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MOBILE APP ANALYTICS: A MULTIPLE DISCRETE-CONTINUOUS CHOICE FRAMEWORK[1]

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The number of mobile apps launched in the market has exponentially grown to more than 2 million, but little is known about how users choose and consume apps of numerous categories. This study develops a utility theory-based structural model for mobile app analytics. We use the theoretical concepts of utility and satiation along with the factor analytic approach, as bases in simultaneously modeling the complex relationships among choice, consumption, and utility maximization for consumers of various mobile apps. Using a unique panel dataset detailing individual user-level mobile app time consumption, we quantify the baseline utility and satiation levels of diverse mobile apps and delineate how app preferences and consumption patterns vary across demographic groups affected by persistent use and time trends. The findings suggest that users' baseline utility substantially diverges across app categories and that their demographic characteristics and habit formation explain the appreciable heterogeneity in baseline utility and satiation. These parameters also exhibit positive and negative correlations in mobile websites and app categories. Our modeling approaches and computational methods can unlock new perspectives and opportunities for handling large-scale, micro-level data, while serving as important resources for big data analytics and mobile app analytics.

Keywords: Mobile analytics, mobile web and apps, time use modeling, satiation, interdependence, structural econometrics

Introduction

The mobile revolution has stimulated a dramatic growth in communication, resulting in the production of data at a scale and pace never before seen in the history of digital technology. The plethora of different applications ("apps") and consumers' relentless use of such innovations generate voluminous data in the form of social media exchanges, purchase transactions, music downloads, car navigation requests, stock investment advice, location alerts, and search queries. In an app-based, networked socioeconomic environment, every text, transaction, digital procedure, virtually any tactile command, and other user input processed over apps can become a data point. The addictive nature of mobile plat-

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forms has abetted continuous data production, even while consumers are asleep. The rise of mobile app technology and its attendant challenges have undoubtedly become a big deal in big data.

In business communities, volume, velocity, and variety are often used to define the nature and varying dimensions of big data (hence the term "3Vs of big data"). Mobile apps provide an intriguing context in which the 3Vs perfectly account for the roles played by big data. As of July 2014, Google had 1.3 million apps available through its Android platform, while its competitor, Apple, offered a selection of 1.2 million apps through its iTunes app store.[2] In addition to this tremendous number of apps, the portability and on-demand accessibility advanced by mobile platforms have accelerated data processing, thereby enabling real-time, streaming-based data consumption on the fly. Mobile apps considerably differ in terms of functionalities and users' consumption preferences; certain apps are used with great frequency, whereas many others are deployed only once or twice in their lifespans before they are completely discarded. The exploding availability and the escalating complexity of dynamic and multimodal apps have thus presented formidable challenges to app developers and platform owners in understanding the business ramifications of placing such IT products at consumers' immediate disposal.

Mobile app analytics, in which app usage is monitored and measured to study the behavior of mobile app users, is at its nascent stage. The number of downloads was an initial key interest, but the direct, quantitative measurement of usage, habits, and engagement have increasingly elicited attention from businesses. For example, the solution accessible from Google's Mobile App Analytics measures user behaviors ranging from app discovery and download to in-app purchase. It enables real-time reporting on where users take action, pause, or disappear through event tracking and flow visualization, thus providing insights into app users' behaviors.[3] Nevertheless, the methods and results derived from commercial mobile app analytics solutions (e.g., Google's Mobile App Analytics, Yahoo's Flurry Analytics, and Countly's Mobile Analytics) require room for improvement given that they are generally descriptive in nature and neglect the complexity inherent to the usage of various mobile apps. An additional shortcoming is that these mechanisms offer a holistic view of app usage only at the aggregate level, thereby preventing analysts from comprehensively attending to the individual user utility that originates from the choice and consumption of an assortment of apps. Furthermore, commercial analytics have a limited capacity to describe or predict interdependence and competition among a large number of apps. Some apps are often used in concert to enhance user experience and utility, but certain apps function only as substitutes for others. In a battle of substitutes, an app competes with another for volume and usage frequency.

Although the number and diversity of apps are increasing at an unprecedented rate, validated empirical schemes, robust computational frameworks and analytics, and actual usage data in large quantities are lacking. Such deficiencies continue to impede our understanding of app usage patterns, as well as the interdependence and competition among such technologies. As mobile users are progressively confronted with an overabundance of apps, they adopt a range of choice mechanisms to sift through multiple options and effectively manage app consumption. These mechanisms allow users to maximize utility given time constraints. To systematically explore the patterns of consumption dependency for a wide selection of apps, this study builds on the work of Bhat (2005) in developing a utility theory-based structural model for multiple discrete/continuous choices in app use. An important component of our model is that it focuses on a user's repeat decisions regarding which app to use and how extensive app use will be after download. The premise that underlies the model is that a consumer's marginal utility diminishes as the level of consumption of any particular app increases—a phenomenon known as *satiation*.

Another essential constituent of our utility-based choice paradigm is the use of a unique panel data set that details mobile app consumption at the individual user level. Guided by the capabilities and considerations of our paradigm, we pursue the following research questions: How do we quantify users' intrinsic preferences for apps (i.e., baseline utility) and the marginal utility derived from app consumption (i.e., satiation)? How do the baseline utility and satiation levels of apps vary across different user demographic groups, and how are they affected by persistent use and time trends? Finally, how is a dimensionality issue addressed when estimating interdependence in unobserved attributes among app categories under conditions wherein numerous app categories exist? Resolving these matters on the basis of a rigorous theoretical framework with empirical validation can enrich our understanding of the baseline utility and satiation levels of numerous mobile apps in diverse categories.

Further, unlike typical discrete-choice models in which a single option is chosen, our multiple discrete-continuous choice approach allows the simultaneous selection of various

[2] http://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/.

