marketing Science*. 36 (5), 645-665. doi: 10.1287/mksc.2017.1043i.

Ramaswamy, V., & Ozcan, K. (2018). Offerings as Digitalized Interactive Platforms: A Conceptual Framework and Implications. *Journal of Marketing*. 82(4), 19-31. doi: 10.1509/jm.15.0365.

Ransbotham, S., Lurie, N., & Liu, H. (2019). Creation and Consumption of Mobile Word of Mouth: How Are Mobile Reviews Different?. *Marketing Science*. 38(5), 733-912. doi: 10.1287/mksc.2018.1115.

Rapp, A., Baker, T., Bachrach, D., Ogilvie, J., & Beitelspacher, L. (2015). Perceived Customer Showrooming Behavior and the Effect on Retail Salesperson Self-Efficacy and Performance. *Journal of Retailing*. 91(2), 358-369. doi: 10.1016/j.jretai.2014.12.007.

Ratchford, B. (2015). Some Directions for Research in Interactive Marketing. *Journal of Interactive Marketing.* 29, 5-7. doi: 10.1016/j.intmar.2015.01.001.

Reinartz, W., Dellaert, B., Krafft, M., Kumar, V. & Varadarajan, R. (2011). Retailing Innovations in a Globalizing Retail Market Environment. *Journal of Retailing*. 87, 53-66. doi: 10.1016/j.jretai.2011.04.009.

Reinartz, W., Wiegand, N., Imschloss, M. (2019). The Impact of Digital Transformation on the Retailing Value Chain. *International Journal of Research in Marketing*. 36(3), 350-366. doi: 10.1016/j.ijresmar.2018.12.002.

Reynolds-McIlnay, R., & Morrin, M. (2019). Increasing Shopper Trust in Retailer Technological Interfaces via Auditory Confirmation. *Journal of Retailing*. 95(4), 128-142. doi: 10.1016/j.jretai.2019.10.006.

Rietveld, J. (2017). Creating and Capturing Value from Freemium Business Models: A Demand-Side Perspective. *Strategic Entrepreneurship Journal*, 12(2), 171-193.

Rogers, E. (2003). Diffusion of Innovations (5th ed.). *Simon and Schuster*.

Rust, R. T., & Oliver, R. L. (2000). Should We Delight the Customer?. *Journal of the Academy of Marketing Science*. 28 (1), 86-94. doi: 10.1177/0092070300281008.

Rutz, O., Aravindakshan, A., & Rubel, Ol. (2019). Measuring and Forecasting Mobile Game App Engagement. *International Journal of Research in Marketing*. 36(2), 185-199. doi: 10.1016/j.ijresmar.2019.01.002.

Sahni, N., & Nair, H. (2019). Sponsorship Disclosure and Consumer Deception: Experimental Evidence from Native Advertising in Mobile Search. *Marketing Science*. 39(1). doi: 10.1287/mksc.2018.1125.

Schulze, C., Schöler, L., & Skiera, Bernd. (2014). Not All Fun and Games: Viral Marketing for Utilitarian Products. *Journal of Marketing*. 78(1), 1-19. doi: 10.1509/jm.11.0528.

Sciandra, M., Inman, J., & Stephen, A. (2019). Smart Phones, Bad Calls? The Influence of Consumer Mobile Phone Use, Distraction, and Phone Dependence on Adherence to Shopping Plans. *Journal of the Academy of Marketing Science*. 47, 574-594. doi: 10.1007/s11747-019-00647-9.

Segijn, C, & Eisend, M. (2019). A Meta-Analysis into Multiscreening and Advertising Effectiveness: Direct Effects, Moderators, and Underlying Mechanisms. *Journal of Advertising.* 48(3), 313-332. doi: 10.1080/00913367.2019.1604009.

Sensortower. (2019). The Top 1% of App Publishers Generate 80% of All New Installs. <https://sensortower.com/blog/top-one-percent-downloads#:~:targetText=Top%201%20Percent%20by%20Downloads,total%20of%2029.6%20billion%20downloads.> Retrieved 9 July 2020.

Shah, A., Eisenkraft, N., Bettman, J., & Chartrand, Tanya. (2016). ‘Paper Or Plastic?’: How We Pay Influences Post-Transaction Connection. *Journal of Consumer Research*. 42(5), 688-708. doi: 10.1093/jcr/ucv056.

Shankar, V. (2018). How Artificial Intelligence (AI) is Reshaping Retailing. *Journal of Retailing*. 94(4), 6-11. doi: 10.1016/S0022-4359(18)30076-9.

Shankar, V., & Balasubramanian, S. (2009). Mobile Marketing: A Synthesis and Prognosis. *Journal of Interactive Marketing*. 23(2), 118-129. doi: 10.1016/j.intmar.2009.02.002.

Shankar, V., & Batra, R. (2009). The Growing Influence of Online Marketing Communications. *Journal of Interactive Marketing*. 23(4), 285-287. doi: 10.1016/j.intmar.2009.07.006.

Shankar, V., & Yadav, M. (2010). Emerging Perspectives on Marketing in a Multichannel and Multimedia Retailing Environment. *Journal of Interactive Marketing*. 24(2), 55-57. doi: 10.1016/j.intmar.2010.02.003.

Shankar, V., Inman, J., Mantrala, M., Kelley, E., & Rizley, R. (2011). Innovations in Shopper Marketing: Current Insights and Future Research Issues. *Journal of Retailing*. 87(1), 29-42. doi: 10.1016/j.jretai.2011.04.007.

Shankar, V., Kleijnen, M., Ramanathan, S., Rizley, R., Holland, S., & Morrissey, S. (2016). Mobile Shopper Marketing: Key Issues, Current Insights, and Future Research Avenues. *Journal of Interactive Marketing*. 34, 37-48. doi: 10.1016/j.intmar.2016.03.002.

Shankar, V., Venkatesh, A., Hofacker, C, & Naik, P. (2010). Mobile Marketing in the Retailing Environment: Current Insights and Future Research Avenues. *Journal of Interactive Marketing*. 24(2), 111-120. doi: 10.1016/j.intmar.2010.02.006.

Shavitt, S., & Barnes, A. (2019). Culture and the Consumer Journey. *Journal of Retailing*. 96(1), 40-54. doi: 10.1016/j.jretai.2019.11.009.

Shen, G. (2015). Users' Adoption of Mobile Applications: Product Type and Message Framing's Moderating Effect. *Journal of Business Research*. 68 (11), 2317-2321. doi: 10.1016/j.jbusres.2015.06.018.

Shen, H., Zhang, M., & Krishna, A. (2016). Computer Interfaces and the “Direct-Touch” Effect: Can iPads Increase the Choice of Hedonic Food?. *Journal of Marketing Research*. 53(5), 745-758. doi: 10.1509/jmr.14.0563.

Shi, S., & Kalyanam, K. (2018). Touchable Apps: Exploring the Usage of Touch Features and Their Impact on Engagement. *Journal of Interactive Marketing*. 44, 43-59. doi: 10.1016/j.intmar.2018.06.001.

Shi, Z., Zhang, K., & Srinivasan, K. (2019). Freemium as an Optimal Strategy for Market Dominant Firms. *Marketing Science*. 38(1). doi: 10.1287/mksc.2018.1109.

