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Essays on User Acquisition, Retention, Experience, Engagement and Purchase Decisions of a Hybrid Mobile Wallet

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by

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Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

August 2017

Dedication

Dedicated to my family.

Acknowledgements

I am deeply grateful to my co-advisers, Professor Ty Henderson and Professor Garrett Sonnier, for their consistent guidance and generous support throughout the past six years. I am indebted to them for expanding my understanding of research, for their pertinent advice on my research, teaching and career, and for giving me the right amount of push and encouragement during hard times. Furthermore, I would like to thank my dissertation committee members, Professor Jun Duan, Professor Leigh McAlister, and Professor Mingyuan Zhou for their inspiring critiques and warm support on my dissertation and earlier projects throughout my graduate career. Special gratitude is also extended to Lisa Burton and Lance Obermeyer for their help in this project. I am also grateful for the financial support of the Marketing Department, Philosophy Department, and IROM Department at the University of Texas at Austin, without which I would not have been able to complete the doctoral program. I would like to thank everyone who has cultivated my curiosity in research and my capacity to perform it from Beijing to Rochester to Fayetteville to Austin, and I would not have learned so much without your edification.

Finally, I want to thank my friends—Eline, Shun-Yang, Crystal, Eunjoo, Huaxia and Ying, Zhuping and Jie, Jacob, Jaehee, Fan, Prasart, Arash, Babak, Dan, Kai, Yixin, Joy and Nancy—for their friendship and encouragement and for sharing this unforgettable memory here in Austin or remotely. Most importantly, I thank my parents for their consistent and unconditional love, faith and support throughout this journey, and my boyfriend Tianjian for going through the tough times with me and making grey days colorful.

Essays on User Acquisition, Retention, Experience, Engagement and Purchase Decisions of a Hybrid Mobile Wallet

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The University of Texas at Austin, 2017

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Abstract: The popularity of "mobile wallets" (or "mobile payment" platforms) is one of the most prominent trends in the mobile commerce (m-commerce) era. However, like most mobile applications (apps), mobile wallet apps usually suffer from low repeat usage rates. Most extant research on mobile users' app usage behavior focuses on the early stage of app usage, such as app download and adoption intentions, and researchers know little about what makes a mobile payment app successful in engaging users, maintaining user base, and achieving favorable economic outcomes. In addition, extant research on mobile users' experience, engagement and usage are based primarily on subjective survey responses, and there has been a lack of empirical investigation on users' actual behavior. To bridge these research gaps, this dissertation empirically examines multiple stages during users' app usage with individual-level tap stream data from a hybrid mobile wallet app.

The first essay explores three intersections: first, it considers *jointly* users' acquisition and retention processes with the mobile wallet app; it also examines the relationship between acquisition and retention; and third, it analyzes the effects of

marketing and operational factors on the previous two processes. Results of the analysis suggest that while an aggressive "onboarding" promotion at "born" stage has a positive effect on user acquisition, it does not have any effect on subsequent retention. In addition, this dissertation finds a negative duration dependence on both acquisition and retention compounded by a negative correlation between the two processes. This negative duration indicates an unfavorable situation, which suggests the ineffectiveness of current marketing promotion strategies in gaining loyal users for the mobile wallet app. The second essay examines user experience and user engagement with the mobile wallet app during multiple usage sessions. Measuring user experience and engagement with observable user actions based on individual-level tap stream data, the essay investigates the effecs of user experience and firms' marketing efforts on user engagement and purchase decisions. The results reveal an intermediate role of user engagement between user experience and purchase decisions. Surprisingly, the negative experience of technical failure does not always discourage users in engaging with the app or making purchases. Through empirical exploration and novel findings on mobile users' app usage pattern, and through new determinations of the effects of marketing in the context of the emerging mobile payment, this dissertation contributes substantively to the literature of mobile marketing.

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General Introduction

This dissertation contains two essays that investigate the marketing of a mobile wallet application (app). My research interest on mobile marketing is motivated by the growing importance of mobile as an interactive marketing platform. Consumers are spending an increasing amount of time and money on mobile devices and platforms. According to one eMarketer study, American adults spent 3 hours and 17 minutes per day on mobile devices, over 80% of which time is spent on mobile applications (apps).[1] Additionally, in 2015, 30% of e-commerce transactions were completed via mobile devices.[2] As a result, mobile platform has shown lucrative investment potential for firms in digital marketing. Worldwide, ad spending on mobile platforms exceeded $100 billion in 2016. In the United States, mobile ads have surpassed search ads since 2015, and they now represent the largest share (40%) of internet ad revenue.[3] In addition to serving as a highly interactive media platform, mobile also offers new business opportunities through mobile apps, and the number of apps available for download has been growing rapidly in the past few years.[4]

Despite growing opportunities, firms in mobile marketing face several new challenges. Importantly, researchers theorize that mobile phone use in recent years has caused decreasing attention spans and shifting foci in internet users.[5] These changes in user behavior emphasize the importance of marketers' abilities to attract users' attention

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[1] "US time spent with mobile," (2017).
[2] Internet retailer 2016 mobile 500 guide.
[3] IAB/PwC Internet ad revenue report, FY 2015.
[4] By June 2017, there were over 3 million apps on Google Play Store, one the largest app stores. That figure represents an 87.5% growth from June 2015. "Google Play: number of available apps 2009–2017," (2017).
[5] According to a study by the Statistical Brain Research Institute, the average human attention span has dropped to 8.25 seconds, a 33% decrease since the year 2000.

instantly and instigate valuable interactions with features of the mobile offering. However, most mobile apps experience high user attribution within days after the app is installed; hence, mobile apps experience extremely low repeat usage from users.[6] This trend reflects a common challenge faced by many marketers in mobile marketing and in the mobile app industry.

This dissertation attempts to understand the aforementioned challenge. It also attempts to explore how marketing and operational efforts affect the performance of a mobile app from the perspectives of four distinct behavior outcomes of mobile users: acquisition, retention, user experience and user engagement. This empirical investigation is set in the context of a hybrid mobile wallet app[7] that facilitates wireless payment in multiple food and beverage venues and occasionally offers mobile coupons that entail price discounts or free items for users to redeem at their chosen venue. My first essay, "A Bivariate Model of User Acquisition and Retention of a Mobile Wallet Application," focuses on acquisition and retention (defined as the first time the service is successfully used through purchase and the second time of successful usage). Essay 1 also investigates the effects of marketing on acquisition and retention, and it explores the relationship between the two processes in a novel non-contractual context. My second essay, "User Experience, Engagement and Purchase Decisions of a Hybrid Mobile Wallet Application," considers the time in between app usage sessions and investigates how some granular incidents and encounters during app browsing (operationalized as user

[6] On average, android apps lose 79% of users within 3 days since app installation.
[7] I sourced the data through networking with a technology start-up company that develops and markets the focal app based in Austin, TX. I would like express my gratitude for their interest in my research and cooperation in providing their data for research.

experience) affect user engagement. Essay 2 also investigate the role user engagement plays in mediating the effects of user experience and marketing on purchase decisions (i.e., actual usage of the service beyond browsing).

This dissertation intends to contribute substantively to the literature of mobile marketing and m-commerce by providing new insights on user behavior in mobile payment. The novelty of this dissertation rests in the emerging field of mobile payment as well as the uniqueness of the interaction among user, the product, and firms' marketing strategies. First, the focal app is a stand-alone intermediary app, as opposed to some well-studied brand apps, which are often proprietary to specific brands or retailers. This means that the focal app is not merely a channel extension of an established brand, and also that the app's main function is to intermediate the pursuit of other products. Thus, users' loyalty behavior with the app is different from that with a brand's mobile extension. Second, the consumer's usage cycle with the app is much shorter than most well-studied contractual services (e.g., telecommunications or cable TV) and most well-studied non-contractual services (e.g., e-mail subscription or purchase of consumer packaged goods in grocery stores). In the mobile context, because of users' shorter attention spans, the important elements of user experience that help engage users may be different from those in the online shopping or gaming context. In mobile scenarios, users try and perhaps abandon products and services on a daily or hourly basis as opposed to on a monthly consumption or subscription basis. Therefore, the mobile context may pose different challenges to engineers and marketers. Third, as a free-download app, the focal app demonstrates unique traits. Similar to most non-contractual services, the focal app does not have set membership length, and there is no cost to terminate. However, in contrast to

most non-contractual services, the focal app requires zero financial cost to adopt, but extra actions (non-financial) to reuse the service, thus reuse (instead of termination) is observed. These three interrelated novelties exhibit new patterns in user behavior and in the effects of marketing in m-commerce.

This dissertation fill in several gaps in extant studies on m-commerce. Extant research on mobile marketing have focused largely on the effectiveness of mobile technologies or mobile platforms as targeting and promotional tools, and their research interests emphasize mobile users' coupon redemption behavior (Danaher et al., 2015; Fong et al., 2015; Li et al., 2017; Dube et al., 2017) and brand purchase intentions (Bellman et al., 2011; Kim et al., 2015). Very little research has explored behavioral outcomes with regard to actual app usage, such as the circumstances of download (Ghose and Han, 2014), app opening patterns (Huang et al., 2012), and continuance intentions of app usage (Zhou, 2013; Ding and Chai, 2015). However, but there has been a lack of observed behavioral data contributing to a systematic investigation on user acquisition and retention behavior. At the intersection of human-computer interaction and interactive marketing, most explorations of user experience and user engagement stem from flow theory (Hoffman and Novak, 1996; Novak et al., 2000, Mathwick and Rigdon, 2004). With a lack of consistent measurements on user experience or user engagement, empirical research has primarily investigated users' perceptions regarding experience and engagement in online shopping and gaming contexts (Castaneda et al., 2007; Rose et al., 2012), and there has been a lack of investigation in the mobile context. With regard to the type of data and interference, only Dinner et al. (2015) have utilized individual-level tap stream data, and they found that app user engagement (measured by the number of times

an app is used) is an important predictor of brand purchase. However, they treat user engagement as an independent variable, and are agnostic about the effects marketing and other factors on user engagement. This dissertation helps bridge those gaps in the literature by empirically answering such research questions using data that contains actual app usage behavior—i.e., tap stream data.

The empirical investigation of this dissertation yields interesting and novel findings on user behavior in the context of a mobile wallet app. For example, in Essay 1, a negative duration dependence is found in both the acquisition and retention process. This negative dependence suggests a completely different pattern of users' loyalty behavior in comparison with previous research on user acquisition and retention in the contractual setting (Schweidel et al., 2008) and in the non-contractual setting (Kumar et al., 2014). In addition, this essay's quasi-experiment—the "onboarding" promotion at the "born" stage—has a short-run effect on acquisition but no effect on subsequent retention. In Essay 2, an investigation on technical failures suggests that negative experience in the concurrent session does not discourage users from spending more time in the app, and technical failures at distinct stages of a session work differently in affecting purchase conversion, possibly due to users' levels of commitment to the app. In addition, this essay shows that promotion affects purchase conversion only indirectly through user engagement. It also shows that current marketing promotion strategies do not encourage spending. Findings from both essays broadly suggest that the firm's current marketing strategy is ineffective in attracting loyal users and that acquiring users quickly through promotion could be counterproductive to consumer retention. Instead, engaging users and compelling them to spend more time exploring and learning about the value proposition

of the app before using it may be a more successful strategy. This dissertation's investigation is valuable because it presents real data on the operation of m-commerce, and thereby it produces managerial implications that help marketers and researchers understand how marketing and operational efforts affect user behavior and purchasing trends in the burgeoning era of m-commerce.

Essay 1: A Bivariate Timing Model of User Acquisition and Retention of a Mobile Wallet Application

INTRODUCTION

The wide adoption of smartphones and wireless technologies has made mobile devices and applications popular marketing platforms.[8] As consumers invest increasing time and money on their mobile devices, mobile commerce (m-commerce) is emerging as the next generation of e-commerce. Global spending on mobile advertising surpassed 100 billion dollars in 2016, and over 2.4 million mobile applications (apps) are available for download on Google Play, the world's largest mobile app store.[9] A noticeable trend in m-commerce is the popularity of mobile payment or mobile wallet services, referring to payment services performed from or via mobile devices.[10] This revolutionary payment option liberates consumers from carrying a physical wallet full of cash or handing bankcards to cashiers, who are usually strangers, thus providing much convenience and increased security for making payments in both online and brick-and-mortar stores. A recent industry report has estimated the global mobile wallet market to be valued at approximately 594 billion dollars in 2016. With a 32% CAGR growth rate, the mobile wallet market is expected to reach 3 trillion dollars by 2022.[11] In the US, the value of

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[8] According to eMarketer, US adults spent 3 hours and 11 minutes per day on mobile devices in 2017, ranking mobile first in terms of media usage among digital media.

[9] Mobile internet ad spending worldwide 2013-2019, by eMarketer; Google Play: number of available apps 2009-2017, by Statista.

[10] Among various technologies that facilitate mobile payment, the most common ones are near field communication (NFC) technology and quick response (QR) code which requires users to wave their mobile devices near a reader module (e.g., a POS machine), or a cloud based platform that requires authenticated credit card information and links the mobile devices with the store POS machine wirelessly.

[11] Mobile Wallet Market (NFC, Remote Wallet) for Retail payments Vending machines Public transportation, Restaurants and other application - Global Industry Perspective, Comprehensive Analysis, Size, Share, Growth, Segment, Trends and Forecast, 2016 - 2022

transactions completed through mobile payment in 2016 reached 27 billion dollars, a 200% increase from 2015.

Despite rapid growth in scale and promising forecasts from industry, the market performance of mobile payment services and mobile wallet apps is far from satisfactory. With increasing awareness among consumers, more technology companies and retailers are inclined to offer various mobile payment solutions. However, among smartphone users in North America in 2016, only one-third have completed a mobile payment—a number that has not increased since the previous year. More alarming to marketers is consumers' low mobile payment repeat usage rate. A recent study on Apple Pay, one of the most recognized mobile wallets, reveals that over the course of 20 months from 2015 to 2016, only 5% of iPhone users who have downloaded the Apple Pay service have used it, and only one-third of Apple Pay users would consider using it again ("Apple Pay's tough twenty months", 2016). The characteristics of a mobile wallet successful at building a consistent user base still remain largely unknown in the mobile technology industry. This knowledge gap creates an interesting problem for mobile marketers and an interesting question for researchers in mobile marketing.

Challenges of low repeat usage and low retention rates among consumers—are problems shared by many other mobile app developers.[12] Because it is a relatively new marketing platform, current research on mobile in marketing and information systems mainly focuses on the earliest stage of consumers' life cycle. Recent studies investigate factors—such as app characteristics or contextual details—that affect users' adoption

[12] A recent study on user retention of mobile apps shows that an average app in the Google Play Store loses 77% of users within 3 days after the app is installed.

intentions toward mobile services or the actual download of mobile apps (Huang et al., 2012; Ghose and Han 2014; Peng et al., 2014). Very few papers look at ongoing usage of mobile apps (e.g., Ding and Chai 2015) from an information systems perspective, leaving a wide gap in research on mobile marketing in terms of understanding the drivers of user retention. In addition, extant research on mobile and mobile apps base their findings largely on either aggregated app download data or survey responses. The effects of marketing on individual users' adoption or retention decisions within a mobile app remain underexplored.

This dissertation helps fill the gap in research on m-commerce by addressing both user acquisition and retention processes of a mobile wallet app. Specifically, this research answers the following questions: first, how do marketing strategies at the time when users join the app (i.e., register an account) affect the acquisition and retention processes? Second, how do different acquisition conditions affect subsequent retention? Third, how do marketing promotion (e.g., type and depth of promotion) and operational factors of mobile apps (e.g., check-in to the app, and product versioning) affect the acquisition and retention processes?

To answer these research questions, we analyze a unique dataset obtained from a mobile wallet app that allows users to pay bills in multiple food and beverage venues. The dataset contains individual-level behavior and transaction records from over five thousand users for whom we are able to observe the entire history of user transaction activities from the moment they join the app by registering an account. Since the app we study offers a free, non-contractual service, the only way for a user to become a meaningful customer for the company is through making payments using the app.

Therefore, we jointly model the duration to both acquisition, defined as time elapsed between joining and successfully using the app for payment for the very first time, and retention, defined as time elapsed between the first mobile payment and the second mobile payment. To account for the correlation between the two processes and duration dependence, we jointly model acquisition duration and retention duration with a bivariate hazard model using a Gaussian copula.

To the best of our knowledge, this study is the first that empirically addresses both user acquisition and retention using transaction-level data in the context of m-commerce. In addition, the study emphasizes a nice quasi-experimental setup in which researchers group app users into three different cohorts based on the marketing strategy regimes that compelled them to join the app. This setup enabled us to explore an important yet often ignored role of marketing strategy regimes at "born" stage, without suffering from potential selection problem.[13] In addition, we incorporate marketing and operational variables to explore the effects of other important factors found in previous literature—such as format and face-value of m-coupons—as well as new operational factors, such as product versioning. The results of analysis suggest that although the marketing strategy regimes under our investigation have an important and positive effect on user acquisition, they do not affect retention. Users acquired with a promotional coupon are less likely to be retained, and operational factors affect both acquisition and retention non-linearly. In addition, the results reveal negative duration dependence in both acquisition and retention, as well as a negative correlation between the two

[13] Users can only view the available promotions after they join the app, hence we do not believe that they differently choose the time to join the app across the three different marketing regimes.

processes for the focal mobile wallet app. With these novel empirical findings and important managerial implications, this paper contributes to the emerging literature on mobile marketing and m-commerce substantively.

The remainder of this paper is organized in the following sections: first, we review recent papers from marketing and information systems literature on (1) mobile payment and mobile wallets; (2) mobile promotion; (3) mobile adoption and usage; and (4) the linkage between user acquisition and retention. Next, we describe the empirical setting and present summary statistics of data acquired. This is followed by a description of the proposed modeling framework that models user acquisition and retention jointly using a Gaussian copula. Finally, we discuss the model results and conclude with managerial implications.

LITERATURE REVIEW

Mobile Wallet and Mobile Payment

The mobile wallet is still a relatively new service that has become popular in the past few years as m-commerce has become more prevalent due to its enabling of consumers to make more convenient and secure transactions from their mobile devices. In the literature of marketing and information systems, a few papers have examined mobile users' attitudes and intentions towards mobile payment primarily based on the Technology Acceptance Model (TAM), and suggested that perceived ease of use, perceived usefulness, and perceived security are strong predictors of adoption intentions of mobile payment (Kim et al., 2010; Shierz et al., 2010). Built on the TAM framework, further research extended the TAM framework, and found that factors such as perceived

compatibility and social effects (e.g., subjective norm and perceived social image), as well as individual mobility are also important factors that affect users' attitudes and intentions towards using apps (Shierz et al., 2010; Lu et al., 2011). Beyond adoption intention, Zhou (2013) uses the information system success model and flow theory in order to further investigate factors affecting users' continued use of mobile payment, and finds that service quality and system quality are important factors that drive users' intent to continue with mobile payment through trust, flow and satisfaction. Notably, this extant research on mobile payment has been conducted using survey data, and thus empirical research with real market data and individual choices is needed to authenticate theories and provide external validity to findings based on subjective survey responses.

Mobile Promotion

Despite burgeoning research on m-commerce, the field is still relatively unexplored. Most marketing literature has primarily focused on the effectiveness of mobile technologies or mobile platforms as new retailing channels (as compared to online or other traditional channels) and as new targeting tools for mobile ads and coupons (i.e., m-coupons). Built-in geographical positioning technology has enabled marketers to use smartphones for real-time targeting based on mobile users' physical location as well as their behavior, and a stream of research has examined the effectiveness of mobile as a promotional platform for mobile ads and m-coupons. Danaher et al. (2015) find that timing, location, face value, and expiry length of m-coupons are the most important factors affecting users' m-coupon redemption. Dickinger and Kleijnen (2008) find that both efforts involved in redeeming coupons and consumers' fear of mobile spam affect users' m-coupon redemption intentions. Li et al (2017) explore weather-based targeting

and find that marketers could also exploit meteorological conditions to increase purchase response to m-coupons through consumers' interactions with ad copy. Using field experiments, Fong et al. (2015) test the effectiveness of different mobile targeting strategies for m-coupons by manipulating timing, location and face value of m-coupons. Their results suggest that competitive locational targeting is an effective targeting strategy with increasing return to promotion. Similarly, Dube et al. (2017) test these mobile targeting strategies through field studies, and further evaluate their effects on coupon redemption rates and firm revenues in a competitive setting. Within the research on m-coupon, Banerjee and Yancey (2010) study factors that affect coupon redemption in the food and beverage industry, which context is the most similar to the empirical context of the current study in this dissertation. They find that effects of discount depth, format and timing of m-coupons are product category-dependent. That is, they find that high-discount items (those with prices cut as compared to free items) trigger higher response in entrée meals, but lower responses in desserts and frozen beverages.

Mobile App Adoption and Usage

From a more general perspective on mobile marketing, several researchers have studied user adoption behavior and usage on mobile applications at the aggregate level. Ghose and Han (2014) estimate app demand on both the Apple iOS and Google Android platforms using a structural model and find that app characteristics such as in-app purchase help increase app demand and hence app developers' revenue. In order to learn about mobile users' app usage patterns, Huang et al. (2012) suggest that contextual information such as time, location, and app usage history, and the concurrent setting of the phone can be utilized to predict users' app opening patterns. Bellman et al. (2011)

find that the adoption of branded apps increases consumers' interest towards the brand and the relevant product category; thus, adoption of branded apps has a positive effect on purchase intention towards the brands. At the disaggregate level, Kim et al. (2015) investigate the adoption and usage of a branded app and suggest that adoption increases consumers' purchase spending towards the brand. As follows, discontinued usage of the branded app predicts decreased spending. Extant research reinforces the importance of app adoption, yet the specific set of circumstances and marketing strategies that explain or predict app adoption have not been thoroughly understood, especially on the individual app level. Among the scarce extant literature on post-adoption usage of mobile apps, Ding and Chai (2015) use online surveys and find that positive emotions can increase users' continuance intention with mobile apps. However, empirical research on user retention using real data is still lacking.

Linkage between User Acquisition and Retention

User acquisition and retention are both well-studied constructs in marketing. Each behavior has been modeled in either contractual contexts (e.g., membership subscription or renewal in telecommunication companies or professional organizations) (Thomas, 2001; Schweidel et al., 2008; Braun and Scheweidel et al., 2011, Ascarza and Hardie, 2013) or non-contractual contexts (such as brand switching between airline companies and donation to non-profit organizations) (Blattberg and Deighton, 1996; Rust et al., 2004; Fader et al., 2010). Previous research has demonstrated the importance of accounting for the correlation between acquisition and retention and has modeled the binary adoption decision jointly with lifetime length using a Tobit model (Thomas, 2001; Reinartz et al., 2002). By treating the acquisition decision as a censoring process, the

Tobit modeling framework corrects the potential disproportionate marketing emphasis on retention by accounting for the correlated error structure of acquisition and retention. With richer data (especially on the acquisition process), a few papers have also modeled the timing of both acquisition and retention using a hazard model (Schweidel et al., 2008; Kumar et al., 2014), which allows for the potential dependence of retention on the timing of acquisition. Another advantage of a hazard model framework is that it allows for duration dependence, which further captures the nature of consumers' loyalty behavior over time. For example, Schweidel et al. (2008) model the number of months until households added HBO service jointly with the number of months they retain cable service using monthly subscription data in a contractual context. The study demonstrates this "double dependence" by assuming the Sarmanov family of distributions over two Weibull marginals for the acquisition and retention durations. They find a negative duration dependence in both acquisition and retention processes and a positive correlation between the two.[14] This result suggests that for the particular service, consumers who are acquired later also retain the service for a longer time, and although the likelihood of acquiring a new customer decreases over time, the chance for an acquired user to discard the service also decreases over time. In a non-contractual context, Kumar et al. (2014) model existing customers' joining and withdrawal timing from an e-mail marketing program of a retailer jointly with the transaction amount from purchase. They model the correlation structure using a vine copula in which each pair of the dependent variables are specified as Gaussian or Frank copulas, and the marginals of the durations until joining and withdrawing are specified to follow a Weibull distribution that captures duration

[14] The fit statistics in their paper find in favor of a latent class model with no correlation between the acquisition and retention processes.

dependence. They find a positive correlation and negative duration dependence in both joining and withdrawal processes and a positive correlation between the two, which yields a similar implication as Schweidel et al. (2008). Empirical research on both acquisition and retention processes in non-contractual context is still limited, and is non-existent in the mobile marketing realm.

EMPIRICAL SETTING

The App

We obtain data from a technology company that developed a mobile wallet app for users to pay bills in food and beverage venues. The app is free to download on both iOS and Android operating system smartphones, and registered users can conveniently check out at a collaborating venue by simply clicking through their own mobile phone without the need to walk to the venue's point-of-sale (POS) machine or wait for their server to collect the bill. Occasionally, the app also sends promotional offers to consumers in terms of price discounts or free items at certain venues. These promotions add to the usefulness of the app. With tremendously simplified pay processes, economic incentives and a relatively wide venue network, this mobile wallet app has been growing customer base since 2013.[15]

We summarize user behavior into three major stages: born, acquired and retained. As illustrated in Figure 1, to be "born," a user needs to join the app by registering an

[15] Unlike retailers' branded mobile wallets—like the Starbucks App, or CakePay by Cheesecake Factory—the mobile wallet app in this research can be used in multiple venues as long as the venue has incorporated the app's back-end system. Therefore, it works more like general mobile wallet across venues like Apple Pay or Google Wallet. The app gained access to over 5000 venues nationwide within the first year of its launch.

account (after downloading and installing the app) and linking it to a bankcard. After joining, the user may browse in the app to learn about the app (e.g., the functions, nearby venues or available promotional offers), and the browse can happen either before the user goes to a venue or at a venue. We label the user as "acquired" only when she/he successfully used the mobile wallet app to pay a bill for the very first time. If the user used the app and paid a second bill, we label that person as a "retained" user. Note that our definition for use acquisition and retention are different from conventions in the studies on contractual services. Since the mobile wallet does not require payment for download or installation and there is no contract for the length of usage or penalty for deleting the app, we do not believe that simply downloading or installing the app qualifies as user acquisition in terms of economic behavior for the company. In addition, the mobile wallet's most important function is its payment solution. Therefore, the acts of opening and browsing the app do not quality as user acquisition because those activities do not create any revenues for the app developer or collaborating venues and brands (unlike social media apps or gaming apps where browsing is a more important activity). The only meaningful activity to signify acquisition is through actual payment through the mobile wallet service. The same logic applies for the definition of retention.

---Insert Figure 1 About Here---

Data and summary statistics

The sample contains data from 5121 users who joined the app during 1 June 2015 to 1 September 2016 in a large metropolitan statistical area in Texas. The company employed two distinct marketing regimes with the "New User Offer" promotion

campaign and experimented with promotion depth over a 16-month period as illustrated in Figure 2. All users who joined the app from 1 October 2014 to 30 June 2015 were offered a "$10 off" coupon that could be redeemed in any venue for a bill no less than $11. The campaign paused for a month from 1 July 2015 to 31 July 2015, and the company did not give the special "New User Offer" to users who joined the app during that time frame. The campaign resumed on 1 August 2015, and users who joined the app during the 1 August to 1 February 2016 period were offered a "$5 off" coupon for redemption of a bill no less than $6 at any venue. During this 16-month period the app also offered other types of coupons (e.g., branded offer or venue-sponsored offer), but none of the offers were changed systematically. Thus, the "New User Offer" campaign created a quasi-experimental setup for researchers to investigate the effect of marketing regimes as "born" conditions on subsequent user acquisition and retention.

---Insert Figure 2 About Here---

During the three-month observation window from 1 June 2015 to 31 August 2015, 1755 users were "born" during June 1st to June 30th 2015 under Regime 1 when "$10 off" was offered to newly registered users, who are labeled as Cohort A. 1532 users were "born" during 1 July 2015 to 31 July 2015 when no new user offer was available, and this group of users are labeled as Cohort B. Finally, 1834 users were "born" during 1 August 2015 to 31 August 2015 under Regime 2 when "$5 off" was offered to newly registered users, and this group of users are labeled as Cohort C. Note that users had no prior knowledge of the "New User Offer" campaign nor how long the offer lasts; hence, it is impossible for them to self-select which cohort to be "born" into based on the promotion. In addition to the quasi-experimental setup, one advantage of sampling the

cohorts during these three adjacent 1-month windows is that there was unlikely to be any major change in consumer behavior or external market environment for the mobile wallet. Therefore, there is no or minimal cohort effect due to the promotion experiment or time of year. Based on the summary statistics in Table 1, users across the three cohorts do not differ much in terms of overall app usage or device characteristics.

---Insert Table 1 About Here---

The key variables of interest in this study are the timing of acquisition and retention. We observe each user for 4800 hours[16] (i.e., 200 days) and compute the acquisition duration and retention duration, operationalized as the number of hours elapsed between "born" and "acquired" and the number of hours between "acquired" and "retained" respectively. Any "acquisition" and "retention" activity beyond the observation window is denoted as a censored observation, and we need to account for the right censoring in our model. The summary statistics in Table 2 shows on average it takes users in Cohort A and C a little less time to be acquired as compared to Cohort B, while the retention duration has a reverse pattern. This difference indicates that being "born" under the "New User Offer" promotion campaign may have an effect on both the acquisition and retention processes.

To ensure that these three cohorts are comparable on all stages of app usage, we further summarize a few behavior variables that represent users' responses to the marketing and operational factors at the time of acquisition and retention such as "Spend"

[16] We do not impose a single cut-off time for all so that we can derive more information from the data. We choose 4800 hours as the cut-off time so that each user has long enough time to explore the app and make decisions on usage.

"Facevalue", "Check-in_A" and "Check-in_R" presented and operationalized in Table 2 as well. A preliminary observation of Table 1 and Table 2 suggests that on average, fewer users in Cohort B redeemed coupons at the time of acquisition, and the face value of the coupon is also smaller as compared to Cohorts A and C. This difference likely exists because Cohort B had no "New User Offer" to redeem. Despite the potential for different coupon redemption behavior, the total net spend amounts are not that different across cohorts. In addition, the number of check-ins to the app before acquisition and retention are similar across cohorts. Our modeling interests are to investigate (1) the effects of these different "born" conditions on both acquisition and retention durations; and (2) the "acquisition" condition on retention duration, from both marketing and operational perspectives.

---Insert Table 2 About Here---

PROPOSED MODELING FRAMEWORK

We propose a bivariate timing model to jointly model users' acquisition and retention durations of the mobile wallet app. We incorporate duration dependence in each of the two processes by adopting a proportional hazard model, and we account for the correlation between the two processes using a bivariate Gaussian copula model.

Modeling multivariate durations is not a new practice in marketing, and in the extant literature, there have been two major approaches. On one track, Park and Fader (2004) use the Sarmanov family distribution to account for the correlation of visit duration between two websites. Under the same modeling framework, Schweidel et al. (2008) use the Sarmanov family distribution to model the correlation between acquisition

and retention durations of a cable TV service. On the other track, Danaher and Smith (2011) introduce the Gaussian copula to model both bivariate responses (e.g., durations of website visit and transaction amount) and multivariate response (e.g., ad exposure of different magazines). Kumar et al. (2014) use both a Gaussian copula and a Frank copula to model the correlation among two durations and the transaction amount.

We adopt the copula modeling framework because of two desired properties. First, it establishes a flexible modeling framework that easily extends to higher dimensional applications[17] if we desire to model multiple processes beyond acquisition and retention in the future. Second, unlike the Sarmanov family of distributions, a Gaussian copula allows for a wide range of correlation coefficients between pairs in the multivariate random variables (almost the full (-1, 1) range), which becomes a less restrictive and more robust choice for various applications (Danaher and Smith, 2011; Song, 2000).

Marginal models for acquisition duration and retention duration

We model both acquisition and retention processes using a Weibull proportional hazard model (Jain and Vilcassim, 1991) for the desired flexibility of a Weibull distribution as it allows for both positive and negative duration dependence. For user $i = 1,...,N$, Let (T_i^B, T_i^A, T_i^R) denote the observed time of "born", "acquired" and "retain"

[17] As the dimension m increases, the number of parameters in the multivariate Gaussian copula density function increases only by the order m^2, which is much slower than other popular choices of multivariate distributions, such as the Sarmanov family of distributions (Farlie-Gumbel-Morgenstern copula), when the number of parameters increases by the order of 2^m.

respectively (Figure 1), and let C_i denote the censoring time.[18] First, let us consider user acquisition. Let $t_{i1} = \min(T_i^A - T_i^B, C_i - T_i^B)$ denote the observed acquisition duration—that is, the time it takes for user i to successfully use the mobile wallet service to pay bills since he or she joins the app. We assume that this duration follows a Weibull distribution with shape parameter α_1 and scale λ_1. The probability of acquiring the mobile wallet service at time t_{i1} is given by:

(1) $$f_1(t_{i1} \mid \alpha_1, \lambda_1, X_i, \beta) = \alpha_1 \lambda_1 \exp(X_i \beta) t_{i1}^{\alpha_1 - 1} \exp\{-\lambda_1 \exp(X_i \beta) t_{i1}^{\alpha_1}\} \ .$$

Given the density function, we can represent the hazard function as proportional hazard with Weibull baseline hazard $h_{01}(t_{i1})$ and hazard from some covariates. The hazard and survival functions, respectively, are given by:

(2) $$h_1(t_{i1} \mid \alpha_1, \lambda_1, X_i, \beta) = h_{01}(t_{i1}) \exp(X_i \beta) = \alpha_1 \lambda_1 t_{i1}^{\alpha_1 - 1} \exp(X_i \beta)$$

and

(3) $$S_1(t_{i1} \mid \alpha_1, \lambda_1, X_i, \beta) = \exp\{-\lambda_1 \exp(X_i \beta) t_{i1}^{\alpha_1}\}$$

where X_i is a vector of covariates that may affect user i's acquisition decision, and β is the effects of the covariates. If we observe the actual acquisition duration during the observation period, i.e., if $T_i^A \le C_i$, the acquisition censoring variable $k_{i1} = 1$; otherwise, $k_{i1} = 0$. The likelihood function of user i's acquisition process can be represented as:

[18] In this paper, we allow C_i to be individual-specific, and give each user 4800 hours as the observation period.