Simon, H. (1979). Dynamics of Price Elasticity and Brand Life Cycles: An Empirical Study. *Journal of Marketing Research*. 16 (4), 439–452. doi: 10.1177/002224377901600401.

Smart Insights. (2019). Top 7 Biggest Flops in the Mobile App Industry. <https://www.smartinsights.com/mobile-marketing/top-7-biggest-flops-mobile-app-industry/> Retrieved 9 July 2020.

Song, J. H., Kim, H., Kim, S., Lee, S., & Lee, J. H. (2016). Effects of Personalized E-Mail Messages on Privacy Risk: Moderating Roles of Control and Intimacy. *Marketing Letters*. 27, 89-101. doi: 10.1007/s11002-014-9315-0.

Sridhar, S., & Fang, E. (2019). New Vistas For Marketing Strategy: Digital, Data-Rich, And Developing Market (D3) Environments. 47, 977–985. *Journal of the Academy of Marketing Science*. doi: 10.1007/s11747-019-00698-y.

Steinhoff, L., Arli, D., Weaven, S., & Kozlenkova, I. (2019). Online Relationship Marketing. *Journal of the Academy of Marketing Science*. 47, 69-393. doi: 10.1007/s11747-018-0621-6.

Streitfeld., D. (2011). In a Race to Out-rave, 5-Star Web Reviews Go for $5. <http://www.nytimes.com/2011/08/20/ technology/finding-fake-reviews-online.html> Retrieved 8 December 2019.

Sultan, F., Rohm, A., & Gao, T. (2009). Factors Influencing Consumer Acceptance of Mobile Marketing: A Two-Country Study of Youth Markets. *Journal of Interactive Marketing*. 23(4), 308-320. doi: 10.1016/j.intmar.2009.07.003.

Tagashira, T., & Minami, C. (2019). The Effect of Cross-Channel Integration on Cost Efficiency. *Journal of Interactive Marketing*. 47, 68-83. doi: 10.1016/j.intmar.2019.03.002.

Terlutter, R., & Capella, M. (2013). The Gamification of Advertising: Analysis and Research Directions of In-Game Advertising, Advergames, and Advertising in Social Network Games. *Journal of Advertising*. 42, 95-112. doi: 10.1080/00913367.2013.774610.

Timoshenko, A., & Hauser, J. R. (2019). Identifying Customer Needs from User-Generated Content. *Marketing Science*. 38 (1), 1–20. doi: 10.1287/mksc.2018.1123.

Tirunillai, S., & Tellis, G. J. (2014). Mining Marketing Meaning from Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation. *Journal of Marketing Research*. 51 (4), 463–479. doi: 10.1509/jmr.12.0106.

Tong, S., Luo, X., & Xu, B. (2019). Personalized Mobile Marketing Strategies. *Journal of the Academy of Marketing Science*. 48, 64-78. doi: 10.1007/s11747-019-00693-3.

Twitter. Form 10-Q 2019 Second Quarter. < https://investor.twitterinc.com/financial-information/quarterly-results/default.aspx>. Retrieved 6 December 2019.

Van Bruggen, G., Antia, K. Jap, S., Reinartz, W., & Pallas, F. (2010). Managing Marketing Channel Multiplicity. *Journal of Service Research*. 13(3), 331-340. doi: 10.1177/1094670510375601.

Van den Ende, J.C.M., Jaspers, F.P.H. & Rijsdijk, S.A. (2013). Should System Firms Develop Complementary Products? A Dynamic Model and an Empirical Test. *Journal of Product Innovation Management*. 30, 1178–1198. doi: 10.1111/jpim.12053.

Van Doorn, J., Lemon, K. N., Mittal, V., Naß, S., Pick, D., Pirner, P., & Verhoef, P. (2010). Consumer Engagement Behavior: Theoretical Foundations and Research Directions. *Journal of Service Research*. 13(3), 253–266. doi: 10.1177/1094670510375599.

Van Heerde, H., Dinner, I., & Neslin, S. (2019). Engaging the Unengaged Customer: The Value of a Retailer Mobile App. *International Journal of Research in Marketing*. doi: 10.1016/j.ijresmar.2019.03.003.

Van Noort, G. & Van Reijmersdal, E.A. (2019). Branded Apps: Explaining Effects of Brands' Mobile Phone Applications on Brand Responses. *Journal of Interactive Marketing*. 45, 16-26. doi: 10.1016/j.intmar.2018.05.003.

Varadarajan, R., Srinivasan, R., Vadakkepatt, G., Yadav, M., Pavlou, P., Krishnamurthy, S., & Krause, T. (2010). Interactive Technologies and Retailing Strategy: A Review, Conceptual Framework and Future Research Directions. *Journal of Interactive Marketing*. 24(2), 96-110. doi: 10.1016/j.intmar.2010.02.004.

Venkatesan, R. (2017). Executing on a Customer Engagement Strategy. *Journal of the Academy of Marketing Science*. 45, 289-293. doi: 10.1007/s11747-016-0513-6.

Verhoef, P., & Bijmolt, T. (2019). Marketing Perspectives on Digital Business Models: A Framework and Overview of the Special Issue. *International Journal of Research in Marketing*. 36(3), 341-349. doi: 10.1016/j.ijresmar.2019.08.001.

Verhoef, P., & Kannan, P. K., & Inman, J. (2015). From Multi-Channel Retailing to Omni-Channel Retailing. *Journal of Retailing*. 91(2), 174-181. doi: 10.1016/j.jretai.2015.02.005.

Verhoef, P., Stephen, A., Kannan, P. K., Luo, X., Abhishek, V., Andrews, M., Bart, Y., Datta, H., Fong, N., Hoffman, D., Hu, M., Novak, T., Rand, W., & Zhang, Y. (2017). Consumer Connectivity in a Complex, Technology-enabled, and Mobile-oriented World with Smart Products. *Journal of Interactive Marketing*. 40, 1-8. doi: 10.1016/j.intmar.2017.06.001.

Vermeulen, I. E., & Seegers, D. (2009). Tried and Tested: The Impact of Online Hotel Reviews on Consumer Consideration. *Tourism Management*. 30, 123–127. doi: 10.1016/j.tourman.2008.04.008.

Villarroel, F. O., Grewal, D., Ludwig, S., De Ruyter, K., Mahr, D. & Wetzels, M. (2019). Cutting through Content Clutter: How Speech and Image Acts Drive Consumer Sharing of Social Media Brand Messages. *Journal of Consumer Research*. 45 (5), 988–1012. doi: 10.1093/jcr/ucy032.

Wakefield, L., & Wakefield, K. (2018). An Examination of Construal Effects on Price Perceptions in the Advance Selling of Experience Services. *Journal of Service Research*. 21(2), 235-248. doi: 10.1177/1094670517738367.

Wang, F., Zuo, L., Yang, Z., & Wu, Y. (2019c). Mobile Searching Versus Online Searching: Differential Effects of Paid Search Keywords on Direct and Indirect Sales. *Journal of the Academy of Marketing Science*. 47, 1151-1165. doi: 10.1007/s11747-019-00649-7.

Wang, R., Malthouse, E., & Krishnamurthi, L. (2015). On the Go: How Mobile Shopping Affects Customer Purchase Behavior. *Journal of Retailing*. 91(2), 217-234. doi: 10.1016/j.jretai.2015.01.002.