(4) $$L_{i1}(\alpha_1,\lambda_1,\beta) = f_1(t_{i1} \mid \alpha_1,\lambda_1,X_i,\beta)^{k_{i1}} S_1(t_{i1} \mid \alpha_1,\lambda_1,X_i,\beta)^{1-k_{i1}} \ .$$

After a user is acquired, we have the opportunity to further observe how long it takes him or her to reuse the mobile wallet service as a retained user since acquisition. Let $t_{i2} = \min(T_i^R - T_i^A, C_i - T_i^A)$ denote the observed retention duration, which is assumed to follow a different Weibull distribution governed by shape parameter α_2, and scale parameter λ_2. We can apply the same proportional hazard specification, and represent the marginal density function as:

(5) $$f_2(t_{i2} \mid \alpha_2,\lambda_2,Z_i,\gamma) = \alpha_2\lambda_2 \exp(Z_i\gamma) t_{i2}^{\alpha_2-1} \exp\{-\lambda_2 \exp(Z_i\gamma) t_{i2}^{\alpha_2}\} \ ,$$

The corresponding hazard and survival functions are:

(6) $$h_2(t_{i2} \mid \alpha_2,\lambda_2,Z_i,\gamma) = h_{02}(t_{i2}) \exp(Z_i\gamma) = \alpha_2\lambda_2 t_{i2}^{\alpha_2-1} \exp(Z_i\gamma)$$

and

(7) $$S_2(t_{i2} \mid \alpha_2,\lambda_2,Z_i,\gamma) = \exp\{-\lambda_2 \exp(Z_i\gamma) t_{i2}^{\alpha_2}\} \ ,$$

where Z_i is a vector of covariates that may affect user i's retention decision, and γ is the effects of the covariates on retention hazard. If we observe the actual retention duration during the observation period, i.e., if $T_i^R \le C_i$, the retention censoring variable $k_{i2} = 1$; otherwise, $k_{i2} = 0$. For those acquired users, the likelihood function of user i's retention process can be represented as:

(8) $$L_{i2}(\alpha_2,\lambda_2,\gamma) = f_2(t_{i2} \mid \alpha_2,\lambda_2,Z_i,\gamma)^{k_{i2}} S_2(t_{i2} \mid \alpha_2,\lambda_2,Z_i,\gamma)^{1-k_{i2}} \ .$$

The shape parameters in the marginal Weibull hazard models capture the duration dependence of the two processes. Taking the acquisition process as an example, if there is positive duration dependence, i.e., $\alpha_1 > 1$, then the longer time passed since users joined the mobile wallet service, the more likely they are to use the app. If there is negative duration dependence, i.e., $\alpha_1 < 1$, then the longer it has been since users joined the app, the less likely they are to use the mobile wallet service. If there is no duration dependence, i.e., $\alpha_1 = 1$ (the nested exponential hazard model), then acquisition hazard is constant over time and solely depends on other factors such as marketing promotion. The shape parameter of the retention hazard model α_2 can be interpreted similarly. By allowing for different shape parameters in the marginal hazard models, we intend to empirically explore whether there are duration dependencies in the acquisition and retention processes, and whether the two processes work differently over time for the app users.

In the acquisition hazard model in equation (2), $X_i =$ (NEWUSER$_i$, CHECK-IN$_i$, IOS$_i$, V4.2PLUS$_i$). NEWUSER relates to the availability of the introductory promotion at the time of joining the app, while CHECK-IN, IOS, and V4.2PLUS are operational-related factors during t_{i1} (i.e., between joing the app and acquisition). To model retention hazard model in equation (6), we specify $Z_i =$ (NEWUSER$_i$, OFFER$_i$, SPEND$_i$, FACEVALUE$_i$, BRAND$_i$, VENUE$_i$, SOCIAL$_i$, CHECK-IN$_i$, IOS$_i$, V4.2PLUS$_i$). Similarly, as in the acquisition model, NEWUSER relates to the availability of the introductory promotion at the time of joining the app. Differently from the acquisition model, CHECK-IN, IOS, and V4.2PLUS in the retention model are operational-related

factors during t_{i2} (i.e., between acquisition and retention). In addition, OFFER, SPEND, FACEVALUE, BRAND, VENUE, SOCIAL are a set of transaction related variables to capture the effects of the acquisition conditions on users' retention.

Effects of marketing and operational efforts on acquisition and retention

One question posed in this paper investigates how different introductory marketing promotions (i.e., "born" conditions) affect subsequent user decisions on time to acquire and retain within the mobile wallet service. A second question concerns how other operational factors affect the two processes. We operationalize NEWUSER$_i$ as an indicator for being born under the "New User Offer" promotion regimes of user i, which refers to Cohorts A or C. We expect this "born" condition to positively affect acquisition hazard because this "New User Offer" is specifically designed to attract users to pay their very first bill with the app. The effect of NEWUSER$_i$ on retention hazard is, however, not clear. On one hand, having a promotion could motivate users to use the app again in order to discover more benefits. On the other, it could also attract a wrong group of users who are not genuinely interested in the mobile payment service. The latter users may instead be only interested in the promotional deals and be thus less likely to reuse the app.

In terms of operational factors, we operationalize CHECK-IN$_i$ as the count of "check-in" that user i has cumulated, and a higher value indicates a higher level of interest in the app. We expect CHECK-IN to have a positive effect on both the acquisition (CHECK-IN_A) and retention hazards (CHECK-IN_R), because the more times users open the app, the more likely they are to use the service. IOS$_i$ represents an indicator for the operating system of user i's smartphone, and we are interested in finding

out whether there is a systematic difference between iPhone (i.e., IOS_i =1) and Android users (i.e., IOS_i =0). Several minor app version upgrades occurred during the observation period, and $V4.2PLUS_i$ is operationalized to indicate whether user *i* is using version 4.2 of the app, which is a more advanced version. Although we do not observe detailed characteristics of different versions of the app, we understood from the company that the more advanced version functions more efficiently and is more user-friendly. These upgrades provide a smoother user experience, and we expect this version indicator to have a positive effect on user acquisition and retention.

Effects of acquisition condition on retention

This paper's second research question concerns the effects of different acquisition conditions—that is, users' behavior and responses to marketing and operational variables at the time of acquisition—on the retention process. Unlike the two marketing regimes wherein users are "born", users experience diverse acquisition conditions due to numerous variables that situate a transaction occurring at a food or beverage venue. We summarize acquisition conditions in terms of users' transaction behavior at acquisition.

We operationalize $OFFER_i$ as an indicator if user *i* redeemed a coupon at acquisition. Previous research has found a positive effect of using m-coupons on concurrent purchases in field studies (Fong et al., 2015; Andrews et al., 2015), but the effect of m-coupons on future purchase has not been studied in the mobile context. Being able to redeem a coupon *could* make the app more enticing and encourage another purchase; or, coupon usage at the acquisition stage could raise users' promotion expectations on future purchases and delay purchase if no coupons are found.

$FACEVALUE_i$ is operationalized as the monetary value of the coupon (e.g., price discounts or free items) if user *i* redeemed one at acquisition. Previous research on mobile promotion have found a positive effect of coupon's face value on both purchase (Fong et al., 2015) and coupon redemption (Danaher et al., 2015). However, again, the effect of the monetary value of a coupon on subsequent purchase has not been studied and like the act of coupon redemption, remains empirically ambiguous.

We operationalize several coupon feature-related variables to control for the type of the coupon. $BRAND_i$, $VENUE_i$ and $SOCIAL_i$ indicate whether the coupon that user *i* redeemed at acquisition is related to a specific brand (e.g., a free drink from a beer brand), whether it is related to a specific venue (e.g., a promotion exclusive to that establishment), or whether the new user is referred to the app by a friend who is already an existing user, respectively. These types of coupons are independent of the "New User Offer" promotion regime and were available throughout the entire observation period. We expect BRAND and VENUE to have positive effect on retention because users are likely to be more familiar with or loyal to a brand or venue in comparison with a new mobile wallet app. Thus, we anticipate that redeeming a coupon from an established brand or venue could greatly increase the attractiveness and usefulness of the app and encourage future usage. Research on online word of mouth (WOM) suggests that WOM referrals have a longer carryover effect and higher response elasticities as compared to traditional marketing (Trusov et al., 2009); hence, we expect SOCIAL to have a positive effect on retention as well. The last behavior variable studied at acquisition is $SPEND_i$, which we operationalize as user *i* 's net spend, representing the total bill less the promotional discount. $SPEND_i$ characterizes the willingness of user *i* is to spend out-of-

pocket at the venue, and lower values could indicate either a low level of interest in consuming at the venue or a high level of interest in consuming just to redeem the coupon. Thus, the effect of $SPEND_i$ may be ambiguous.

Modeling the dependence between acquisition and retention

The direct effects of acquisition conditions on retention in equation (6) reveal only one aspect of the relationship between user acquisition and retention, which are dependent processes because they reflect two subsequent behaviors of the same user. The correlation between these two dimensions of a mobile app service is still unknown to researchers, but it is critical for marketers to understand the correlation when designing marketing promotions. To capture the potential correlation between user acquisition and retention, we employ a Gaussian copula to model the bivariate hazard with each of the marginal models taking the form of equations (1) through (8).

To illustrate the setup, suppose that U_1 and U_2 are random variables with marginal density function $f_1(U_1)$ and $f_2(U_2)$, respectively; and let $f(U_1,U_2)$ denote the joint density function for the bivariate random variable $U=(U_1,U_2)$. According to Sklar's theorem (1959), the joint density can be expresses as follows:

(9) $$f(U_1,U_2)=c(F_1(U_1),F_2(U_2))\times f_1(U_1)\times f_2(U_2)$$

where $F_1(U_1)$ and $F_2(U_2)$ are the CDF's of U_1 and U_2, respectively, and $c(F_1(U_1),F_2(U_2))$ is the copula distribution function. As mentioned at the beginning of this section, to account for the correlation between the acquisition and retention processes, we choose the Gaussian copula function because of two desired properties.

First, the Gaussian copula establishes a flexible modeling framework that easily extends to higher dimensional applications[19] if we desire to model multiple processes beyond acquisition and retention in the future. Second, the Gaussian copula allows for a wide range of correlation coefficients between pairs in the multivariate random variables (almost the full (-1, 1) range), which therefore become less restricting and more robust a choice for various applications (Danaher and Smith, 2011; Song, 2000).

Furthermore, we consider survival copulas in our model specification to account for the right censoring of data in our empirical application, and it is equivalent to model with copulas (Kumar et al., 2014; Shih and Louis, 1995). With the choice of Gaussian copula, we can represent the bivariate joint density for the observed acquisition and retention durations as follows:

$$
\begin{aligned}
f(t_{i1}, t_{i2}) &= c(S_1(t_{i1}), S_2(t_{i2})) \times f_1(t_{i1}) \times f_2(t_{i2}) \\
&= \frac{1}{\sqrt{1-\rho^2}} \exp\{\frac{\rho^2(\bar{\omega}_{i1}^2 + \bar{\omega}_{i2}^2) - 2\rho\bar{\omega}_{i1}\bar{\omega}_{12}}{2(1-\rho^2)}\} \times f_1(t_{i1}) \times f_2(t_{i2}),
\end{aligned} \tag{10}
$$

where ρ is the correlation coefficient, $\bar{\omega}_{i1} = \Phi^{-1}(S_1(t_{i1}))$, $\bar{\omega}_{i2} = \Phi^{-1}(S_1(t_{i2}))$, and $\Phi^{-1}(.)$ is the inverse of the standard normal CDF.

Accounting for right censoring in the data

We need to consider three possible scenarios of censoring in our application. The first scenario is when user i has not acquired the mobile wallet service yet during the

[19] As the dimension m increases, the number of parameters in the multivariate Gaussian copula density function increases only by the order m^2, which is much slower than other popular choices of multivariate distributions, such as the Sarmanov family of distribution (Farlie-Gumbel-Morgenstern copula), once number of parameters increases by the order of 2^m.

observation period $(k_{i1} = 0)$. The time of acquisition in this particular scenario lies in the interval $t_{i1} \in (C_i, \infty)$, and the probability that user i acquires the mobile wallet service after time C_i is the marginal survival function $S_1(t_{i1})$ given by equation (3).

The second scenario is when user i acquired the mobile wallet service but has not used it a second time during the observation period $(k_{i1} = 1, k_{i2} = 0)$. In this scenario, we need to consider the probability that user i retains the mobile wallet service after time C_i conditional on his or her acquisition duration t_{i1}, represented as the conditional survival function $S_2(t_{i2} \mid t_{i1})$. Under the bivariate Gaussian copula assumption for the joint density, the conditional survival function is (Kumar et al., 2014):

$$S(t_{i2} \mid t_{i1}) = \Phi\left(\frac{\bar{\omega}_{i2} - \rho\bar{\omega}_{i1}}{\sqrt{1-\rho^2}}\right) , \tag{11}$$

where $\Phi(.)$ is the standard normal CDF. Therefore, the unconditional probability that user i retains the mobile wallet service after time C_i is $f_1(t_{i1}) \times S_2(t_{i2} \mid t_{i1})$.

The third scenario is when user i is retained during the observation period and there is no censoring in either the acquisition or retention time $(k_{i1} = 1, k_{i2} = 1)$. In this scenario, the probability that user i acquires the mobile wallet service in t_{i1} and retains the service in t_{i2} is $f(t_{i1}, t_{i2})$ given in equation (10).

The user-level likelihood can then be expressed as:

$$
\begin{aligned}
L_i(\alpha_1,\lambda_1,\alpha_2,\lambda_2,\beta,\gamma,\rho \mid t_{i1},t_{i2},X_i,Z_i,k_{i1},k_{i2}) &= S_1(t_{i1} \mid \alpha_1,\lambda_1,\beta,X_i)^{1-k_{i1}} \\
&\times (f_1(t_{i1} \mid \alpha_1,\lambda_1,\beta,X_i) S_2(t_{i2} \mid t_{i1},\alpha_2,\lambda_2,\gamma,\rho,Z_i)^{k_{i1}(1-k_{i2})} \\
&\times f(t_{i1},t_{i2} \mid \alpha_1,\lambda_1,\alpha_2,\lambda_2,\beta,\gamma,\rho,X_i,Z_i)^{k_{i1}k_{i2}}
\end{aligned} \quad , \tag{12}
$$

and the overall log-likelihood function is:

$$
\begin{aligned}
&LL(\alpha_1,\lambda_1,\alpha_2,\lambda_2,\beta,\gamma,\rho \mid t_{i1},t_{i2},X_i,Z_i,k_{i1},k_{i2}) \\
&= \sum_{i=1}^{N} \log(L_i(\alpha_1,\lambda_1,\alpha_2,\lambda_2,\beta,\gamma,\rho \mid t_{i1},t_{i2},X_i,Z_i,k_{i1},k_{i2}))
\end{aligned} \quad . \tag{13}
$$

Model estimation

We follow a two-stage procedure that has been shown to yield consistent estimates for the model parameters (Shih and Louis, 1995; Danaher and Smith, 2011; Kumar et al., 2014). In the first stage, we estimate the parameters of each marginal model specified in equations (1)–(8) using maximum likelihood estimation. Then we estimate the correlation parameter ρ of the bivariate Gaussian copula while fixing the parameters of the marginal models estimated from the first step. The log-likelihood function we maximize in this step is given as follows:

$$
LL(\rho) = \sum_{i=1}^{N} (k_{i1}k_{i2} \log\{c(S_1(t_{i1}),S_2(t_{i2}))) + k_{i1}(1-k_{i2}) \log\{S_2(t_{i2} \mid t_{i1},\alpha_2,\lambda_2,\gamma,\rho,Z_i)\}) \tag{14}
$$

in which only data from acquired users are used because the correlation parameter must depend on observed acquisition time. In the second stage, we use the point estimates from the previous stage as initial conditions and maximize the full log-likelihood function specified in equation (13) with respect to all the parameters.

RESULTS

We estimate two models using maximum likelihood estimation in R. Model 1 is our proposed bivariate duration model with Gaussian copula (joint model) specified in equations (1)–(14). Model 2 is a baseline model that treats acquisition and retention as independent processes and overlooks the correlation between the two (marginal model). We compare the fit of the models in Table 3. Based on log-likelihood and Bayesian information criterion (BIC), our proposed model fits the data better than the marginal model.

---Insert Table 3 About Here---

Table 4 reports the parameter estimates from the model (Model 1) and the baseline model (Model 2). By taking account of the correlation between the two processes, Model 1 yields estimation that is more efficient with narrower confidence intervals. We focus on interpreting parameter estimations from Model 1 in the following subsections.

---Insert Table 4 About Here---

Duration dependence

We start by discussing duration dependence in both the acquisition and retention processes. The shape parameters α_1 and α_2 from the marginal Weibull models are both smaller than one, indicating negative duration dependence in both processes. As illustrated in Figure 3, this result means that the baseline hazards $h_{01}(t_{i1})$ and $h_{02}(t_{i2})$ both decrease over time. We expected the negative duration dependence due to the nature

of services like the focal mobile wallet. That is, many users join the app, often even at a specific venue, for immediate usage of mobile payment service; therefore, as time elapses since users join the app without using it successfully to make a payment, users are less likely to remember to use it again. Similarly, for retention where the baseline hazard starts at a lower level, the longer time has passed since acquisition, the less likely users will remember to use it again. Figure 3 shows that the baseline hazard rate for both acquisition and retention drop rapidly within a few hours to half a day since users join the app, and after 20 hours (about a day), the baseline hazard plateaus.

Research on bivariate durations provides benchmarks for the results of this study. Schweidel et al. (2008) model user acquisition and retention durations for a paid cable service, and Kumar et al. (2014) model opt-in and opt-out durations for an e-mail marketing campaign. A negative duration dependence is found in both papers, suggesting that the events are less likely to happen as time goes by. However, the nature of behavior behind the negative duration dependence of the retention duration in our study differs from both of those previous studies. In both of the studies, the second event represents "exit"[20] and a negative duration dependence of the retention process is good news as customers are less likely to exit as time goes by. However, the second event in our study represents "re-entry" so although a negative duration dependence makes sense in our context, it is not an optimistic finding for marketers as it essentially indicates the app's decreasing attractiveness.

[20] In Schweidel et al. (2008), the retention duration represents the duration of remaining in the service, and in Kumar et al. (2014), the opt-out duration represents the duration of accepting the e-mail marketing campaign.

---Insert Figure 3 About Here---

Introductory marketing regimes at "born" on acquisition and retention

Our first research question concerns the effects of different "born" conditions on user acquisition and retention of our focal mobile wallet app. The coefficient β_1 of NEWUSER from Table 4 is significant and positive, and it indicates that being "born" under the "New User Offer" marketing regimes increases the acquisition hazard. If we compare the hazard ratio between user i in Cohort A or C and user j from Cohort B, keeping everything else constant, the hazard for user i to be acquired is 1.105 times that for user j.

On the retention hazard, the coefficient γ_1 of NEWUSER from Table 4 is not significant from our joint model, indicating that being "born" under the "New User Offer" regimes has no effect on the retention process. Notably, if we ignore the correlation between acquisition and retention and model them independently, as Model 2 demonstrates, being "born" under the "New User Offer" regimes has a positive effect on the retention hazard, which could lead to an overestimation on the actual effect of the "New User Offer" promotion campaign.

Effects of acquisition conditions on retention

We answer the second research question on the direct effect acquisition conditions may have on user retention by examining the section of parameter estimates on the retention equation in Table 4 (i.e., γ_2 through γ_7). The negative coefficient estimate of OFFER (i.e., γ_2) indicates that using a coupon at acquisition discourages user

retention. If we compare a user who redeemed a coupon at acquisition with one who did not, the hazard ratio of retention of the former is only 0.72 times that of the latter. This finding differs from previous research on the effect of using m-coupons on concurrent purchases (Fong et al., 2015; Andrews et al., 2015). It suggests that users acquired with a coupon may raise their expectations for the next purchase, and hence such users may be more difficult to retain.

We examine the effects of coupon features as well. The statistical insignificance of the coefficient estimate of the interaction term OFFER × FACEVALUE (i.e., γ_4) suggests no effect of monetary value of the coupon. In terms of types of coupon, our model suggests that BRAND coupon is the only helpful type.[21] Additionally, compared with a user acquired using other types of offer (i.e., other than BRAND, VENUE and SOCIAL), a user who is acquired with a brand-related offer has 1.46 times the retention hazard of the former. Users are not particularly loyal to the venue even if they are acquired using a VENUE coupon, and a SOCIAL coupon through friend referral does not appear to encourage repeated usage of the app. These results concerning coupon features are not completely consistent with previous findings on m-coupon (Fong et al., 2015; Danaher et al., 2015) or WOM referral ads (Trusov et al., 2009), and they may suggest a new pattern of consumer behavior in the context of mobile wallet app.

The coefficient estimate of SPEND (i.e., γ_3) is negative, indicating that users who spend more money at acquisition are less likely to reuse the app. After transforming back to the original scale (i.e., dividing the coefficient estimate by the range), our model

[21] Although the independent model suggests that SOCIAL coupon also has a positive effect on retention, once we account for the correlation between acquisition and retention, the effect is not significant anymore.

suggests that spending $10 more at acquisition will lower the a hazard ratio to 0.985, and spending $100 more at acquisition will lower the hazard ratio to 0.86. This result could be caused either by a loss of interest in the app after realizing that the app does not prove useful economically at acquisition or by a natural consequence of infrequent consumption of expensive meals.

Operational factors on acquisition and retention

Moving to the third research question, we examine how operational factors affect both user acquisition and retention. The coefficient estimates of CHECK-IN_A (i.e., β_2) and CHECK-IN_R (i.e., γ_8) are both significant and positive. These results suggest that more check-ins to the app encourage both acquisition and retention. After transforming the coefficient to the original scale, we find that one more check-in to the app between "born" and "acquired" increases the acquisition hazard ratio to 1.186, and five more check-ins increase the acquisition hazard ratio to 2.35. For the retention process, one more check-in to the app between "acquired" and "retained" increases the retention hazard ratio to 1.005, and five more check-ins increase the retention hazard ratio to only 1.024. Therefore, the effect of CHECK-IN on acquisition is larger than that on retention. This finding is consistent with our expectation that the positive effect may be caused by a higher level of interest in the app. However, the interest level does not increase linearly in time and could plateau very soon after acquisition.

The coefficient estimate for the app version indicator (V4.2PLUS) also suggests that distinct attributes of the app based on different product versions will affect acquisition and retention processes in various ways. The estimate β_4 is not significant,

and γ_{10} is significant and positive, indicating that using a more advanced version does not affect user acquisition, but an app update to an advanced version greatly encourages retention. The null effect on acquisition could be mitigated by a curiosity factor at earlier stages when users do not know the app and would make the effort to use the app regardless of whether it is easy to use. However, ease of use and high system quality increase repeated usage. Thus, our research is consistent with extant research under the TAM framework (Schierz et al., 2010; Lu et al., 2011; Zhou, 2013)

An examinination of the effect of operation system suggests that the iOS indicator has a positive effect on acquisition but a negative effect on retention. Without much data on user demographics, we cannot say that iPhone users are more likely to be acquired and less likely to stay with the service because of their unique personality.

Dependence between acquisition and retention

Finally, we investigate the correlation between acquisition and retention processes, and this completes the remaining dependence between the two that cannot be accounted for through the direct effect of acquisition on retention. We find a negative correlation between user acquisition and retention, and the estimated correlation coefficient ρ is -0.3537. We need to interpret the correlation coefficient with the duration dependence in the acquisition and retention processes. Users are decreasingly likely to be acquired over time, and for acquired users, the faster they are acquired, the longer it takes for them to reuse the app. Compounded by the negative dependence duration of the retention process, the current analysis depicts a challenging scenario for the company.

Notably, both Schweidel et al. (2008) and Kumar et al. (2014) find positive correlation between the two durations. Since the goal for the second event is reversed from our study, the implications from the negative correlation between the two are essentially similar to ours. To turn around the current adverse situation, it is important for the company to rethink current marketing and operational efforts and spend limited resources on users who are more likely to retain.

CONCLUSIONS AND IMPLICATIONS

In this paper, we have jointly modeled user acquisition and retention of a mobile wallet app through a bivariate timing model. Built on a unique dataset that contains individual-level actual app usage data from 5121 users, the model empirically investigates the effects of marketing and operational efforts on both user acquisition and retention processes within an emerging mobile wallet app. In addition, the model accounts for two types of relationships between user acquisition and retention: the direct effect of acquisition conditions on retention and the correlation between the two.

This study is ground on the intersection of mobile marketing and research on consumers' acquisition and retention decisions. While other work in mobile marketing has examined factors leading to the adoption and continued usage of mobile apps, those extant findings are all based on survey responses. While other work on consumers' loyalty behaviors has jointly modeled acquisition and retention durations, very few focus on the non-contractual context, and nothing yet has been done in the mobile context. To the best of our knowledge, this study is the first to address user acquisition and retention jointly using real data in the context of the emerging mobile wallet category.

Our analysis yields several findings that have important managerial implications. First, we find that the introductory marketing regimes at the "born" stage of app usage encourage user acquisition but have no effect on retention. Second, users acquired with a promotional coupon, regardless of face value, are less likely to retain usage. This result could possibly be due to increased user expectations of the app. Third, operational variables—such as check-ins to the app, app version and operating system of the mobile device—affect acquisition and retention non-linearly. Finally, negative duration dependence in each of the two processes compounded by a negative correlation between the two outcomes reveals an unfavorable scenario for the focal app, suggesting a need for improvements in both marketing and operational efforts.

It is never an easy task to build or market a new app with an instantly high level of "stickiness" and a sustainable user base. For a mobile wallet app that works in a particular industry (e.g., food and beverage venues only), inducing consumers' habit of usage and loyal behavior can be more difficult to achieve due to a lack of established brand equity. The results of our study suggest alternative loyalty programs in the future. These alternatives include collaboration with established brands because many consumers seem to be more loyal to the collaborating brand than to the app. Therefore, offering branded items is a more effective strategy in driving retention than is a traditional price discount.

From the operational and engineering perspectives, our study also offers empirical evidence for the importance of keeping users interested in the app and of frequently reminding users of the technology with app updates. More research in this vein is necessary. This study is limited by the lack of information on app features across versions

and on the features of the same version on different operation systems. It is too early to conclude that iPhone users behave differently from Android users or that Version 4.2 is easier to use than Version 4.1 of the app. Future research on app features and performance will be informative in giving instructions on product design of such a mobile wallet app.

Accounting for the commonly found negative correlation between user acquisition and retention, our analysis suggests it worthwhile to find mindful users who will take time to learn about the app before rushing quickly to use it and then forgetting about it. This will require segmenting the current sample into groups based on their loyalty behavior and app usage so that the company could find an ideal group of consumers in which to invest. For example, it would be ideal to identify a group of users who has less negative duration dependence (or even positive duration dependence) in the acquisition process or a group of users who are less deal-driven and truly value the mobile wallet service. We hope this paper serves as a starting point for future investigations in this endeavor.

Essay 2: User Experience, Engagement, and Purchase Decisions of a Hybrid Mobile Wallet Application

INTRODUCTION

The successful diffusion of smartphones and wireless technologies worldwide has made the mobile industry one of the most active fields for marketers in recent years. In 2015, ad spending for the mobile platform reached $20.7 billion, which represent a 66% growth from 2014 and 100% growth from 2010. In addition to its role as a highly interactive ad media, mobile platform offers numerous business opportunities through mobile applications (apps). More companies are opting in to create a new mobile products or services or are extending existing business to the mobile platform, turning mobile commerce (m-commerce) into a natural extension of e-commerce.[22]

Growing along with the scope of m-commerce is the rising popularity of mobile wallet apps. A mobile wallet app refers to an app that enables payment services from or via a mobile device. This revolutionary payment option liberates consumer from carrying cash or handing bankcards to cashiers, who are usually strangers, when making a payment. Thus, mobile wallets provide a great deal of convenience and security for transactions in both online and brick-and-mortar stores.

Like mobile apps in other categories, however, mobile wallet apps suffer from notoriously low usage rates and even lower repeat usage, despite optimistic industry forecasts and increasing consumer awareness. Only one third of smartphone users in North America made a mobile payment in 2016, and that number has not grown since the

[22] By September 2016, the number of apps on Google Play Store, the largest mobile app store, has reached 2.4 million, which is an increase of 71% from February 2015. In addition, one third of online transactions were completed via mobile devices in 2015.

previous year. Apple Pay, the most recognized mobile wallet, experienced a 41% decrease in repeat usage in the first quarter of 2016 as compared to same time in 2015. Because of the increasing capital funneled into mobile payment, understanding what drives usage and repeat usage of a mobile wallet app has never been more critical, and yet remains an unanswered question for marketers.

In this paper, we empirically investigate factors that predict mobile users' app usage behavior from the perspective of user experience, user engagement and purchase decisions with a mobile wallet app. User experience and engagement are two critical and closely-related concepts in research on human-computer interaction. Nielson Norman Group generally defines user experience as all aspects of an end user's interaction with the web company, its services, and its products. User engagement, on the other hand, refers to the quality of user experience with an emphasis on the positive aspects of the interaction between an end-user and a web application (Lehmann et al., 2012). In the online environment, various theories have been developed to define, understand and measure user experience and user engagement, yet researchers have not reached an agreement on a single standard answer. Study results often depend on the empirical contexts and application types.

Compared to internet browsing on a computer, user experience and user engagement with mobile apps could be more challenging to manage due to the limitations of smaller screens and users' shorter attention spans. Therefore, the effort requires an integrated approach from design, engineering and marketing perspectives to understand the substance and drivers a mobile user's experience and engagement with an app. Despite some general constructs—such as perceived usefulness and perceived usability

(for user experience) and time spent (for user engagement)—extant research on user experience and user engagement focuses heavily on the gaming and online shopping contexts. Thus, factors that constitute meaningful and positive user-app interaction in the mobile wallet context are largely unknown. In addition, previous literature on user experience and user engagement relies generally on the psychometric measurements based on survey responses, which may not reflect users' actual usage of mobile apps. Therefore, it is necessary to incorporate actual data that contains observed users' behaviors and interactions with the app.

This essay intends to bridge a gap in the research on mobile marketing and human-computer interaction by investigating the following questions: first, what are the most important elements of user experience that contribute to user engagement for a mobile wallet app? Second, how do user experience and user engagement affect purchase decisions (conversion and amount) with a mobile wallet app? Third, how do marketing and operational factors affect user engagement and purchase decisions?

To investigate these questions, we analyze a unique data set from an interesting hybrid mobile wallet app that contains individual-level, tap-stream data with complete browsing and purchase history from a cohort of app users and their responses to the company's marketing and operational efforts, such as m-coupons and app version upgrading. The results of the analysis yield empirical findings on user experience consistent with the flow model (Novak et al., 2000). We find that engagement has an intermediate role in the relationship between user experience and user engagement. A purchase during the previous day has a negative carry-over effect on user engagement and purchase conversion. In addition, marketing promotions only affect purchase

conversion indirectly through user engagement, and they have a directly negative effect on net spend. To our best knowledge, this paper is the first empirical study that explores the relationship among user experience, user engagement and purchase decisions using individual-level real data from a mobile wallet app, and we contribute substantively to the literature in mobile marketing and human-computer interaction.

In the following sections, we provide more background information on mobile wallets, and review related research on user experience and engagement in online and mobile environments. Then, we describe the empirical context of this study and operationalize measurements of user experience, user engagement and other variables of interest. Following our analysis framework and model, we discuss the results and conclude with managerial implications.

BACKGROUND AND LITERATURE REVIEW

Why mobile wallet?

The market for mobile wallets has been growing rapidly since 2015.[23] Technology-wise, the most commonly-adopted technologies include near field communications (NFC) and quick response (QR) code, both of which require users to wave their mobile devices near a reader module, such as a point of sale (POS) machine. Other technology formats involve a cloud-based platform and require authenticated bankcard information, which links users' mobile devices with the store POS machine wirelessly. Usability-wise, some mobile wallets offer payment services across multiple

[23] The value of transactions via mobile wallets is expected to reach 27 billion dollars in the US by the end of 2016, which is a 200% increase from 2015.

retailers (e.g., Apple Pay, Google Wallets or digitalized bank apps from financial institutes), while others only work within the network of a particular retailer or brand (e.g., Starbucks, Walmart, or the Cake Pay app by Cheesecake Factory). These differences in technologies and usability of mobile wallet apps provide mobile users with completely different user-app interactions and experiences.