Wang, W., Li, G., Fung, R., & Cheng, T.C.E. (2019a). Mobile Advertising and Traffic Conversion: The Effects of Front Traffic and Spatial Competition. *Journal of Interactive Marketing*. 47, 84-101. doi: 10.1016/j.intmar.2019.02.001.

Wang, Y., & Chaudhry, A. (2018). When and How Managers' Responses to Online Reviews Affect Subsequent Reviews. *Journal of Marketing Research*. 55 (2), 163–177. doi: 10.1509/jmr.15.0511.

Wang, Y., Wu, C., & Zhu, T. (2019b). Mobile Hailing Technology and Taxi Driving Behaviors. *Marketing Science*. 38(5), 734-755. doi: 10.1287/mksc.2019.1187.

Watson, IV. G., Worm, S., Palmatier, R., & Ganesan, S. (2015). The Evolution of Marketing Channels: Trends and Research Directions. *Journal of Retailing*. 91(4), 546-568. doi: 10.1016/j.jretai.2015.04.002.

Wedel, M., & Kannan, P. K. (2016). Marketing Analytics for Data-Rich Environments. *Journal of Marketing*. 80(6), 97-121. doi: 10.1509/jm.15.0413.

Winer, R. (2009). New Communications Approaches in Marketing: Issues and Research Directions. *Journal of Interactive Marketing*. 23(2), 108-117. doi: 10.1016/j.intmar.2009.02.004.

Wooder, S., & Baker, S. (2012). Extracting Key Lessons in Service Innovation. *Journal of Product Innovation Management*. 29(1), 13-20. doi: 10.1111/j.1540-5885.2011.00875.x.

Wu, F., & Huberman, B. A. (2008). How Public Opinion Forms, Internet and Network Economics. *Internet and Network Economics*. 334–341.

Xu, J., Forman, C., Kim, J., & Ittersum, K. (2014). News Media Channels: Complements or Substitutes? Evidence from Mobile Phone Usage. *Journal of Marketing*. 78(4), 97-112. doi: 10.1509/jm.13.0198.

Xu, X., Chen, R., & Jiang, L. (2020). The Influence of Payment Mechanisms on Pricing: When Mental Imagery Stimulates Desire for Money. *Journal of Retailing*. 96(2), 178-188. doi: 10.1016/j.jretai.2019.08.002.

Yadav, M. S., & Pavlou, P. (2014). Marketing in Computer-Mediated Environments: Research Synthesis and New Directions. *Journal of Marketing*. 78(1), 20-40. doi: 10.1509/jm.12.0020.

Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The Influence of User-Generated Content on Traveler Behavior: An Empirical Investigation on the Effects of e-word-of-mouth to Hotel Online Bookings. *Computers in Human Behavior*. 27 (2), 634–639. doi: 10.1016/j.chb.2010.04.014.

Zhang, D. & Adipat, B. (2005). Challenges, Methodologies, and Issues in the Usability Testing of Mobile Applications. *International Journal of Human-Computer Interaction*. 18 (3), 293-308. doi: 10.1207/s15327590ijhc1803_3.

Zhang, S., Pauwels, K., & Peng, C. (2019). The Impact of Adding Online-to-Offline Service Platform Channels on Firms' Offline and Total Sales and Profits. *Journal of Interactive Marketing*. 47, 115-128. doi: 10.1016/j.intmar.2019.03.001.

Zhu, F., & Zhang, X. M. (2010). Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing*. 74 (2), 133–148. doi: 10.1509/jm.74.2.133.

Zubcsek, P., Katona, Z., & Sarvary, M. (2017). Predicting Mobile Advertising Response Using Consumer Co-Location Networks. *Journal of Marketing*. 81(4), 109-126. doi: 10.1509/jm.15.0215.

Summary (In English)

The penetration of mobile-technology into the daily lives of people has skyrocketed since the introduction of the iPhone in 2007. Now, after over a decade, mobile phones are the all-time, inseparable companions of the consumers. The spread of social media coupled with the advancements in technological infrastructures fueled the creation of an uninterrupted online consumer. Consequently, the integration of the mobile into the daily routines of the consumers has shifted the relationship with companies in various ways. The consumer now has access to detailed information on products, has more control over the pricing, timing and location of their purchases. The realization of this empowerment has resulted in changes in how consumers act. Firms, on the other side first need to understand these behavioral changes and then, respond accordingly to the consumers via renovated marketing strategies. This dissertation reflects both sides of the mobile eco-system by combining novel data sets reflecting the actions of mobile businesses and the reactions of mobile users.

In Chapter 2, I offer an extended overview and propose an integrated framework of mobile marketing research in the last decade. In a market where growth rate is exponential, Chapter 2 paints the recent landscape of mobile marketing research and offers a renewed framework for it. Within this fresh framework, I first discuss the transformation of the consumers and the consequent mobile-first transformation of existing businesses and the emergence of new ones. I, then focus on the two-way relationship (business to consumer and consumer to business) between the two. Chapter 2 contributes to our understanding of the evolution of the mobile marketing field and elaborates on the various sub-streams of research it creates, among which, mobile applications (apps) stand out. Chapter 3 and Chapter 4 of this dissertation focus on the growing app market.

Chapter 3 investigates factors associated with app downloads during an app's first year of existence using a novel data set spanning 979 newly released applications, acquired from a leading mobile analytics company and enriched with publicly available data. Results from time-varying-parameter models estimated separately for free and paid apps reveal that gaining traction with users shortly after release seems critical; and that app platform owners can be very influential in these early days. However, as apps mature,

affecting the number of downloads becomes increasingly more difficult. These findings add new insights to the growing literature on mobile applications and provide practical implications for their developers.

Chapter 4 examines the bi-directional relationship between businesses and users facilitated through user reviews and updates – as a form of continuous product development. Based on an automated text analysis of about 1M reviews and a content analysis of about 3K mobile application updates, observed over 460 apps' first year on the market, I seek to shed light on the impact of incorporating feedback extracted from user reviews in the development of successive generations of mobile apps on user ratings. The results reveal that the rewards associated with responding to user requests and the penalties due to ignoring these requests can be substantial and depend on the topic of the feedback and the timing of the response. The implications of Chapter 4 may extend to the broader New Product Development literature especially with respect to the fundamental question of whether and when to pro-act on, or re-act to the voice of the customer.

In sum, this dissertation advances our understanding of the mobile marketing field, and more specifically, the mobile applications market within. Since its emergence, mobile applications market has been attracting the attention of all kinds of businesses (ranging from individual developers to well-known brands) due to the lucrative opportunities apps offer and the market's low barriers to entry. Yet, in this crowded space, only a small portion of apps can survive. Utilizing novel data sets, I first discuss the customer's mobile app adoption journey. Once, the step of adoption has been achieved, I show that successive developments of the mobile application's value proposition and its efficiency can assist survival in this highly competitive market. Drawing from multiple research streams, this dissertation contributes to various literatures such as mobile applications, user generated content, and new product development. Implications, within the mobile applications domain, not only provide potential app developers with valuable insights, but also offer existing developers remedies to resuscitate their applications along the way, following their release on the market. In the broader sense, the findings from both studies relate to creating successful products in digital markets and continuous product development.