Mobile wallet apps offer an ideal context for marketers and researchers to deepen their understanding of consumer behavior in the m-commerce era for two reasons. First, mobile wallet apps record detailed tap-stream data during users' entire browsing-purchase process, which provides rich information on how users spend their time and money in using the apps. Second, with real-time geographic information generated by the device, mobile wallet apps have the potential to design effective promotion and targeting schemes, as compared to their traditional and online counterparts. As a new category experiencing rapid growth, mobile wallet technology plays a vital role in the future of m-commerce. However, research on the design of mobile wallet apps or on user behavior in mobile payment apps is scarce in the information systems field and nonexistent in the marketing literature. Therefore, opportunities for researchers in mobile marketing abound.

User experience

User experience is one of the most important concepts in the research of human-computer interaction and design and has been associated with a wide variety of meanings. Forlizzi and Battarbee (2004) review different theories of and approaches to understand user experience in interactive systems. The authors describe user experience as a three-fold

result built upon "fluent, cognitive and expressive" user-product interactions, and they emphasize the role of emotions in user experience. Hassenzahl and Tractinsky (2006) describe user experience as a "consequence of a user's internal state, the characteristics of the design system, and the context within which the interaction occurs." The authors also suggest that the focus of recent theoretical research has shifted from the functionality to the experiential and emotional perspectives of user-product interaction.

Because of a wide variety of theories, there has not been a consistent metric used when it comes to measuring user experience. Bargas-Avila and Hornbæk (2011) provide a qualitative review on empirical studies of user experience published between 2005 and 2009. The authors identify a shift of focus "from work towards leisure, from controlled tasks towards open use situations, and from desktop computing towards consumer products and art". Based on extensive surveys, researchers find that perceived quality of service and contextual information—such as triggering context, task at hand and social context—are valid measurements of user experience (Korhonen et al., 2010; Wac et al., 2011). Park et al. (2013) find that usability, affect and users' value are important elements of user experience. Ickin et al. (2012) suggest that the interface design, the app performance (e.g., speed, freeze), device features, usage context and users' lifestyle are some of the factors that affect mobile users' perceived quality of experience (QoE). Jaroucheh et al. (2011) suggest that the QoE should concern both current and historical user interaction with the product and context. Notably, almost all current findings in the literature are based on subjective survey responses.

In the marketing literature, most extant research on user experience originates from the context of online navigation. Built on the flow model (Hoffman and Novak, 1996),

Novak et al., (2000) conceptualize flow on the internet as a cognitive state experienced during navigation that is determined by high levels of skill and control, challenge and arousal, as well as focused attention, interactivity and telepresence. They test and operationalize constructs of the flow model using survey responses of web users and find empirical support for the conceptual model through structural equation modeling. Mathwick and Rigdon (2004) extend the conceptual flow model and propose play as a positive experience resulting from flow, which affect consumers' attitudes towards websites and focal brands. Castaneda et al. (2007) measure user cumulative online experience as the number of hours spent online and find a moderating effect of this cumulative online experience on consumers' attitude toward the website within the Technology Acceptance Model (TAM) framework. In an online shopping context, Rose et al. (2012) define user experience as the cumulative outcome of consistent exposure to the retailer's website, and they find this experience construct to be positively associated with consumers' satisfaction, trust and purchase intention towards the brand.

User Engagement

A concept closely related to user experience, user engagement is defined as the quality of the user experience that emphasizes positive aspects of user interaction with a product or service (O'Brien and Toms, 2008; Lehmann et al., 2012). User engagement reflects the depth of users' involvement with the interactive system and the overall efficacy of the system. Developments in human-computer interaction research suggests that user engagement contains two main categories concerning qualities of the user experience—those are the pragmatic qualities related to the functionality of the system and also the

hedonic qualities that involve enjoyment and aesthetics of the system (O'Brien and Toms, 2008; Hassenzahl et al., 2010).

Due to myriad characteristics of interactive products and services, no single standard metric to measure user engagement exists, as measurements depend heavily on the nature of the interaction. In the online shopping context, O'Brien (2010) and O'Brien and Toms (2008) propose a six-factor User Engagement Scale (UES), which includes focused attention, perceived usability, endurability of the overall experience, aesthetics of the website, felt involvement in the shopping experience and novelty. Wiebe et al. (2014) adopt the six-factor UES to the online gaming context and verify its applicability. With regard to empirical methods, a recent review by Lehmann et al. (2012) categorizes current user engagement measurement into three groups: self-reported engagement (e.g., survey responses), cognitive engagement (physiological measures such as facial expression and heart rate), and online behavior metrics (e.g., page view, time spent, visit frequency, etc.). Notably, most findings from extant empirical research on user engagement are based on self-reported engagement.

Empirical studies on user engagement in marketing are scarce. Kim et al. (2013) measure mobile users' engagement intentions using self-reported willingness to continue to engage and to recommend. The authors find empirical evidence for the effect of motivations, perceived value and satisfaction on user engagement. Dinner et al. (2015) measure user engagement of a branded app as the number of times the app is used. Using individual-level app usage and purchase data, they find that marketing, app upgrades and purchase history all affect user engagement, and user engagement has a positive effect on both online and offline sales of the brand.

Our view on user experience and engagement

The goal of this paper is not to propose a new conceptual theory about user experience and user engagement. Rather, we strive to build reasonable measurements of both constructs using actual behavioral data, and to test extant theories of user experience and user engagement in the mobile wallet context.

We measure user experience with a mobile wallet app as a composite measure with three components. The first component is concurrent experience, which includes various activities or events that a user generates or encounters during the current usage session. The second component is previous experience, which includes measures of the recency of the previous usage session and significant activities (e.g., purchase) that occurred in the immediate past. The third component is cumulative experience, which measures the level of skill and tenure of the user with app. We adopt a behavioral metrics approach and measure user engagement in a given usage session as the count of tapping activities and the duration of a usage session.

Theories on user experience and user engagement suggest that the two concepts are not parallel constructs at the same conceptual level. Conceptually, user engagement represents the overall quality of the user's experience and is therefore a higher-level concept, which may be the consequence of positive user experience. The flow model suggests that compelling online experience leads to acute involvement in the act of online navigation (Novak et al., 2000), and we expect similar findings in the mobile context. We hypothesize and discuss specific effects of each component of user experience in subsequent sections.

EMPIRICAL SETTING

We obtain tap-stream data from an emerging hybrid mobile wallet app. The main function of the app is a mobile wallet, which enable users to pay bills in food and beverage venues by conveniently clicking through the app on their mobile devices. In addition, the app occasionally sends m-coupons offering price discounts or free items to its users. The app has formed partnerships with a considerable number of venues in the investigated area. Thus, in contrast to retailer-specific mobile wallets, this study's focal app is comparable to Apple Pay or Google Wallet but is specific to the food and beverage industry.

Defining a usage session

The unit of analysis in this empirical setting is a usage session (session), which is defined as a stream of activities that take place within a relatively short period (e.g., 6 hours) in a specific venue, and are generated towards a successful payment (i.e., purchase). However, in reality, a session does not always end with a successful purchase due to many plausible reasons (e.g., technical failure, or the motivation of the session is simply to explore the app). As the example sessions for a user illustrated in Figure 1, during the three sessions shown, the user made a purchase in session number one, browsed around without purchase in session number two, and made a second purchase in session number three. Our research objective is to understand not only user experience and user engagement during each session, regardless of purchase, but also to learn the primary drivers of successful purchase decisions.

---Insert Figure 1 About Here---

Figure 2 illustrates user experience during a typical session. User activity begins with opening the app and launching the dashboard screen, which contains a list of nearby venues automatically generated according to the real-time location services of the user's mobile device. If the user's motivation is to purchase food or drink at a certain venue, she/he next clicks "Open Tab"[24] at the specific venue's page or "Join Tab" if the user will split the final tab (bill) with another user. The app will then generate a code with the user's name on the screen, and the user provides this code to venue staff while making an order so that the bill is linked to the user's account. When the user is ready to pay, she/he does not need to ask staff for the bill but instead clicks "Query Tab" in the app, which generates detailed bill information on the next screen. The last step is to click "Pay Tab" and complete the transaction without interacting with venue staff outside the process of ordering. If the user intends to redeem available m-coupons, she/he will select them before opening or joining a tab. The entire process is accomplished via the mobile wallet app. The only step that involves human interaction is providing the code while placing an order, so the process saves wait time while checking out and also makes the payment process more secure.

---Insert Figure 2 About Here---

Note that Figure 2 is a general depiction of a complete user session that ends with a purchase. Although there are many other in-app activities that users can operate (e.g., browsing among venues before physically going to one), here we only focus on the

[24] The term "tab" is common shorthand for a bill in the food and beverage industry, and the term is used extensively in this mobile wallet app.

activities that are necessary to make a payment because they reflect the core functional interactivity of the app.

Data and summary statistics

The data obtains tap-stream data from a cohort of 528 unique users who joined the app between 26 August 2015 and 27 September 2015.[25] For each user, we observe a complete history of his tapping behavior, app upgrading and transaction behavior (e.g., when and where, money spent and coupon redemption) in the app. We aggregate the data to the user-session level, and obtain 1,047 unique sessions—716 of which ended with a successful purchase—yielding a 68.39% conversion rate. As presented in Table 1, 76.89% of first sessions end with a successful purchase, and the purchase conversion rate decreases by the session count. Notably, half of the sessions in our sample are users' first sessions, and less than ¼ of the sessions are second session. This data indicates that the app loses a significant number of users after the first session. This observation is consistent with the problem of high attribution faced by many mobile apps.

---Insert Table 1 About Here---

Transaction information based on converted observations (i.e., sessions that end with purchase) is summarized in Table 2. Among the 716 purchase incidents, 58% are first-time purchases, and these purchases are made by new users more often than by return users. 89.25% of all purchases are made with m-coupons, and the average amount of redemption is $10.80. Notably, although the percentage of purchase with coupon does

[25] The company did not have detailed records on user activities of tap-stream data until a major version release on 26 August 26 2015. Since the cutoff point for our dataset is 27 September 2015, this study monitors data derived from a one-month observation period.

not seem to change much for the first four purchases, the average net spend and the coupon redemption amount decrease, indicating that the descending promotion depth may affect users' purchase amount. These summary tables provide a general overview of app usage and purchase patterns for the sample of users of the focal mobile wallet app.

---Insert Table 2 About Here---

ANALYSIS FRAMEWORK

Operationalization of variables

Dependent Variables

We are interested in investigating two constructs as dependent variables: user engagement and purchase decisions. User engagement is an app-usage outcome that is an important construct to all types of mobile apps or other interactive systems. Purchase decisions are economic outcomes that are particularly interesting and important to mobile wallet apps in that they can reveal how users spend money via mobile wallet.

---Insert Table 3 About Here---

Table 3 demonstrates the measurement of dependent variables. We measure user engagement by *ACTIVITY* and *DURATION*, operationalized as the number of tapping activities generated during a session and total time spent on a session, respectively. High values of *ACTIVITY* mean that the user generates more browsing activities, and these values could indicate that the user is very explorative in the app. High values of *DURATION* mean that the user spends more time in the app. Higher levels in either both

ACTIVITY or *DURATION* could indicate more interest in the app.[26] A summary of user engagement measures is presented in Table 4.

---Insert Table 4 About Here---

We measure purchase decisions by *CONVERSION* and *SPEND*, which represent a binary variable of purchase incidence and net spend (i.e., expenditures after applying any coupons), respectively. For a mobile wallet app, purchase decisions are more relevant since they represent the successful adoption of the app's primary function.

User Experience

We view user experience as an overall user interaction with the app having three components: concurrent experience, previous experience and cumulative experience. Concurrent experience includes a number of events that a user triggers during a concurrent session beyond the minimum functional activities through which users proceed to complete a session as shown in Figure 2. These events, operationalized in Table 5, represent some special activities (e.g., sharing the bill with a friend,or having an error message while using the app) and could help marketers and engineers identify meaningful functionality or technical failure of the app that affects user experience.

---Insert Table 5 About Here---

Previous experience in this setup measures what a user has just encountered in the app during the most recent session. We construct two variables from the tap-stream data, *PURCHASE PAST DAY* and *DAYS SINCE LAST SESSION*, to investigate whether there

[26] Note that the data mostly contain relatively new users who have joined the app for no longer than a month. When users are unfamiliar with the app, user exploration of browsing activities for longer durations is desirable. If we were dealing with experienced users, this interpretation may not hold true.

is any carry-over effect from the previous success in using the app or a recency effect from the last session.

Cumulative experience in this setup measures the total interactions a user has cumulated since she/he joined the app. In this study, we calculate *CUM.SESSIONS* (the number of cumulative sessions) and *CUM.UPGRADE* (the number of cumulative app versions to which that the user has upgraded). Cumulative experience measures how skillful and experienced the user is with the app. We expect that a "tenured" user may behave differently from a novice.

Modeling user engagement

We model the two engagement variables as a function of user experience, users' response to marketing promotion and operational factors and external environmental factors such as day of the week and type of venue. Let $y_{it}^1 = (\ln\_Activity_{it}, \ln\_Duration_{it})$ denote the natural log of the observed *ACTIVITY* and *DURATION* of user i at session t, for $i = 1,...,N$, and $t = 1,...,T$, using a multivariate regression model:

$$
\begin{aligned}
y_{it}^1 = {} & \beta_0^1 + \beta_1^1 CANCEL_{it} + \beta_2^1 SHARE_{it} \\
& + \beta_3^1 ERR\_OPEN_{it} + \beta_4^1 ERR\_QUERY_{it} + \beta_5^1 ERR\_PAY_{it} \\
& + \beta_6^1 WEEKEND_{it} + \beta_7^1 BAR\_RESTAURANT_{it} \\
& + \beta_8^1 PURCHASEPASTDAY_{it} + \beta_9^1 \ln\_DAYSSINCELASTSESSION_{it} \\
& + \beta_{10}^1 CUM.SESSIONS_{it} + \beta_{11}^1 CUM.UPGRADE_{it} \\
& + \beta_{12}^1 \ln\_FACEVALUE_{it-1} + \beta_{13}^1 LATESTVERSION_{it} + \varepsilon_{it}^1, \\
\varepsilon_{it}^1 \sim {} & N(0, \Sigma^1).
\end{aligned} \tag{15}
$$

Flow theory suggests that greater flow corresponds to greater affect and exploratory behavior (Novak et al. 2000); thus, we expect positive user experiences to affect user engagement positively. In terms of the effect of concurrent experience, we expect *CANCEL* to have a negative effect on engagement, as it is an indicator of termination of a purchase or a loss of interest in continuing the purchase with the app. We expect *SHARE* to have a positive effect on engagement, as being able to split bill with a friend in a social setting could make the experience more fun and personal and thence encourage a user to spend more time browsing the app. Since error messages could indicate a technical interruption and slower speed of interaction (Novak et al., 2000), which could hurt the flow, we expect all events with error messages to have negative effects on engagement.

In terms of previous user experience, the effect of *PURCHASE PAST DAY* could be ambiguous in this context. On one hand, it could have a positive effect on current engagement as the user becomes more skillful at using the app, hence greater flow and user engagement. On the other hand, it could have a negative effect on current engagement because users may not stay interested in purchasing at a venue for two consecutive days. We also expect the recency factor to have an effect on current user engagement. The direction of the effect, however, could be ambiguous. When a long time has passed since the last session, the user could have forgotten how to use the app, and decreased skill could have a negative effect on the flow, creating a potential negative effect. On the other hand, if the user wants to use the app, he might be willing to spend more time learning how to use the app or browse in the app, creating a potential positive effect.

The last component of user experience is cumulative experience. Novak et al. (2000) find that more experienced consumers are more likely to use the web for task-oriented activities rather than exploratory activities. Dahlen (2002) also finds that more experienced users tend to have shorter web sessions, fewer web visits and more practical and routine usage (instead of more exploratory behavior). Therefore, we expect *CUM.SESSIONS* to have a negative effect on user engagement. We expect *CUM.UPGRADE* to have a positive effect on user engagement because it measures the interest level a user has on the app. Having voluntarily upgraded to multiple versions[27] of the app is an indicator of high level of interest in the app, and that type of user could be more willing to browse around and explore new features of the app.

The variable $FACEVALUE_{it-1}$ represents the monetary value of the m-coupon user *i* has redeemed during the previous session, if she/he has used any coupon. Previous research on mobile promotions has found a positive effect of the m-coupon's face value on current purchase (Fong et al., 2015) and coupon redemption behavior (Danaher et al., 2015), but its effect on user engagement is not clear. We expect the effect of previous coupon redemption to be positive, because coupons are supplemental to the wallet function, and they may make the app more enticing. A highly interested and motivated user is more likely to spend time exploring due to an interest in the app or for more deals.