Samenvatting (in het Nederlands)

Mobiele technologie is sinds de introductie van de iPhone in 2007 duizelingwekkend snel deel gaan uitmaken van ons dagelijks leven. Nu, na meer dan tien jaar, zijn mobiele telefoons de alomtegenwoordige, onafscheidelijke metgezel van de consument. De groei van sociale media in combinatie met de ontwikkelingen op het gebied van technologische infrastructuur hebben er nog meer voor gezorgd dat de consument ononderbroken online kan zijn. Alles bij elkaar heeft de integratie van de mobiele telefoon in de dagelijkse routines van de consumenten op verschillende manieren een verandering teweeggebracht in de relatie met bedrijven. De consument heeft nu toegang tot uitgebreide informatie over producten, heeft meer controle over de prijs of zelfs over wanneer en waar hij iets koopt. Deze verworvenheden hebben geresulteerd in veranderingen in de manier waarop consumenten handelen. Bedrijven moeten deze veranderingen in gedrag in eerste instantie begrijpen en van daaruit beantwoorden aan de behoeften van de consument via vernieuwde marketingstrategieën. Dit proefschrift geeft beide kanten van het mobiele ecosysteem weer door nieuwe datasets die de handelingen van mobiele bedrijven weerspiegelen, te combineren met de reacties van mobiele gebruikers.

In Hoofdstuk 2 geef ik een uitgebreid overzicht en stel ik een geïntegreerd kader voor mobielemarketingonderzoek van de laatste tien jaar voor. Deze markt kent een exponentiële groei en daarom geef ik in Hoofdstuk 2 een kijk op het huidige mobielemarketingonderzoek en stel ik hiervoor een vernieuwd kader voor. Binnen dit nieuwe kader bespreek ik eerst de transformatie van de consumenten en de daaropvolgende 'mobile-first'-transformatie van bestaande bedrijven en de opkomst van nieuwe bedrijven. Vervolgens richt ik me op de tweezijdige relatie tussen consument en bedrijf. Hoofdstuk 2 helpt ons de evolutie van mobiele marketing beter te begrijpen en wijdt uit over de verschillende deelstromen van onderzoek die hierdoor ontstaan, waaronder voornamelijk die van mobiele applicaties (apps). Hoofdstuk 3 en Hoofdstuk 4 van dit proefschrift zijn gericht op de groeiende markt van apps.

Hoofdstuk 3 onderzoekt de factoren die te maken hebben met downloads van apps gedurende het eerste levensjaar van een app aan de hand van een nieuwe dataset met 979 pas uitgebrachte applicaties die werden aangekocht bij een toonaangevend mobileanalyticsbedrijf en verrijkt met openbaar beschikbare data. De resultaten van modellen met tijdsvariërende parameters die afzonderlijk voor gratis en betaalde apps werden geschat, tonen aan dat de aanlokkelijkheid bij gebruikers kort na de lancering van cruciaal belang lijkt, en dat platformeigenaren van apps zeer invloedrijk kunnen zijn in deze eerste gebruiksdagen. Maar naarmate apps ouder worden, wordt het steeds moeilijker om het aantal downloads te beïnvloeden. Deze bevindingen voegen nieuwe inzichten toe aan de groeiende literatuur over mobiele applicaties en bieden praktische implicaties voor hun ontwikkelaars.

In Hoofdstuk 4 wordt de bidirectionele relatie onderzocht tussen bedrijven en gebruikers aan de hand van gebruikersbeoordelingen en updates – als een vorm van ononderbroken productontwikkeling. Op basis van een geautomatiseerde tekstanalyse van ongeveer 1 miljoen beoordelingen en een inhoudelijke analyse van ongeveer 3000 updates van mobiele applicaties die werden geobserveerd bij 460 apps in het eerste jaar dat ze op de markt waren, probeer ik meer inzicht te verschaffen in de impact van het opnemen van feedback uit gebruikersbeoordelingen in de ontwikkeling van volgende generaties mobiele apps op de gebruikerswaarderingen. De resultaten tonen aan dat de voordelen die verband houden met het beantwoorden van gebruikersverzoeken en de negatieve gevolgen van het negeren van deze verzoeken aanzienlijk kunnen zijn en afhankelijk zijn van het onderwerp van de feedback en het tijdstip van het antwoord. De implicaties uit Hoofdstuk 4 kunnen verder gaan dan de uitgebreidere literatuur over de ontwikkeling van nieuwe producten, vooral met betrekking tot de fundamentele vraag of en wanneer pro- of reactief in te spelen op wat de consument wil.

Kortom, dit proefschrift geeft ons meer inzicht in mobiele marketing, maar vooral in de markt van mobiele applicaties binnen dit domein. De markt van mobiele applicaties trekt sinds dag 1 de aandacht van verschillende soorten bedrijven (van individuele ontwikkelaars tot bekende merken) vanwege de lucratieve mogelijkheden die apps bieden en de laagdrempeligheid waarmee de markt kan worden betreden. Maar in deze overvolle markt kan slechts een klein deel van de apps overleven. Aan de hand van nieuwe datasets bespreek ik eerst hoe de consument zich aanpast aan het gebruik van mobiele apps. Zodra de aanpassing is gebeurd, toon ik aan dat opeenvolgende ontwikkelingen van de waardepropositie van de mobiele applicatie en de efficiëntie ervan kunnen bijdragen aan het overleven in deze uiterst competitieve markt. Aan de hand van meerdere onderzoeksstromen draagt dit proefschrift bij aan verschillende literatuur, zoals die over mobiele applicaties, door gebruikers gegenereerde inhoud en nieuwe productontwikkeling. Implicaties binnen het domein van mobiele applicaties geven mogelijke app-ontwikkelaars niet alleen waardevolle inzichten, maar bieden bestaande ontwikkelaars ook remedies om hun applicaties weer nieuw leven in te blazen tijdens hun levensloop wanneer ze eenmaal op de markt zijn uitgebracht. In bredere zin geven de bevindingen uit beide onderzoeken een kijk op hoe succesvolle producten in digitale markten kunnen worden gemaakt, en op ononderbroken productontwikkeling.

Summary (in Turkish)

Mobil teknolojilerin insanların günlük hayatına nüfuz etmesi, 2007 yılında iPhone'un piyasaya sürülmesi ile büyük bir hız kazandı. Şimdi, on yıldan fazla bir süre sonra, mobil telefonlar günümüz tüketicisinin tüm zamanlarında, ayrılmaz bir yoldaşı haline geldiler. Teknolojik altyapılardaki gelişmelerin, sosyal medyanın yaygınlaşması ile bir araya gelmesi, kesintisiz bir çevrimiçi tüketicinin ortaya çıkışını daha da hızlandırdı. Tüm bunlar birlikte ele alındığında, mobilin tüketicilerin günlük rutinlerine entegrasyonu, şirketlerle olan ilişkileri çeşitli şekillerde değiştirdi. Günümüz tüketicisi, artık ürünler hakkında detaylı bilgilere kolay erişim sağlayabiliyor. Bunun yanında, alışverişlerinin zamanı, yeri ve fiyatlandırması üzerinde, eskiye kıyasla, çok daha fazla kontrole sahip. Bu güçlenmenin farkına varmak, tüketici davranışlarında da bir takım değişiklikleri beraberinde getirdi. Diğer taraftan, firmaların bu davranışsal değişiklikleri anlamlandırmaları ve ardından, yenilenmiş pazarlama stratejileri aracılığıyla tüketicilere uygun şekilde yanıt vermeleri gerekmektedir. Bu tez, mobil işletmelerin aksiyonlarını ve mobil kullanıcıların reaksiyonlarını yansıtan özgün veri setlerini birleştirerek, mobil ekosistemin her iki tarafını da ele almaktadır.