The variable *LATESTVERSION* is an indicator of whether user *i* 's device is upgraded to the latest available version. A latest version usually features user-friendly improvements in comparison with older versions; thus, newer versions are more likely to

[27] There are three versions of the app available during our observation period (4.2.0, 4.2.3, 4.3.0)

provide better user experience and encourage users to spend more time exploring the app. Therefore, we expect this operational variable to have a positive effect on user engagement.

In addition, we also control for two external environmental factors. *WEEKEND* is an indicator of whether the session takes place during a weekend (i.e., Friday night through Sunday night) and *BAR_RESTAURANT* is an indicator of whether the session takes place at a bar or restaurant (as compared to other types of venues such as clubs or coffee shops). Previous research in mobile promotion has investigated the effect of location and timing of m-coupons (Fong et al., 2015; Danaher et al., 2015). The two control variables we use represent a different set of timing and location factors. An effect due to these variables could be potentially informative to marketers and provide direction on the timing of sending push notifications or collaborating with certain types of venues to achieve higher levels of user engagement.

Modeling purchase decisions

Purchase is the ultimate and potentially the only profitable user behavior for a mobile wallet app. We are interested in modeling both the purchase *CONVERSION* decision and the purchase amount decision in terms of *SPEND* (operationalized in Table 3).

Our capture of *SPEND* data solely from app users who made a purchase may raise a potential selection problem in this study. To overcome this issue and obtain unbiased estimates, we model the purchase decisions through a Type 2 Tobit model (Greene, 2003). Let y_{it}^2 represent user i's purchase *CONVERSION* at session t, and if $y_{it}^2 = 1$, we then

observe his *SPEND* y_{it}^{3}. In the Tobit model, purchase *CONVERSION* is modeled through a probit regression, and *SPEND* is modeled through a linear regression, as presented in equations (16)–(19):

$$y_{it}^{2} = \begin{cases} 1, y_{it}^{2*} \geq 0 \\ 0, otherwise \end{cases} \tag{16}$$

where y_{it}^{2*} is a latent utility that determines the observed value of *CONVERSION* . Both y_{it}^{2*} and the *SPEND* y_{it}^{3} are modeled as a linear function of user experience, overall user engagement and marketing and operational factors, and the error terms are assumed to follow a bivariate normal distribution with mean 0 and covariance matrix $\Sigma^{2,3}$.

$$\begin{aligned} y_{it}^{2*} &= \beta_0^2 + \beta_1^2 CANCEL_{it} + \beta_2^2 SHARE_{it} \\ &+ \beta_3^2 ERR\_OPEN_{it} + \beta_4^2 ERR\_QUERY_{it} + \beta_5^2 ERR\_PAY_{it} \\ &+ \beta_6^2 WEEKEND_{it} + \beta_7^2 BAR\_RESTAURANT_{it} \\ &+ \beta_8^2 PURCHASEPASTDAY_{it} + \beta_9^2 \ln\_DAYSSINCELASTSESSION_{it} \\ &+ \beta_{10}^2 CUM.SESSIONS_{it} + \beta_{11}^2 CUM.UPGRADE_{it} \\ &+ \beta_{12}^2 \ln\_FACEVALUE_{it-1} + \beta_{13}^2 LATESTVERSION_{it} \\ &+ \beta_{14}^2 \ln\_ACTIVITY_{it} + \varepsilon_{it}^2, \\ \varepsilon_{it}^2 &\sim N(0, \sigma^2). \end{aligned} \tag{17}$$

$$
\begin{aligned}
y_{it}^{3} = {} & \beta_0^3 + \beta_1^3 \ln\_ACTIVITY_{it} \\
& + \beta_2^3 WEEKEND_{it} + \beta_3^3 BAR\_RESTAURANT_{it} \\
& + \beta_4^3 PURCHASEPASTDAY_{it} + \beta_5^3 \ln\_DAYSSINCELASTSESSION_{it} \\
& + \beta_6^3 CUM.SESSIONS_{it} + \beta_7^3 CUM.UPGRADE_{it} \\
& + \beta_8^3 \ln\_FACEVALUE_{it} + \beta_9^3 LATESTVERSION_{it} + \varepsilon_{it}^3,
\end{aligned} \tag{18}
$$

$$
(\varepsilon_{it}^2, \varepsilon_{it}^3) \sim N(0, \Sigma^{2,3}) \tag{19}
$$

where $\Sigma^{2,3} = \begin{bmatrix} 1 & \rho\sigma^3 \\ \rho\sigma^3 & \sigma^3 \end{bmatrix}$.

For purchase decisions, we expect user engagement[28] to have a positive effect on *CONVERSION*, because a higher level of involvement and positive interactions could indicate a higher level of interest and positive affect. We do not expect engagement to have a strong effect on *SPEND*.

Previous research has found that user experience is positively associated with consumers' satisfaction, trust and purchase intention in an online shopping context (Rose et al., 2012). Therefore, we expect user experience to affect purchase *CONVERSION* positively in the mobile context as well. For concurrent user experience, we expect *CANCEL* and all events with error messages to have a negative effect on *CONVERSION*. However, once *CONVERSION* is achieved, we do not expect concurrent user experience to affect the subsequent *SPEND* (i.e., consumption decisions).

[28] Since *ACTIVITY* and *DURATION* are highly correlated variables. We use ln_*ACTIVITY* to represent engagement in modeling the purchase decisions.

Regarding the effects of previous and cumulative user experience, we expect *PURCHASE PAST DAY* to affect both *CONVERSION* and *SPEND*. That noted, the direction of the effect may be ambiguous. It could be easier for a return user to make another purchase as compared to a new user. However, in the context of food and beverage purchase at a venue where most users do not consume daily, a purchase made yesterday could more likely to be followed by a break rather than another purchase today. We expect cumulative experience to have a positive effect on purchase decisions, as more *CUM.SESSIONS* or *CUM.UPGRADE* could indicate a high level of interest in using the app.

To investigate the effect of marketing promotion on purchase decisions, we treat *CONVERSION* and *SPEND* slightly differently. Similar to user engagement, we assume that *CONVERSION* is driven by previous response to promotion because concurrent response to promotion only happens after the *CONVERSION* decision, and not all purchases are made with a coupon. We expect *FACEVALUE* at the previous session to have a positive effect on concurrent *CONVERSION* because higher monetary values provide more economic incentive to use the app. In contrast, we believe that concurrent coupon redemption has a more direct effect on concurrent *SPEND*. For concerns of potential endogeneity, we instrument concurrent *FACEVALUE.* We find an indicator of app version to be a valid instrument variable, as the app version should not affect users' consumption decisions in a food and beverage venue, yet it may affect the users' ability to find or redeem a coupon. We plug in the predicted value from stage 2 in the 2SLS regression for concurrent *FACEVALUE* for the SPEND equation.

In terms of operational factors, we expect that having *LATEST VERSION* could positively affect purchase *CONVERSION* because the most updated app version is designed to be easier to use or with favorable features that encourage purchase via the app. However, the design and function of the app may not affect users' actual consumption decisions.

Relationship between user experience, engagement and purchase

In addition to this project's main research questions, we are also interested in empirically testing the relationship between user experience, user engagement and purchase decisions. As shown in Figure 3, four different regression models (M1 through M4) were estimated to test the intermediate role of user engagement. We expect the estimates of regression coefficients in all four models to be significant, and with the intermediate effect of user engagement, we expect the size of the effects of user experience in terms of absolute value in M4 to be smaller than that in M3.

---Insert Figure 3 About Here---

We estimate the models shown in equations (15) through (19) using the *lm()* and *heckit()* functions in R, and obtain maximum likelihood estimates of the parameters.

RESULTS

The effect of user experience on user engagement

The parameter estimates for the engagement equation in equation (15) are presented in Table 6. We first discuss the effects of user experience on user engagement. As expected, *SHARE* has a positive effect on both *ACTIVITY* and *DURATION,* indicating that the option

of splitting bills is a favorable feature of the app that encourages users to perform exploratory behavior. However, the sign of the effect of *CANCEL* and all the activities with an error messages contradict our expectations. A positive effect means that canceling a tab or encountering errors encourages users to explore more in the app and spend more time. This finding is surprising and contrary to flow theory. An important fact to keep in mind is that all users in our sample are relatively new to the app, thus, it is plausible that they are curious to learn more about the app by spending more time to explore it, and therefore may not be easily discouraged by error messages. However, we need to be cautious in generalizing this interpretation to a different cohort of users.

---Insert Table 6 About Here---

The second component of user experience is previous experience. We find that *PURCHASE PAST* DAY has a negative effect on engagement, revealing the particular nature of the consumer behavior in this empirical context, and users' interest level in using the app is low immediately after a purchase. *DAYS SINCE LAST SESSION,* on the other hand, has a positive effect on engagement, as expected. Essentially, if a long time has passed since the last session, the user may become less familiar with the app, and she/he needs to spend more time in the app to learn how to use it again.

The last piece of user experience is cumulative experience. We find that *CUM.SESSIONS* has a negative effect on engagement, which result is consistent with previous empirical research. *CUM.UPGRADE* has a positive effect on engagement, as expected, which means that frequent app version upgrading is helpful to engage users' exploratory behavior with the app.

The effect of user experience on purchase decisions

The parameter estimates for the purchase decisions are presented in Table 7. We look at different components of experience to gain a thorough understanding of the effect of user experience on purchase decisions. First, we find that concurrent user experience has a significant effect on purchase *CONVERSION*. As expected, *CANCEL* is negatively associated with purchase *CONVERSION*. Surprisingly, *ERR_QUERY* appears to be a harmless technical failure among other types of error, and it has a positive effect on purchase *CONVERSION*. A plausible explanation of this finding is that if the technical failure happens early in the session, then it might discourage user to continue using the app or to make a purchase. If the technical failure happens at the very end (i.e., pay), it may not affect the users' actual in-store purchase and consumption, but users may quit the mobile wallet process and complete the transaction with other payment methods that are not observable in our dataset. Only when the technical failure happens at the "harmless" moment (i.e., after consumption and before paying), then the user might be patient and re-try the process to fix the problem. Therefore, to facilitate a smooth transaction, engineers could focus more on eliminating errors at both early and late stages of a session, but may not need to worry about errors at the query stage.

We find that experience at the previous session has a negative effect on purchase decisions. Specifically, *PURCHASE PAST DAY* has a negative carry over effect on *CONVERSION* and a negative effect on *SPEND*. Similarly as in the engagement equation, the negative effects characterize the particular pattern of consumer behavior in food and beverage venues: if a user made purchase yesterday, it is less likely that she/he dines out again today, and even if that user does, she/he would spend less money.

We find that cumulative experience also has a negative effect on purchase decisions. This finding can be explained from prior empirical research where more experienced users are found to have lower response to marketing variables due to decreased cognitive effort (Dahlen, 2002), which could negatively affect both purchase *CONVERSION* and *SPEND*.

---Insert Table 7 About Here---

Intermediate role of user engagement

We find a positive effect of user engagement on purchase conversion, as shown in Table 7. As expected, this effect could be caused by high levels of interest in the app or satisfactory interactions with it. Furthermore, we find that user engagement has an intermediate role in the relationship between user experience and purchase decisions. Theoretically, user engagement is the consequence of positive user experience, and purchase is the consequence of deep user engagement and positive affect. Thus, user engagement is contextualized between user experience and purchase conversion as both an end and a means, simultaneously. Empirically, we tested this potential intermediate effect, as depicted in Figure 3, and find that regression coefficients in M1 through M4 are all significant. In addition, the estimate of the effects of most user experience variables in M3 are smaller in absolute value than those in M4, as presented in Table 8 in the appendix.

Effect of marketing promotion on engagement and purchase decisions

The effect of marketing promotion on user engagement is displayed in Table 6. As expected, the lagged *FACEVALUE* from the previous purchase has a positive effect on user engagement. Its effect is significant on *DURATION* and indicates that higher coupon values

encourage users to spend more time in a session. This effect is likely produced because the added economic value increases users' perceived usefulness of the app, and hence flow is more evident and positively affect user engagement.

The effect of marketing promotion on purchase decisions is displayed in Table 7. Although Table 7 suggests that previous *FACEVALUE* of m-coupon does not have a direct effect on current purchase *CONVERSION*, because of the intermediate role of user engagement, we could conclude that *FACEVALUE* affects purchase *CONVERSION* indirectly through engagement. In addition, it has a negative effect on users' net *SPEND*, indicating that in contrast with smaller promotional discount, if coupons with large discount are redeemed, then users would be less willing to spend their own money.

Effect of operational factors on engagement purchase decisions

The effects of operational factors on user engagement are displayed in Table 6. As expected, using the latest version of the app positively affects user engagement. This finding confirms the importance of being updated to the latest version, as a more advanced app may provide greater flow through smoother experience, better function and greater enjoyment. Marketers may consider sending push notifications with messages for app upgrade reminders and new features of the app.

The effect of operational factors on purchase decisions is displayed in Table 7. The results suggest that using the latest app versions positively affects purchase *CONVERSION.* This news is good for marketers and engineers as it indicates that feature improvements have a direct positive effect on *CONVERSION.* Similar to previous implications on user engagement, marketers may consider promoting changes and improvements in product features when a newer version is released.

CONCLUSIONS AND IMPLICATIONS

In this study, we empirically explore user experience and user engagement of a hybrid mobile wallet app, and we investigate the relationship among user experience, engagement and purchase decisions. Using a unique dataset that contains individual-level tap-stream data on 1047 sessions from 528 users of a mobile wallet app, we carefully extract measurements of user experience and engagement, and we model the relationship between the two constructs and purchase decisions. In addition, we strive to obtain unbiased inference by accounting for potential selection concerns in modeling purchase decisions and endogeneity of marketing promotion.

This paper builds on the intersection of human-computer interaction and mobile promotion. Despite a growing interest in understanding user experience and engagement in interactive systems, the majority of extant research in human-computer interaction is based on investigations derived from self-reported measurements from survey responses. In the mobile marketing field, empirical enquiry in understanding user experience, engagement is scant. To the best of our knowledge, this study is among the first to measure the two important and related constructs, and model the relationship among user experience, engagement and other economic outcomes using actual behavior data in the context of mobile apps.

This study yields several important empirical findings that have both theoretical and managerial implications. First, we find that user experience directly affects user engagement and purchase decisions. Most of these findings are consistent with flow theory and the TAM framework. Second, user engagement has an intermediate role in the relationship between user experience and purchase decisions. Third, marketing promotion

has an indirect effect on purchase conversion through engagement and a direct negative effect on net spend. Fourth, upgrading to the latest app version has a positive effect on both user engagement and purchase conversion. Finally, reflecting the nature of user behavior in this particular context (i.e., purchase at food and beverage venues), purchase on the previous day has a negative carry over effect on current purchase decisions.

Our measurement of mobile users' engagement adopts metrics commonly used in online gaming and shopping contexts (e.g., page view and time spent on a website). However, because of a different user-app interaction, user engagement with a mobile wallet app does not measure the same construct as it does with a gaming app. A limitation of this study is a lack of data from a larger observation period; thus, our measurements and interpretation of user engagement are limited to relatively inexperienced new users. Ultimately, for an interactive system that requires streamlined experience and smooth transactions, it may not be optimal to encourage prolonged durations or extensive browsing in a session because longer duration could indicate the malfunction of the service or inefficiency in product engineering. Future research should incorporate the level of experience and skill of users when developing measures for user engagement.

This paper is a first step in exploring traits that make a mobile wallet engaging and successful. Regarding the effectiveness of marketing promotion, our findings suggest that either the current marketing program is counter-productive or the company has acquired a cohort of "deal-seekers" who do not value the convenience of the mobile wallet service and are only interested in redeeming coupons at minimum cost. These possibilities could be true to many other mobile apps and technology startups with an ambitious acquisition agenda because it is tempting to run short-run promotions and quickly gain a large number

of “new users”. However, in these scenarios, companies often end up with undesired temporary users, who use the app only to gain economic benefits through the usually-generous introductory promotion. Our findings emphasize the necessity that marketers in small startups reconsider the design of an effective promotion and targeting strategy. For example, it could be worthwhile to identify and distinguish “deal-seekers” from true users who are persuaded by the mobile wallet service. Marketers and engineers should also design discriminating promotion and loyalty programs based on a thorough evaluation of users’ app usage patterns and users’ responsiveness to promotion.