İkinci bölüm, son on yıldaki mobil pazarlama araştırmalarına kapsamlı bir genel bakış sunmakta ve entegre bir mobil pazarlama çerçevesi önermektedir. Büyüme oranının üstel olduğu bir pazarda, ikinci bölüm, mobil pazarlama araştırmalarının son dönemdeki manzarasını çizmekte ve bunun için yenilenmiş bir çerçeve sunmaktadır. Bu yeni çerçeve içerisinde, öncelikle tüketicilerin dönüşümü ve bunun sonucunda, mevcut işletmelerin mobil öncelikli dönüşümü ve yeni mobil işletmelerin ortaya çıkışı tartışılmaktadır. Daha sonra, iki taraf arasındaki iki yönlü ilişkiye (işletmeden tüketiciye ve tüketiciden işletmeye) odaklanılmıştır. İkinci bölüm, mobil pazarlama alanının gelişimine ilişkin anlayışımıza katkıda bulunmakta ve oluşturduğu çeşitli alt araştırma dallarını ayrıntılarıyla açıklamaktadır. Bu alt dallar arasında, mobil uygulamalar özellikle öne çıkmaktadır. Bu tezin üçüncü ve dördüncü bölümleri, bu öne çıkan ve büyümekte olan mobil uygulamalar pazarına odaklanmıştır.

Üçüncü bölüm, önde gelen bir mobil analiz şirketinden satın alınan ve herkese açık verilerle zenginleştirilmiş, pazara yeni girmiş olan 979 uygulamayı kapsayan yeni bir veri kümesini kullanarak, bir uygulamanın var oluşunun ilk yılı boyunca, mobil uygulama

indirme rakamlarına etki eden faktörleri araştırmaktadır. Ücretsiz ve ücretli uygulamalar için ayrı ayrı tahmin edilen, zamanla değişen parametreli modellerden elde edilen sonuçlar, piyasaya sürüldükten kısa bir süre sonra kullanıcıların ilgisini çekmenin kritik olduğunu ve uygulama platformu sahiplerinin bu ilk günlerde çok etkili olabileceğini ortaya koymuştur. Bununla birlikte, uygulamalar zaman içerisinde olgunlaştıkça, indirme rakamlarını etkilemenin giderek daha zor hale geldiği gözlenmiştir. Bu bulgular, büyümekte olan mobil uygulamalar literatürüne yeni içgörüler eklemekte ve uygulama geliştiricileri için pratik çıkarımlar sağlamaktadır.

Dördüncü bölüm, mobil işletmeler ve kullanıcılar arasındaki iki yönlü ilişkiyi incelemektedir. Bu iki yönlü ilişki, kullanıcılar tarafından gelen değerlendirmeler ve işletmeler tarafından, sürekli ürün geliştirme biçimi olarak kullanılan güncellemeler yoluyla mümkün olmaktadır. Bı bölümde, kullanıcı incelemelerinden çıkarılan geri bildirimlerin, uygulama güncellemeleri aracılığıyla ürün geliştirmeye dahil edilmesinin, mobil uygulamaların kulanıcı derecelendirmelerine etkisi incelenmektedir. Bunun için, dört yüz atmışın üzerinde uygulamanın piyasadaki ilk yılı boyunca gözlemlenmiş, bu süre boyunca yaklaşık 1 milyon kullanıcı değerlendirmesinin otomatize edilmiş metin analizinden ve yaklaşık üç bin mobil uygulama güncellemesinin içerik analizinden yararlanılmıştır. Sonuçlar, kullanıcı isteklerine yanıt vermeyle ilişkili ödüllerin, ya da bu isteklerin göz ardı edilmesinden kaynaklanan cezaların, önemli boyutlara ulaşabileceğini ve bu etkilerin, geri bildirimin konusuna ve yanıtın zamanlamasına bağlı olduğunu ortaya koymaktadır. Dördüncü bölümün çıkarımları, özellikle müşterinin sesine göre, harekete geçip geçmeme, bununla birlikte harekete geçerken ne zaman proaktif, ne zaman reaktif bir strateji izlenmesi gerektiğine ilişkin temel soruları ile ilgili olarak daha geniş bir alana sahip olan yeni ürün geliştirme literatürüne kadar uzanabilir.

Özet olarak, bu tez, mobil pazarlama alanı ve daha spesifik olarak, onun kapsadığı mobil uygulamalar pazarı hakkındaki anlayışımızı geliştirmektedir. Ortaya çıkışından bu yana, mobil uygulamalar pazarı, uygulamaların sunduğu kazançlı fırsatlar ve piyasanın girişi önündeki düşük bariyerler nedeniyle her türden işletmenin (bireysel geliştiricilerden tanınmış markalara kadar uzanan) ilgisini çekmektedir. Ancak, bu kalabalık alanda, uygulamaların yalnızca küçük bir kısmı hayatta kalabilmiştir. Bu tez, yeni ve orijinal veri kümelerini kullanarak ilk önce müşterinin mobil uygulamayı indirme yolculuğunu tartışmaktadır. Uygulama indirme adımına ulaşıldıktan sonra, mobil uygulamanın değer önerisine ve verimliliğine güncellemeler aracılığıyla yapılan geliştirmenin, bu son derece rekabetçi pazarda hayatta kalmaya yardımcı olabileceği gösterilmektedir. Birden fazla araştırma dalından beslenmiş olan bu tez, mobil uygulamalar, kullanıcı tarafından oluşturulan içerikler ve yeni ürün geliştirme gibi çeşitli literatürlere katkıda bulunmaktadır. Mobil uygulamalar alanındaki çıkarımlar, yalnızca potansiyel uygulama geliştiricilerine değerli içgörüler sağlamakla kalmayıp, aynı zamanda mevcut geliştiricilere, piyasada piyasaya sürüldükten sonra uygulamalarını yol boyunca yeniden canlandırmaları için çözümler sunmaktadır. Daha geniş anlamda, her iki çalışmadan da elde edilen bulgular, dijital pazarlarda başarılı ürünler yaratmak ve sürekli ürün geliştirme ile ilişkilendirilebilir.

About the Author

Zeynep Aydin was born in Ankara, Turkey on October 13th, 1984. She received her Bachelors' degree with honors in Statistics from Middle East Technical University, Ankara and her Master's degree in Industrial Engineering from Bilkent University, Ankara. Her research interests lie in quantitative modeling (Bayesian Modeling, Time Series Models and Text Analysis) with empirical applications on mobile marketing and user generated content. She presented her work at leading international conferences such as European Marketing Academy Conference and Marketing Science Conference. Her work has recently appeared in *Journal of Business Research*, and she continues to submit her work to top-tier journals. She held a research position at Bilkent University, (2014-2016), where she taught marketing courses spanning a broad number of topics ranging from consumer behavior to probability and statistics both in undergraduate and graduate levels. She has become the mother to Alp Bulut in November, 2015.

The ERIM PhD Series

The ERIM PhD Series contains PhD dissertations in the field of Research in Management defended at Erasmus University Rotterdam and supervised by senior researchers affiliated to the Erasmus Research Institute of Management (ERIM). All dissertations in the ERIM PhD Series are available in full text through the ERIM Electronic Series Portal: http://repub.eur.nl/pub. ERIM is the joint research institute of the Rotterdam School of Management (RSM) and the Erasmus School of Economics (ESE) at the Erasmus University Rotterdam (EUR).

Dissertations in the last four years

Ahmadi, S., *A motivational perspective to decision-making and behavior in organizations*,
Promotors: Prof. J.J.P. Jansen & Dr T.J.M. Mom,
EPS-2019-477-S&E, https://repub.eur.nl/pub/116727

Akemu, O., *Corporate Responses to Social Issues: Essays in Social Entrepreneurship and Corporate Social Responsibility*,
Promotors: Prof. G.M. Whiteman & Dr S.P. Kennedy, EPS-2017-392-ORG,
https://repub.eur.nl/pub/95768

Albuquerque de Sousa, J.A., *International stock markets: Essays on the determinants and consequences of financial market development*, Promotors:
Prof. M.A. van Dijk & Prof. P.A.G. van Bergeijk, EPS-2019-465-F&A,
https://repub.eur.nl/pub/115988

Alserda, G.A.G., *Choices in Pension Management*, Promotors:
Prof. S.G. van der Lecq & Dr O.W. Steenbeek, EPS-2017-432-F&A,
https://repub.eur.nl/pub/103496

Arampatzi, E., *Subjective Well-Being in Times of Crises: Evidence on the Wider Impact of Economic Crises and Turmoil on Subjective Well-Being*,
Promotors: Prof. H.R. Commandeur, Prof. F. van Oort & Dr. M.J. Burger,
EPS-2018-459-S&E, https://repub.eur.nl/pub/111830

Avci, E., *Surveillance of Complex Auction Markets: a Market Policy Analytics Approach*,
Promotors: Prof. W. Ketter, Prof. H.W.G.M. van Heck &
Prof. D.W. Bunn, EPS-2018-426-LIS, https://repub.eur.nl/pub/106286

Balen, T.H. van, *Challenges of Early Stage Entrepreneurs: the Roles of Vision Communication and Team Membership Change*,
Promotors: Prof. J.C.M. van den Ende & Dr M. Tarakci, EPS-2019-468-LIS,
https://repub.eur.nl/pub/115654

Bernoster, I., *Essays at the Intersection of Psychology, Biology, and Entrepreneurship*, Promotors: Prof. A.R. Thurik, Prof. I.H.A. Franken & Prof. P.J.F Groenen, EPS-2018-463-S&E, https://repub.eur.nl/pub/113907

Bouman, P., *Passengers, Crowding and Complexity: Models for Passenger Oriented Public Transport*, Prof. L.G. Kroon, Prof. A. Schöbel & Prof. P.H.M. Vervest, EPS-2017-420-LIS, https://repub.eur.nl/pub/100767

Bunderen, L. van, *Tug-of-War: Why and when teams get embroiled in power struggles*, Promotors: Prof. D.L. van Knippenberg & Dr. L. Greer, EPS-2018-446-ORG, https://repub.eur.nl/pub/105346

Burg, G.J.J. van den, *Algorithms for Multiclass Classification and Regularized Regression*, Promotors: Prof. P.J.F. Groenen & Dr. A. Alfons, EPS-2018-442-MKT, https://repub.eur.nl/pub/103929

Chammas, G., *Portfolio concentration*, Promotor: Prof. J. Spronk, EPS-2017-410-F&E, https://repub.eur.nl/pub/94975

Dalmeijer, K., *Time Window Assignment in Distribution Networks*, Promotors: Prof A.P.M. Wagelmans & Dr R. Spliet, EPS-2019-486-LIS, https://repub.eur.nl/pub/120773

Dennerlein, T. *Empowering Leadership and Employees' Achievement Motivations: the Role of Self-Efficacy and Goal Orientations in the Empowering Leadership Process*, Promotors: Prof. D.L. van Knippenberg & Dr J. Dietz, EPS-2017-414-ORG, https://repub.eur.nl/pub/98438

Dolgova, E., *On Getting Along and Getting Ahead: How Personality Affects Social Network Dynamics, Promotors*: Prof. P.P.M.A.R Heugens & Prof. M.C. Schippers, EPS-2019-455-S&E, https://repub.eur.nl/pub/119150

Duijzer, L.E., *Mathematical Optimization in Vaccine Allocation*, Promotors: Prof. R. Dekker & Dr W.L. van Jaarsveld, EPS-2017-430-LIS, https://repub.eur.nl/pub/101487

Eijlers, E., *Emotional Experience and Advertising Effectiveness: on the use of EEG in marketing*, Prof. A. Smidts & Prof. M.A.S. Boksem, Eps-2019-487-MKT, https://repub.eur.nl/pub/124053

El Nayal, O.S.A.N., *Firms and the State: An Examination of Corporate Political Activity and the Business-Government Interface,* Promotor: Prof. J. van Oosterhout & Dr. M. van Essen, EPS-2018-469-S&E, https://repub.eur.nl/pub/114683

Feng, Y., *The Effectiveness of Corporate Governance Mechanisms and Leadership Structure: Impacts on strategic change and firm performance*, Promotors: Prof. F.A.J. van den Bosch, Prof. H.W. Volberda & Dr J.S. Sidhu, EPS-2017-389-S&E, https://repub.eur.nl/pub/98470

Frick, T.W., *The Implications of Advertising Personalization for Firms, Consumer, and Ad Platfroms,* Promotors: Prof. T. Li & Prof. H.W.G.M. van Heck, EPS-2018-452-LIS, https://repub.eur.nl/pub/110314

Fytraki, A.T., *Behavioral Effects in Consumer Evaluations of Recommendation Systems*, Promotors: Prof. B.G.C. Dellaert & Prof. T. Li, EPS-2018-427-MKT, https://repub.eur.nl/pub/110457

Ghazizadeh, P. *Empirical Studies on the Role of Financial Information in Asset and Capital Markets,* Promotors: Prof. A. de Jong & Prof. E. Peek, EPS-2019-470-F&A, https://repub.eur.nl/pub/114023

Giurge, L., *A Test of Time; A temporal and dynamic approach to power and ethics*, Promotors: Prof. M.H. van Dijke & Prof. D. De Cremer, EPS-2017-412-ORG, https://repub.eur.nl/pub/98451

Gobena, L., *Towards Integrating Antecedents of Voluntary Tax Compliance*, Promotors: Prof. M.H. van Dijke & Dr P. Verboon, EPS-2017-436-ORG, https://repub.eur.nl/pub/103276

Groot, W.A., *Assessing Asset Pricing Anomalies*, Promotors: Prof. M.J.C.M. Verbeek & Prof. J.H. van Binsbergen, EPS-2017-437-F&A, https://repub.eur.nl/pub/103490

Hanselaar, R.M., *Raising Capital: On pricing, liquidity and incentives,* Promotors: Prof. M.A. van Dijk & Prof. P.G.J. Roosenboom, EPS-2018-429-F&A, https://repub.eur.nl/pub/113274