Tables and Figures

Essay 1-Table 1: Summary Statistics of User Acquisition and Retention across Cohorts

Cohort	Size	% Acquired	% Retained	% iOS Device	% Using Coupon when Acquired
A	1755	74.1%	26.1%	65.93%	83.00%
B	1532	71.7%	27.5%	67.23%	76.32%
C	1834	75.2%	30.9%	70.01%	84.06%
Total	5121	73.8%	28.2%	67.78%	81.45%

Essay 1-Table 2: Summary Statistics of Behavioral Variables across Cohorts

		Cohort A		Cohort B		Cohort C	
Variables	*Operationalization*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Acquisition Duration (hrs)	Number of hours elapsed between "born" and "acquired"	102.49[a]	441.83	160.64	522.89	117.45	462.66
Retention Duration (hrs)	Number of hours elapsed between "acquired" and "retained"	464.01	568.17	430.81	517.61	465.15	528.71
Spend ($)	Total "out-of-pocket" spend when “acquired”	24.32	31.56	23.39	21.55	22.43	21.69
Facevalue ($)	Dollar value of coupon redeemed when “acquired”	9.95	6.64	7.34	7.30	9.37	7.36
Check-in_A	Number of check-ins between "born" and "acquired"	2.33	1.54	1.92	1.28	2.08	1.48
Check-in_R	Number of check-ins between "acquired" and "retained"	21.92	19.00	25.43	22.73	23.05	19.54

a. Here we report the average and standard deviations of acquisition and retention durations only using uncensored observations.

Essay 1-Table 3: Model Fit Comparison

	Model 1: Joint Model	**Model 2: Marginal Model**
Log-likelihood	-23246	-23288
BIC	46654.22	46729.67

Essay 1-Table 4: Parameter Estimates

Parameters	Model 1: Joint Model			Model 2: Marginal Model		
	Mean	*95% CI Lower*	*95% CI Upper*	*Mean*	*95% CI Lower*	*95% CI Upper*
Acquisition Duration						
λ_1	0.2441	0.2145	0.2736	0.2521	0.2214	0.2829
α_1	0.1599	0.1556	0.1641	0.1613	0.1571	0.1654
β_1 NEWUSER	0.0996	0.0233	0.1759	0.1085	0.0318	0.1851
β_2 CHECK-IN_A[b]	2.2217	1.9652	2.4782	1.7958	1.5215	2.0702
β_3 IOS	0.4318	0.3599	0.5037	0.4235	0.3514	0.4956
β_4 V4.2PLUS_A	-0.0004	-0.0770	0.0761	-0.0013	-0.0790	0.0763
Retention Duration						
λ_2	0.0423	0.0298	0.0548	0.0228	0.0168	0.0289
α_2	0.3079	0.2896	0.3262	0.3422	0.3261	0.3584
γ_1 NEWUSER	0.1094	-0.0014	0.2202	0.1713	0.0518	0.2908
γ_2 OFFER	-0.3267	-0.4732	-0.1801	-0.4434	-0.6049	-0.2819
γ_3 SPEND[c]	-1.3110	-1.8745	-0.7474	-1.3422	-1.9674	-0.7170
γ_4 OFFER $\times$ FACEVALUE	-0.0739	-0.5921	0.4442	-0.1647	-0.7522	0.4228
γ_5 OFFER $\times$ BRAND	0.3792	0.2494	0.5090	0.4818	0.3404	0.6231
γ_6 OFFER $\times$ VENUE	0.0958	-0.0659	0.2575	0.1123	-0.0696	0.2943
γ_7 OFFER $\times$ SOCIAL	0.0296	-0.1149	0.1741	0.1694	0.0136	0.3252
γ_8 CHECK-IN_R[d]	3.6228	3.2069	4.0387	4.5569	4.2220	4.8918
γ_9 IOS	-0.4059	-0.5148	-0.2970	-0.3948	-0.5138	-0.2757
γ_{10} V4.2PLUS_R	0.3335	0.1885	0.4785	0.3941	0.2368	0.5515
Correlation Coefficient						
ρ	-0.3537	-0.4171	-0.2903	/	/	/

b.c.d.: To eliminate the effect of outliers, we standardized the original data by subtracting the minimum and then dividing by the range.

Essay 2-Table 1: Summary Table for Session Count and Purchase Conversion Rate

n-th Session	Count	Conversion Rate
1	528	76.89%
2	244	65.16%
3	108	64.81%
4	60	63.33%
5	33	57.58%
6	19	47.37%
7	12	50.00%
8	8	25.00%
9	6	33.33%
10	5	40.00%
10+[a]	24	12.50%
Grand Total	1047	68.39%

a. The maximum is 26 in our dataset.

Essay 2-Table 2: Summary Table for Transactional Variables

n-th Purchase	Count	% Used Coupon	Avg. Net Spend ($)	Avg. Face Value ($)
1	416	91.59%	26.31	11.66
2	140	87.86%	21.93	10.58
3	78	91.03%	22.47	9.47
4	32	90.63%	17.48	6.41
5	15	73.33%	19.34	5.33
6	12	83.33%	15.69	8.25
7	7	57.14%	16.92	2.57
8	16	62.50%	8.92	16.06
Grand Total	716	89.25%	23.84	10.80

Essay 2-Table 3: Operationalization of Dependent Variables

Construct	*Variables*	*Operationalization*
User Engagement	Activity	Total number of activities (i.e., taps) during a session
	Duration (mins)	Minutes elapsed duration a session
Purchase Decisions	Conversion	Whether a session is ended with a purchase; binary variable
	Spend ($)	Net dollar spent if a purchase is made

Essay 2-Table 4: Summary Table of Engagement Variables by Session

n-th Session	Activity Count		Duration (min)[b]	
	Mean	*SD*	*Mean*	*SD*
1	10.67	6.38	150.79	1362.94
2	10.48	7.76	66.26	193.54
3	10.79	8.29	69.04	121.84
4	11.28	9.37	97.78	201.34
5	9.15	6.70	50.18	88.38
6	10.16	7.28	108.11	230.18
7	13.67	17.94	79.25	86.86
8	12.88	17.35	136.12	356.20
9	6.83	6.71	45.33	59.10
10	4.40	3.29	43.00	79.38
10+	8.96	13.22	47.54	172.97
Grand Total	10.58	7.67	111.26	976.18

b. Duration is calculated as the number of minutes elapsed between the starting timestamp and the ending timestamp of a session

Essay 2-Table 5: Operationalization of User Experience Variables

User Experience	*Variables*	*Operationalization*
Concurrent Experience	Cancel	Whether a user changes his mind tries to cancel an opened tab; binary
	Share	Whether a user tries to join an existing tab and split bill with a friend; binary
	Err_Open	Whether a user encounters an error message when trying to open a tab
	Err_Query	Whether a user encounters an error message when trying to query the tab and get bill information; binary
	Err_Pay (mins)	Whether a user encounters an error message during the process of making payment; binary
Previous Experience	Purchase Past day[c]	Whether a user has used the app successful during the past day; binary
	Days since Last Session	Number of days passed since the last session; a recency measurement
Cumulative Experience	Cum. Sessions	Session counts a use has cumulated before the current one
	Cum. Upgrade	Number of app versions a user has used

c. We also tried past session, past 2-day, 3-day for different previous experience, and only past day stands out as an exploratory previous experience

Essay 2-Table 6: Parameter Estimates for Engagement Equations

Parameters	**ln _ACTIVITY**			**ln _DURATION**		
	Mean	*S.E.*	*T value*	*Mean*	*S.E.*	*T value*
INTERCEPT	**1.026**	0.149	6.886	**-1.686**	0.753	-2.240
CANCEL	**0.324**	0.079	4.104	**0.816**	0.398	2.050
SHARE	**0.333**	0.153	2.18	**1.405**	0.771	1.822
ERR_OPEN	**0.365**	0.107	3.409	**1.398**	0.540	2.588
ERR_QUERY	**0.372**	0.065	5.708	**1.474**	0.330	4.474
ERR_PAY	**0.371**	0.134	2.764	0.955	0.679	1.407
WEEKEND	**0.101**	0.052	1.956	**0.729**	0.262	2.788
BAR_RESTAURANT	**0.419**	0.120	3.494	0.610	0.606	1.007
PURCHASE PAST DAY	**-0.322**	0.079	-4.052	**-1.420**	0.401	-3.541
ln _DAYS SINCE LAST SESSION	**0.016**	0.007	2.320	**0.122**	0.034	3.588
CUM.SESSIONS	**-0.065**	0.019	-3.333	**-0.392**	0.098	-3.989
CUM.UPGRADE	**0.532**	0.082	6.503	**2.422**	0.413	5.864
LAGGED ln _FACEVALUE	0.027	0.022	1.215	**0.280**	0.110	2.534
LATEST VERSION	0.089	0.062	1.424	**0.777**	0.314	2.474
AIC		2453.822			5761.291	
BIC		2527.75			5835.219	

*Bold letters indicate significant result at the 90% confidence level.

Essay 2-Table 7: Tobit Regression for Purchase Decisions

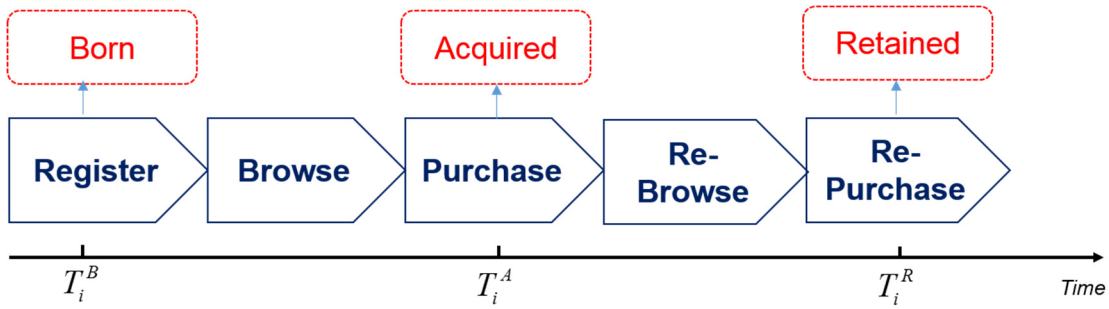
Parameters	*Mean*	*S.E.*	*T value*
Probit Selection for CONVERSION			
INTERCEPT	**-2.968**	0.340	-8.740
ln_ACTIVITY	**1.413**	0.094	15.074
CANCEL	**-0.343**	0.176	-1.954
SHARE	0.463	0.445	1.039
ERR_OPEN	-0.360	0.230	-1.566
ERR_QUERY	**0.249**	0.151	1.647
ERR_PAY	-0.265	0.300	-0.883
WEEKEND	-0.049	0.114	-0.427
BAR_RESTAURANT	**0.549**	0.231	2.374
PURCHASE PAST DAY	**-0.521**	0.156	-3.334
ln _DAYS SINCE LAST SESSION	**-0.026**	0.015	-1.767
CUM.SESSIONS	**-0.102**	0.040	-2.570
CUM.UPGRADE	0.097	0.183	0.528
LAGGED ln _FACEVALUE	0.032	0.049	0.640
LATEST VERSION	**0.276**	0.133	2.081
Outcome Equation for ln_ SPEND			
INTERCEPT	**3.242**	0.542	5.987
ln_ACTIVITY	0.051	0.096	0.530
WEEKEND	**0.275**	0.076	3.618
BAR_RESTAURANT	0.099	0.251	0.396
PURCHASE PAST DAY	**-0.627**	0.136	-4.620
ln _DAYS SINCE LAST SESSION	0.012	0.010	1.263
CUM.SESSIONS	0.010	0.034	0.292
CUM.UPGRADE	**-0.409**	0.196	-2.086
INSTRU. ln _FACEVALUE[d]	**-0.295**	0.179	-1.648
LATEST VERSION	0.063	0.091	0.693
Error Terms			
σ^3	**0.981**	0.026	37.299
ρ	0.112	0.124	0.904

d. Here we use the predicted value from the second stage of the 2SLS estimation with an instrument variable
*Bold letters indicate significant result at the 90% confidence level.

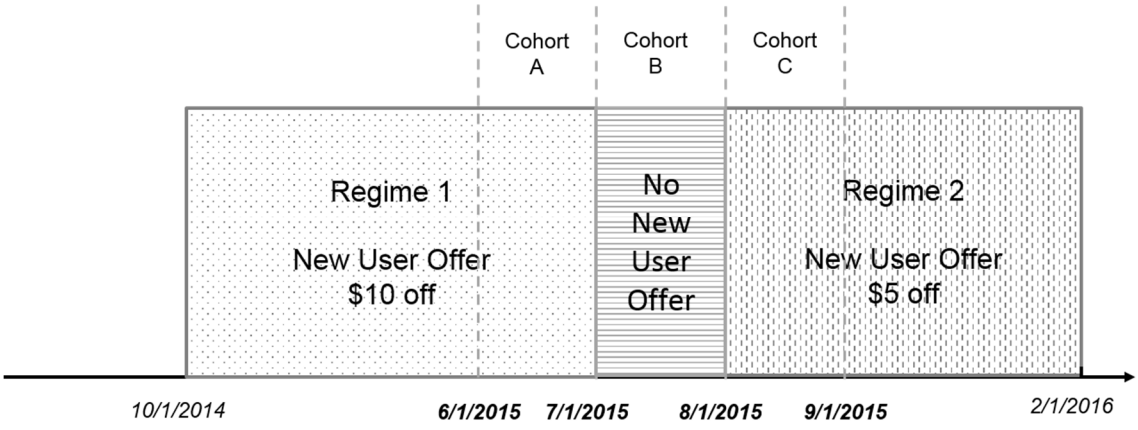
Essay 2-Table 8: Intermediate Effect of Engagement on Purchase Conversion

Parameters	**Experience on Engagement**			**Engagement on Purchase**			**Experience on Purchase**			**Intermediate Effect of Engagement**		
	M1			**M2**			**M3**			**M4**		
	Mean	*S.E.*	*T value*	*Mean*	*S.E.*	*T value*	*Mean*	*S.E.*	*T value*	Mean	S.E.	*T value*
INTERCEPT	**1.026**	0.149	6.886	**-2.218**	0.182	-12.2	**-1.07**	0.257	-4.164	**-2.962**	0.344	-8.622
ln_ACTIVITY				**1.378**	0.086	16.09				**1.41**	0.096	14.637
CANCEL	**0.324**	0.079	4.104				0.133	0.15	0.89	**-0.34**	0.177	-1.918
SHARE	**0.333**	0.153	2.18				**0.774**	0.366	2.119	0.489	0.434	1.125
ERR_OPEN	**0.365**	0.107	3.409				0.167	0.208	0.803	-0.368	0.234	-1.572
ERR_QUERY	**0.372**	0.065	5.708				**0.686**	0.132	5.179	0.238	0.152	1.564
ERR_PAY	**0.371**	0.134	2.764				0.294	0.259	1.132	-0.265	0.298	-0.891
WEEKEND	**0.101**	0.052	1.956				0.075	0.092	0.824	-0.047	0.113	-0.414
BAR_RESTAURANT	**0.419**	0.120	3.494				**0.806**	0.206	3.918	**0.548**	0.234	2.345
PURCHASE PAST DAY	**-0.322**	0.079	-4.052				**-0.692**	0.131	-5.271	**-0.522**	0.157	-3.322
ln _DAYS SINCE LAST SESSION	**0.016**	0.007	2.32				-0.003	0.012	-0.287	**-0.025**	0.015	-1.723
CUM.SESSIONS	**-0.065**	0.019	-3.333				**-0.113**	0.033	-3.433	**-0.101**	0.042	-2.39
CUM.UPGRADE	**0.532**	0.082	6.503				**0.617**	0.147	4.199	0.102	0.188	0.544
LAGGED ln _FACEVALUE	0.027	0.022	1.215				0.034	0.037	0.924	0.028	0.048	0.579
LATEST VERSION	0.089	0.062	1.424				**0.31**	0.108	2.879	**0.274**	0.131	2.088
AIC					732.67			1084.5			685.81	
BIC					742.53			1153.5			759.73	

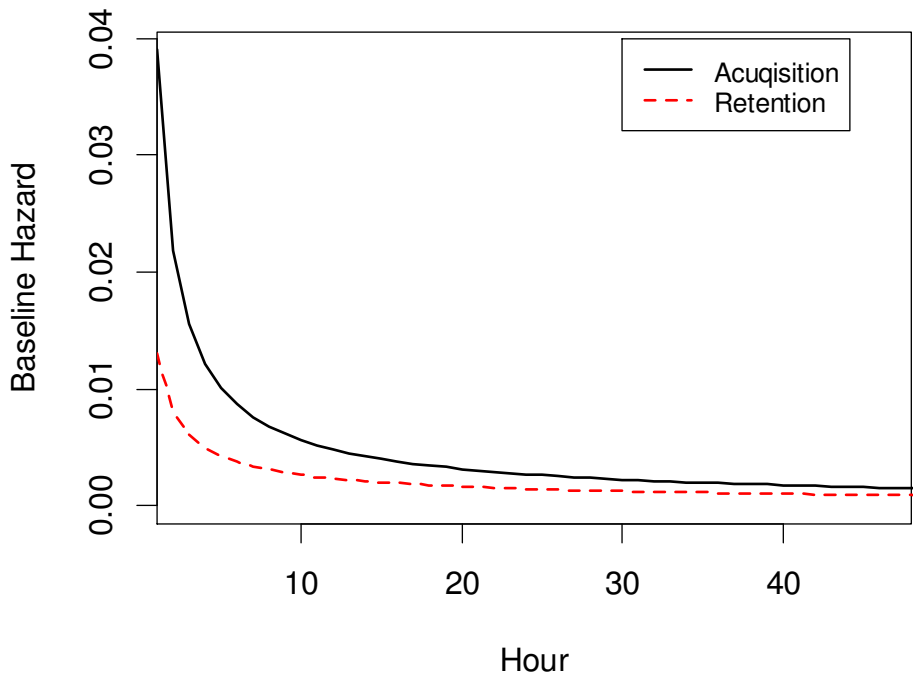
Essay 1-Figure 1: Stages of User Behavior