Harms, J. A., *Essays on the Behavioral Economics of Social Preferences and Bounded Rationality*, Prof. H.R. Commandeur & Dr K.E.H. Maas, EPS-2018-457-S&E, https://repub.eur.nl/pub/108831

Hendriks, G., *Multinational Enterprises and Limits to International Growth: Links between Domestic and Foreign Activities in a Firm's Portfolio,* Promotors: Prof. P.P.M.A.R. Heugens & Dr. A.H.L Slangen, EPS-2019-464-S&E, https://repub.eur.nl/pub/114981

Hengelaar, G.A., *The Proactive Incumbent: Holy grail or hidden gem? Investigating whether the Dutch electricity sector can overcome the incumbent's curse and lead the sustainability transition*, Promotors: Prof. R.J. M. van Tulder & Dr K. Dittrich, EPS-2018-438-ORG, https://repub.eur.nl/pub/102953

Jacobs, B.J.D., *Marketing Analytics for High-Dimensional Assortments,* Promotors: Prof. A.C.D. Donkers & Prof. D. Fok, EPS-2017-445-MKT, https://repub.eur.nl/pub/103497

Jia, F., *The Value of Happiness in Entrepreneurship*,
Promotors: Prof. D.L. van Knippenberg & Dr Y. Zhang, EPS-2019-479-ORG,
https://repub.eur.nl/pub/115990

Kahlen, M. T., *Virtual Power Plants of Electric Vehicles in Sustainable Smart Electricity Markets*, Promotors: Prof. W. Ketter & Prof. A. Gupta,
EPS-2017-431-LIS, https://repub.eur.nl/pub/100844

Kampen, S. van, *The Cross-sectional and Time-series Dynamics of Corporate Finance: Empirical evidence from financially constrained firms*, Promotors: Prof. L. Norden & Prof. P.G.J. Roosenboom, EPS-2018-440-F&A, https://repub.eur.nl/pub/105245

Karali, E., *Investigating Routines and Dynamic Capabilities for Change and Innovation,* Promotors: Prof. H.W. Volberda, Prof. H.R. Commandeur &
Dr J.S. Sidhu, EPS-2018-454-S&E, https://repub.eur.nl/pub/106274

Keko. E, *Essays on Innovation Generation in Incumbent Firms*,
Promotors: Prof. S. Stremersch & Dr N.M.A. Camacho, EPS-2017-419-MKT,
https://repub.eur.nl/pub/100841

Kerkkamp, R.B.O., *Optimisation Models for Supply Chain Coordination under Information Asymmetry,* Promotors: Prof. A.P.M. Wagelmans &
Dr. W. van den Heuvel, EPS-2018-462-LIS, https://repub.eur.nl/pub/109770

Khattab, J., *Make Minorities Great Again: a contribution to workplace equity by identifying and addressing constraints and privileges*,
Promotors: Prof. D.L. van Knippenberg & Dr A. Nederveen Pieterse,
EPS-2017-421-ORG, https://repub.eur.nl/pub/99311

Kim, T. Y., *Data-driven Warehouse Management in Global Supply Chains*,
Promotors: Prof. R. Dekker & Dr C. Heij, EPS-2018-449-LIS,
https://repub.eur.nl/pub/109103

Klitsie, E.J., *Strategic Renewal in Institutional Contexts: The paradox of embedded agency*, Promotors: Prof. H.W. Volberda & Dr. S. Ansari,
EPS-2018-444-S&E, https://repub.eur.nl/pub/106275

Koolen, D., *Market Risks and Strategies in Power Systems Integrating Renewable Energy*,
Promotors: Prof. W. Ketter & Prof. R. Huisman, EPS-2019-467-LIS,
https://repub.eur.nl/pub/115655

Kong, L. *Essays on Financial Coordination*, Promotors: Prof. M.J.C.M. Verbeek, Dr. D.G.J. Bongaerts & Dr. M.A. van Achter. EPS-2019-433-F&A,
https://repub.eur.nl/pub/114516

Kyosev, G.S., *Essays on Factor Investing*, Promotors: Prof. M.J.C.M. Verbeek &
Dr J.J. Huij, EPS-2019-474-F&A, https://repub.eur.nl/pub/116463

Lamballais Tessensohn, T., *Optimizing the Performance of Robotic Mobile Fulfillment Systems*, Promotors: Prof. M.B.M de Koster, Prof. R. Dekker & Dr D. Roy, EPS-2019-411-LIS, https://repub.eur.nl/pub/116477

Leung, W.L., *How Technology Shapes Consumption: Implications for Identity and Judgement*, Promotors: Prof. S. Puntoni & Dr G Paolacci, EPS-2019-485-MKT, https://repub.eur.nl/pub/117432

Li, X. *Dynamic Decision Making under Supply Chain Competition*, Promotors: Prof. M.B.M de Koster, Prof. R. Dekker & Prof. R. Zuidwijk, EPS-2018-466-LIS, https://repub.eur.nl/pub/114028

Liu, N., *Behavioral Biases in Interpersonal Contexts*, Supervisors: Prof. A. Baillon & Prof. H. Bleichrodt, EPS-2017-408-MKT, https://repub.eur.nl/pub/95487

Maas, A.J.J., *Organizations and their external context: Impressions across time and space*, Promotors: Prof. P.P.M.A.R Heugens & Prof. T.H. Reus, EPS-2019-478-S&E, https://repub.eur.nl/pub/116480

Maira, E., *Consumers and Producers*, Promotors: Prof. S. Puntoni & Prof. C. Fuchs, EPS-2018-439-MKT, https://repub.eur.nl/pub/104387

Nair, K.P., *Strengthening Corporate Leadership Research: The relevance of biological explanations*, Promotors: Prof. J. van Oosterhout & Prof. P.P.M.A.R Heugens, EPS-2019-480-S&E, https://repub.eur.nl/pub/120023

Nullmeier, F.M.E., *Effective contracting of uncertain performance outcomes: Allocating responsibility for performance outcomes to align goals across supply chain actors*, Promotors: Prof. J.Y.F.Wynstra & Prof. E.M. van Raaij, EPS-2019-484-LIS, https://repub.eur.nl/pub/118723

Okbay, A., *Essays on Genetics and the Social Sciences*, Promotors: Prof. A.R. Thurik, Prof. Ph.D. Koellinger & Prof. P.J.F. Groenen, EPS-2017-413-S&E, https://repub.eur.nl/pub/95489

Peng, X., *Innovation, Member Sorting, and Evaluation of Agricultural Cooperatives*, Promotor: Prof. G.W.J. Hendriks, EPS-2017-409-ORG, https://repub.eur.nl/pub/94976

Petruchenya, A., *Essays on Cooperatives: Emergence, Retained Earnings, and Market Shares*, Promotors: Prof. G.W.J. Hendriks & Dr Y. Zhang, EPS-2018-447-ORG, https://repub.eur.nl/pub/105243

Plessis, C. du, *Influencers: The Role of Social Influence in Marketing*, Promotors: Prof. S. Puntoni & Prof. S.T.L.R. Sweldens, EPS-2017-425-MKT, https://repub.eur.nl/pub/103265

Pocock, M., *Status Inequalities in Business Exchange Relations in Luxury Markets*, Promotors: Prof. C.B.M. van Riel & Dr G.A.J.M. Berens, EPS-2017-346-ORG, https://repub.eur.nl/pub/98647

Pozharliev, R., *Social Neuromarketing: The role of social context in measuring advertising effectiveness*, Promotors: Prof. W.J.M.I. Verbeke & Prof. J.W. van Strien, EPS-2017-402-MKT, https://repub.eur.nl/pub/95528

Reh, S.G., *A Temporal Perspective on Social Comparisons in Organizations,* Promotors: Prof. S.R. Giessner, Prof. N. van Quaquebeke & Dr. C. Troster, EPS-2018-471-ORG, https://repub.eur.nl/pub/114522

Riessen, B. van, *Optimal Transportation Plans and Portfolios for Synchromodal Container Networks*, Promotors: Prof. R. Dekker & Prof. R.R. Negenborn, EPS-2018-448-LIS, https://repub.eur.nl/pub/105248

Schie, R. J. G. van, *Planning for Retirement: Save More or Retire Later?* Promotors: Prof. B. G. C. Dellaert & Prof. A.C.D. Donkers, EOS-2017-415-MKT, https://repub.eur.nl/pub/100846

Schouten, K.I.M. *Semantics-driven Aspect-based Sentiment Analysis,* Promotors: Prof. F.M.G. de Jong, Prof. R. Dekker & Dr. F. Frasincar, EPS-2018-453-LIS, https://repub.eur.nl/pub/112161

Sihag, V., *The Effectiveness of Organizational Controls: A meta-analytic review and an investigation in NPD outsourcing*, Promotors: Prof. J.C.M. van den Ende & Dr S.A. Rijsdijk, EPS-2019-476-LIS, https://repub.eur.nl/pub/115931

Smolka, K.M., *Essays on Entrepreneurial Cognition, Institution Building and Industry Emergence*, Promotors: P.P.M.A.R. Heugens, & Prof. J.P. Cornelissen, Eps-2019-483-S&E, https://repub.eur.nl/pub/118760

Straeter, L.M., *Interpersonal Consumer Decision Making*, Promotors: Prof. S.M.J. van Osselaer & Dr I.E. de Hooge, EPS-2017-423-MKT, https://repub.eur.nl/pub/100819

Stuppy, A., *Essays on Product Quality,* Promotors: Prof. S.M.J. van Osselaer & Dr N.L. Mead. EPS-2018-461-MKT, https://repub.eur.nl/pub/111375

Subaşi, B., *Demographic Dissimilarity, Information Access and Individual Performance*, Promotors: Prof. D.L. van Knippenberg & Dr W.P. van Ginkel, EPS-2017-422-ORG, https://repub.eur.nl/pub/103495

Suurmond, R., *In Pursuit of Supplier Knowledge: Leveraging capabilities and dividing responsibilities in product and service contexts,*

Promotors: Prof. J.Y.F Wynstra & Prof. J. Dul. EPS-2018-475-LIS, https://repub.eur.nl/pub/115138

Toxopeus, H.S. *Financing sustainable innovation: From a principal-agent to a collective action perspective,* Promotors: Prof. H.R. Commandeur & Dr. K.E.H. Maas. EPS-2019-458-S&E, https://repub.eur.nl/pub/114018

Turturea, R., *Overcoming Resource Constraints: The Role of Creative Resourcing and Equity Crowdfunding in Financing Entrepreneurial Ventures,* Promotors: Prof. P.P.M.A.R Heugens, Prof. J.J.P. Jansen & Dr. I. Verheuil, EPS-2019-472-S&E, https://repub.eur.nl/pub/112859

Vandic, D., *Intelligent Information Systems for Web Product Search*, Promotors: Prof. U. Kaymak & Dr Frasincar, EPS-2017-405-LIS, https://repub.eur.nl/pub/95490

Verbeek, R.W.M., *Essays on Empirical Asset Pricing*, Promotors: Prof. M.A. van Dijk & Dr M. Szymanowska, EPS-2017-441-F&A, https://repub.eur.nl/pub/102977

Visser, T.R. Vehicle Routing and Time Slot Management in Online Retailing, Promotors: Prof. A.P.M. Wagelmans & Dr R. Spliet, EPS-2019-482-LIS, https://repub.eur.nl/pub/120772

Vlaming, R. de.,*Linear Mixed Models in Statistical Genetics*, Prof. A.R. Thurik, Prof. P.J.F. Groenen & Prof. Ph.D. Koellinger, EPS-2017-416-S&E, https://repub.eur.nl/pub/100428

Vries, H. de, *Evidence-Based Optimization in Humanitarian Logistics*, Promotors: Prof. A.P.M. Wagelmans & Prof. J.J. van de Klundert, EPS-2017-435-LIS, https://repub.eur.nl/pub/102771

Wang, R., *Corporate Environmentalism in China*, Promotors: Prof. P.P.M.A.R Heugens & Dr F. Wijen, EPS-2017-417-S&E, https://repub.eur.nl/pub/99987

Wasesa, M., *Agent-based inter-organizational systems in advanced logistics operations*, Promotors: Prof. H.W.G.M van Heck, Prof. R.A. Zuidwijk & Dr A. W. Stam, EPS-2017-LIS-424, https://repub.eur.nl/pub/100527

Wessels, C., *Flexible Working Practices: How Employees Can Reap the Benefits for Engagement and Performance*, Promotors: Prof. H.W.G.M. van Heck, Prof. P.J. van Baalen & Prof. M.C. Schippers, EPS-2017-418-LIS, https://repub.eur.nl/

Wiegmann, P.M., *Setting the Stage for Innovation: Balancing Diverse Interests through Standardisation,* Promotors: Prof. H.J. de Vries & Prof. K. Blind, EPS-2019-473-LIS, https://repub.eur.nl/pub/114519

Wijaya, H.R., *Praise the Lord!: Infusing Values and Emotions into Neo-Institutional Theory*, Promotors: Prof. P.P.M.A.R. Heugens & Prof. J.P. Cornelissen, EPS-2019-450-S&E, https://repub.eur.nl/pub/115973

Williams, A.N., *Make Our Planet Great Again: A Systems Perspective of Corporate Sustainability*, Promotors: Prof. G.M. Whiteman & Dr. S. Kennedy, EPS-2018-456-ORG, https://repub.eur.nl/pub/111032

Witte, C.T., *Bloody Business: Multinational investment in an increasingly conflict-afflicted world*, Promotors: Prof. H.P.G. Pennings, Prof. H.R. Commandeur & Dr M.J. Burger, EPS-2018-443-S&E, https://repub.eur.nl/pub/104027

Ye, Q.C., *Multi-objective Optimization Methods for Allocation and Prediction*, Promotors: Prof. R. Dekker & Dr Y. Zhang, EPS-2019-460-LIS, https://repub.eur.nl/pub/116462

Yuan, Y., *The Emergence of Team Creativity: a social network perspective*, Promotors: Prof. D. L. van Knippenberg & Dr D. A. Stam, EPS-2017-434-ORG, https://repub.eur.nl/pub/100847

Zhang, Q., *Financing and Regulatory Frictions in Mergers and Acquisitions*, Promotors: Prof. P.G.J. Roosenboom & Prof. A. de Jong, EPS-2018-428-F&A, https://repub.eur.nl/pub/103871