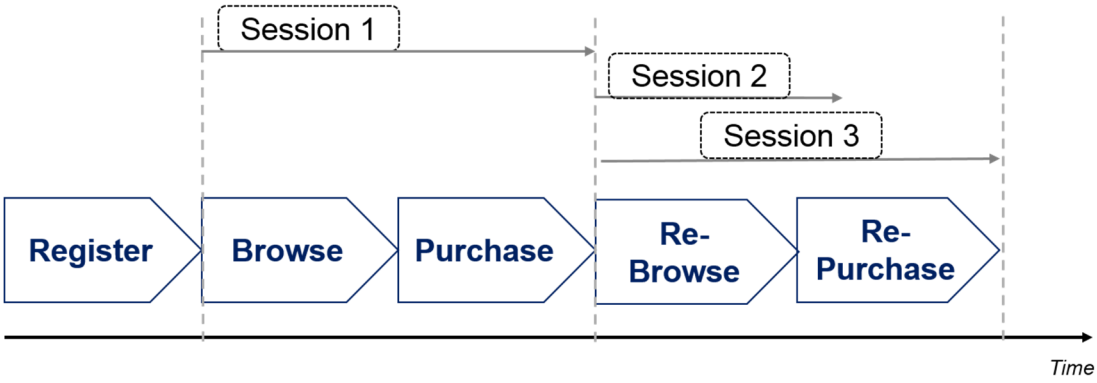
Essay 1-Figure 2: Cohorts and Marketing Regimes



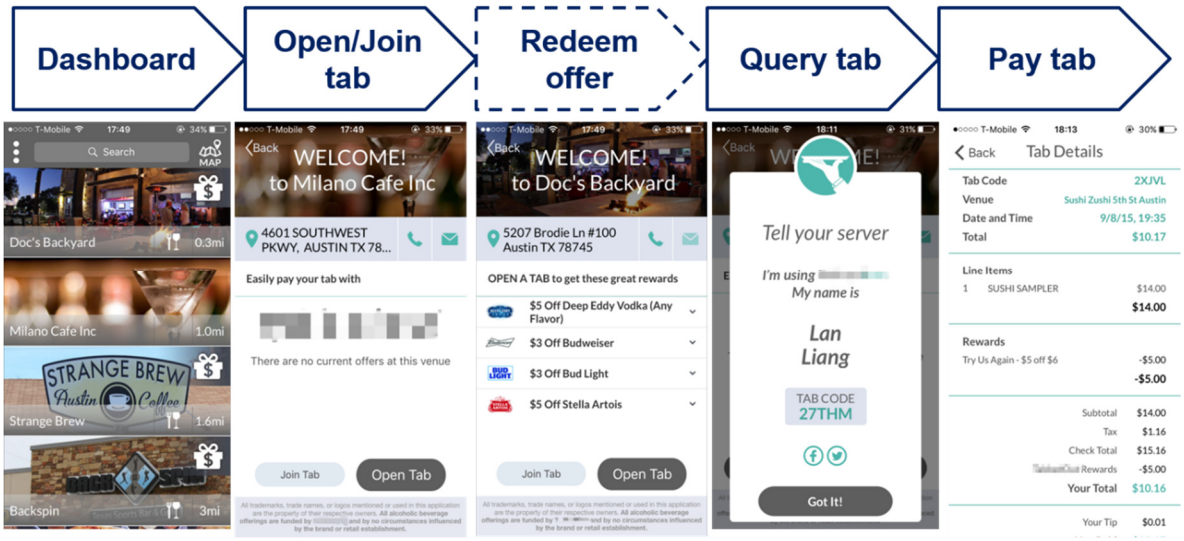
Essay 1-Figure 3: Baseline Hazard Rate $h_0(t)$ for Acquisition and Retention Processes



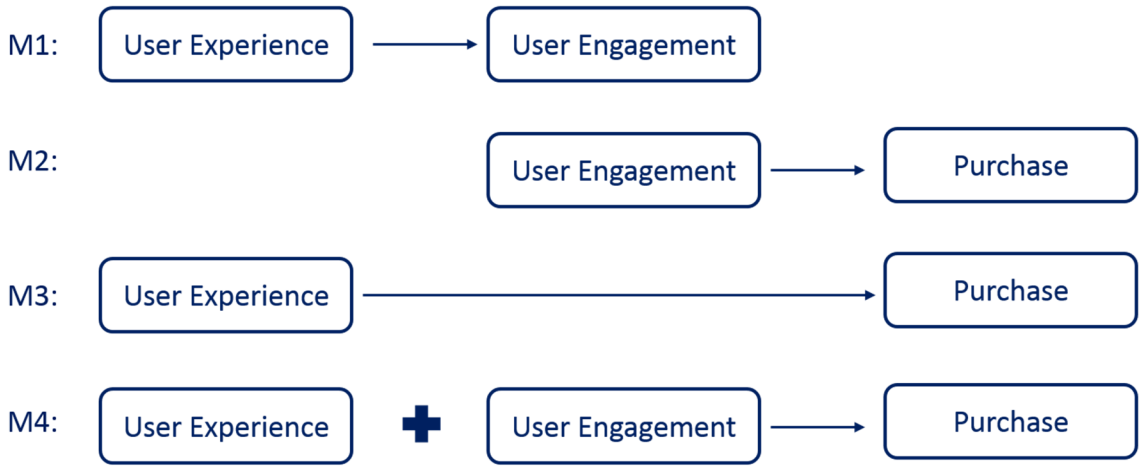
Essay2-Figure 1: Example Sessions of a User



Essay 2-Figure 2: A Typical Session



Essay2-Figure 3: Intermediate Effect of Engagement on Purchase Conversion



Bibliography

Andrews, M., Luo, X., Fang, Z., & Ghose, A. (2015). Mobile ad effectiveness: Hyper-contextual targeting with crowdedness. *Marketing Science*, *35*(2), 218–233.

Ascarza, E., & Hardie, B. G. (2013). A joint model of usage and churn in contractual settings. *Marketing Science*, *32*(4), 570–-590.

Banerjee, S., & Yancey, S. (2010). Enhancing mobile coupon redemption in fast food campaigns. *Journal of Research in Interactive Marketing*, *4*(2), 97-110.

Bargas-Avila, J. A., & Hornbæk, K. (2011, May). Old wine in new bottles or novel challenges: a critical analysis of empirical studies of user experience. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2689-2698). ACM.

Bellman, S., Potter, R. F., Treleaven-Hassard, S., Robinson, J. A., & Varan, D. (2011). The effectiveness of branded mobile phone apps. *Journal of interactive Marketing*, *25*(4), 191-200.

Blattberg, R. C., & Deighton, J. (1996). Manage marketing by the customer equity test. *Harvard business review*, *74*(4), 136.

Braun, M., & Schweidel, D. A. (2011). Modeling customer lifetimes with multiple causes of churn. *Marketing Science*, *30*(5), 881-902.

Castañeda, J. A., Muñoz-Leiva, F., & Luque, T. (2007). Web Acceptance Model (WAM): Moderating effects of user experience. *Information & management*, *44*(4), 384-396.

Dahlen, M. (2002). Learning the web: Internet user experience and response to web marketing in Sweden. *Journal of Interactive Advertising*, *3*(1), 25-33.

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

Dinner, I. M., van Heerde, H. J., & Neslin, S. (2015). Creating customer engagement via mobile apps: How app usage drives purchase behavior.

Danaher, P. J., & Smith, M. S. (2011). Modeling multivariate distributions using copulas: applications in marketing. *Marketing Science*, *30*(1), 4-21.

Dickinger, A., & Kleijnen, M. (2008). Coupons going wireless: Determinants of consumer intentions to redeem mobile coupons. *Journal of interactive marketing*, *22*(3), 23-39.

Ding, Y., & Chai, K. H. (2015). Emotions and continued usage of mobile applications. *Industrial Management & Data Systems*, *115*(5), 833-852.

Fader, P. S., Hardie, B. G., & Shang, J. (2010). Customer-base analysis in a discrete-time noncontractual setting. *Marketing Science*, *29*(6), 1086-1108.

Fong, N. M., Fang, Z., & Luo, X. (2015). Geo-Conquesting: Competitive Locational Targeting of Mobile Promotions. *Journal of Marketing Research*, *52*(5), 726-735.

Forlizzi, J., & Battarbee, K. (2004, August). Understanding experience in interactive systems. In *Proceedings of the 5th conference on Designing interactive systems: processes, practices, methods, and techniques* (pp. 261-268). ACM.

Ghose, A., & Han, S. P. (2014). Estimating demand for mobile applications in the new economy. *Management Science*, *60*(6), 1470-1488.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Hassenzahl, M., & Tractinsky, N. (2006). User experience-a research agenda. *Behaviour & information technology*, *25*(2), 91-97.

Hassenzahl, M., Diefenbach, S., & Göritz, A. (2010). Needs, affect, and interactive products – Facets of user experience. *Interacting With Computers*, 22(5), 353–362.

Hoffman, D. L., & Novak, T. P. (1996). Marketing in hypermedia computer-mediated environments: Conceptual foundations. *The Journal of Marketing*, 50-68.

Huang, K., Zhang, C., Ma, X., & Chen, G. (2012, September). Predicting mobile application usage using contextual information. In *Proceedings of the 2012 ACM Conference on Ubiquitous Computing* (pp. 1059-1065). ACM.

Ickin, S., Wac, K., Fiedler, M., Janowski, L., Hong, J. H., & Dey, A. K. (2012). Factors influencing quality of experience of commonly used mobile applications. *IEEE Communications Magazine*, *50*(4).

Jain, D. C., & Vilcassim, N. J. (1991). Investigating household purchase timing decisions: A conditional hazard function approach. *Marketing Science*, *10*(1), 1-23.

Jaroucheh, Z., Liu, X., & Smith, S. (2011). Recognize contextual situation in pervasive environments using process mining techniques. *Journal of Ambient Intelligence and Humanized Computing*, *2*(1), 53-69.

Janette Lehmann , Mounia Lalmas , Elad Yom-Tov, Georges Dupret. (2012). Models of user engagement, Proceedings of the 20th international conference on User Modeling, Adaptation, and Personalization, July 16-20, , Montreal, Canada

Kim, C., Mirusmonov, M., & Lee, I. (2010). An empirical examination of factors influencing the intention to use mobile payment. *Computers in Human Behavior*, *26*(3), 310-322.

Kim, Y. H., Kim, D. J., & Wachter, K. (2013). A study of mobile user engagement (MoEN): Engagement motivations, perceived value, satisfaction, and continued engagement intention. *Decision Support Systems*, *56*, 361-370.

Kim, S. J., Wang, R. J. H., & Malthouse, E. C. (2015). The effects of adopting and using a brand's mobile application on customers' subsequent purchase behavior. *Journal of Interactive Marketing*, *31*, 28-41.

Kumar, V., Zhang, X., & Luo, A. (2014). Modeling Customer Opt-In and Opt-Out in a Permission-Based Marketing Context. *Journal of Marketing Research*, *51*(4), 403-419.

Korhonen, H., Arrasvuori, J., & Väänänen-Vainio-Mattila, K. (2010, December). Analysing user experience of personal mobile products through contextual factors. In *Proceedings of the 9th International Conference on Mobile and Ubiquitous Multimedia* (p. 11). ACM.

Li, C., Luo, X., Zhang, C., & Wang, X. (2017). Sunny, Rainy, and Cloudy with a Chance of Mobile Promotion Effectiveness. *Marketing Science*.

Lu, Y., Yang, S., Chau, P. Y., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management*, *48*(8), 393-403.

Mathwick, C., & Rigdon, E. (2004). Play, flow, and the online search experience. *Journal of consumer research*, *31*(2), 324-332.

Novak, T. P., Hoffman, D. L., & Yung, Y. F. (2000). Measuring the customer experience in online environments: A structural modeling approach. *Marketing science*, *19*(1), 22-42.

O'Brien, H. L., & Toms, E. G. (2008). What is user engagement? A conceptual framework for defining user engagement with technology. *Journal of the Association for Information Science and Technology*, *59*(6), 938-955.

O'Brien, H. L. (2010). The influence of hedonic and utilitarian motivations on user engagement: The case of online shopping experiences. *Interacting with computers*, *22*(5), 344-352.

Park, J., Han, S. H., Kim, H. K., Cho, Y., & Park, W. (2013). Developing elements of user experience for mobile phones and services: survey, interview, and observation approaches. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *23*(4), 279-293.

Park, Y. H., & Fader, P. S. (2004). Modeling browsing behavior at multiple websites. *Marketing Science*, *23*(3), 280-303.

Peng, K. F., Chen, Y., & Wen, K. W. (2014). Brand relationship, consumption values and branded app adoption. *Industrial Management & Data Systems*, *114*(8), 1131-1143.

Reinartz, W., Thomas, J. S., & Kumar, V. (2005). Balancing acquisition and retention resources to maximize customer profitability. *Journal of marketing*, *69*(1), 63-79.

Rose, S., Clark, M., Samouel, P., & Hair, N. (2012). Online customer experience in e-retailing: an empirical model of antecedents and outcomes. *Journal of Retailing*, *88*(2), 308-322.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of marketing*, *68*(1), 109-127.

Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic commerce research and applications*, *9*(3), 209-216.

Schweidel, D. A., Fader, P. S., & Bradlow, E. T. (2008). A bivariate timing model of customer acquisition and retention. *Marketing Science*, *27*(5), 829-843.

Shih, J. H., & Louis, T. A. (1995). Inferences on the association parameter in copula models for bivariate survival data. *Biometrics*, 1384-1399.

Sklar, A. (1959), "Fonctions de répartition à n dimensions et leurs marges", *Publ. Inst. Statist. Univ. Paris*, **8**: 229–231

Song, P. X. K. (2000). Multivariate Dispersion Models Generated from Gaussian Copula. *Scandinavian Journal of Statistics*, 305-320.

Thomas, J. S. (2001). A methodology for linking customer acquisition to customer retention. *Journal of Marketing Research*, *38*(2), 262-268.

Wac, K., Ickin, S., Hong, J. H., Janowski, L., Fiedler, M., & Dey, A. K. (2011, August). Studying the experience of mobile applications used in different contexts of daily life. In *Proceedings of the first ACM SIGCOMM workshop on Measurements up the stack* (pp. 7-12). ACM.

Wiebe, E. N., Lamb, A., Hardy, M., & Sharek, D. (2014). Measuring engagement in video game-based environments: Investigation of the User Engagement Scale. *Computers in Human Behavior*, *32*, 123-132.

Zhou, T. (2013). An empirical examination of continuance intention of mobile payment services. *Decision Support Systems*, *54*(2), 1085-1091.

US time spent with mobile (2017, January 26). Retrieved from https://www.emarketer.com/Report/US-Time-Spent-with-Mobile-Deep-Dive-Mobile-App-Web-Time/2001835

Internet retailer 2016 mobile 500 guide.

IAB Internet advertising revenue report, 2015 full year report (2016, April). Retrieved from www.iab.net

Mobile Wallet Market (NFC, Remote Wallet) for Retail payments Vending machines Public transportation, Restaurants and other application - Global Industry Perspective, Comprehensive Analysis, Size, Share, Growth, Segment, Trends and Forecast, 2016 – 2022

Mobile internet ad spending worldwide 2013-2019. (2015, April). Retrieved from https://www.emarketer.com/Article/Mobile-Ad-Spend-Top-100-Billion-Worldwide-2016-51-of-Digital-Market/1012299

Google Play: number of available apps 2009-2017. (2017, June). Retrieved from https://www.statista.com/statistics/266210/number-of-available-applications-in-the-google-play-store/

The average app loses 77% of its users in the first three days. (2015, June 23). Retrieved from https://arc.applause.com/2015/06/23/app-retention-rates-2015/

Apple Pay's tough twenty months. (2016, June 27). Retrieved from http://www.pymnts.com/news/mobile-payments/2016/apple-pay-adoption-usage-2016/

Mobile Use, Attention Spans and How to Reach the Next Generation of Social Customers.(2016, March 11). Retrieved from http://www.socialmediatoday.com/marketing/mobile-use-attention-spans-and-how-reach-next-generation-social-customers

The Definition of User Experience. Retrieved from https://www.nngroup.com/articles/definition-user-experience/