[3] http://www.google.com/analytics/mobile/.

options. Diminishing marginal utility horizontally motivates multiple discrete purchases. That is, if consumers experience diminishing marginal utility for each of several potential apps with comparable attractiveness, then they will evaluate and choose these options simultaneously. For example, users evenly distribute the time that they spend on various mobile apps across socializing, entertainment, and productivity tasks. Some of such co-choice incidences are, in reality, motivated by app design. A case in point is game apps that enable users to share their achievements with their Facebook friends by way of a "share" button that the users can click on after completing a level or reaching a new record. An additional potential cause of multiple choice incidences is data aggregation. In our analysis, we devote a week to extracting the nontrivial interdependency patterns regarding app choice and consumption. A narrow time slice (e.g., daily or hourly) may diminish the multi-choice feature. Moreover, our mobile analytics approach incorporates a factor analytic structure into the multiple discrete-continuous choice framework. Capturing correlations among options in their unobserved baseline utility and satiation is empirically challenging with the use of multiple discrete-continuous choice models. Covariance parameters increase in a quadratic fashion with an expanding number of options, thus resulting in prohibitive burdens in model estimation. Using the proposed factor analytic structure, we circumvent this empirical challenge.

Finally, our analytical approach deals with the variety of app data that are characterized by individual heterogeneity, which complicates and constrains the understanding of consumers' app time-use. In particular, the demographic characteristics of users affect their intrinsic preferences for apps and the marginal utility derived from app consumption. Because behavioral heterogeneity in IT usage has been frequently observed across different demographic groups (e.g., Wixom and Todd 2005), the patterns underlying app choice and consumption are expected to vary across age, gender, income, and educational groups. Researchers have yet to develop a comprehensive systematic analytics approach that explores the influence of demographic characteristics on the consumption of numerous mobile apps and their implications for individual utility trajectories. The methods and processes detailed in this work can serve as important resources for big data analytics and unlock new perspectives for mobile app analytics. To reiterate, the specific contributions of our proposed analytics frameworks are as follows:

- We develop a utility theory-based structural model that simultaneously identifies consumer app choices and usage patterns within a single utility maximization framework.

- To efficiently capture dependencies among alternative apps in their unobserved baseline utility and satiation, we propose a mobile analytics approach that incorporates a factor analytic structure into the multiple discrete-continuous choice framework.

- Our proposed analytics method offers a systematic approach that explores the influence of individual heterogeneity (i.e., demographic characteristics) on consumption patterns and choice preferences across numerous mobile apps.

The proposed mechanism of user app choice and consumption presents equally important implications for firms' strategy building, particularly for mobile competitive analysis, mobile targeting, and mobile media planning. As app developers and publishers migrate from paid download models to in-app purchase and ad-supported business models, they steadily illuminate how much time consumers spend using their apps in comparison with competing apps. Increased time devoted to a focal app is likely to generate additional in-app advertising revenues and purchases and is likely to enhance consumer engagement with a brand, thereby endowing businesses with competitive advantage. We illustrate the pragmatic value of our proposed analytics approach by carrying out a competitive analysis of a focal app and selected competing apps. We also put forward managerial guidelines for new user prediction in mobile targeting. Finally, as advertisers raise spending on mobile advertising, they select optimal mobile media vehicles (i.e., mobile apps and websites) to maximize their advertising exposure and thereby stimulate desired consumer economic behaviors. We describe the strategic value of our quantitative paradigm and mechanism in maximizing the consumption of apps through mobile media planning in the app-based economy.

Theoretical Background

User Behavior on Mobile Platforms and Apps

Research on mobile platforms and apps has proliferated in consonance with their increasing use. Ghose and Han (2011) investigate user behavior on the mobile Iternet by mapping the interdependence between the generation and usage of mobile content. The authors find negative temporal interdependence; the more frequent the consumption of mobile content in the previous period, the less the content generated in the current period or vice versa. Ghose et al. (2013) report that ranking and geographical proximity exhibit a more pronounced influence on mobile devices than on PCs. Einav et al. (2014) find that the adoption of mobile shopping applications is associated with both an immediate and sustained growth in overall platform-based purchase. Xu et al. (2016) show that users' adoption of tablets enhanced the overall growth of Alibaba's e-commerce market, with an annual increase of approximately U.S. $923.5 million.

Our study also builds on an evolving body of literature on mobile apps. Carare (2012), for instance, employs a reduced-form model and Apple App Store data to delineate user behavior on mobile apps. The author reveals that app consumers are willing to pay an additional $4.50 for top- ranked apps, but that their preference for apps with bestseller status sharply declines for highly ranked products. A recent study by Xu et al. (2014) demonstrates that the introduction of a mobile app by a major national media company significantly increases demand on the corresponding mobile news website. Using publicly available data from Apple's App Store, Garg and Telang (2013) discover that top-ranked paid apps available for the iPhone elicit 150 times more downloads than do other apps ranked in the top 200. Ghose and Han (2014) discover that app demand increases with the introduction of an in-app purchase option, which enables users to complete transactions within an app.

A thorough review indicates that the current literature on mobile apps focuses exclusively on demand in the form of downloads or paid purchases, but pays scant attention to the actual choices and consumption patterns regarding mobile apps.

Multiple Discrete-Continuous Choice Models

To capture the dependence between choice and quantity decisions, researchers have proposed several analytics approaches, including the structural single utility (e.g., Chiang 1991; Chintagunta 1993; Hanemann 1984; Kim et al. 2002) and the error-dependence (or reduced-form) methods (e.g., Krishnamurthi and Raj 1988; Tellis 1988; Zhang and Krishnamurthi 2004). The former specifies a utility function and assumes that the optimal choice and quantity are derived as an equilibrium solution from the utility function; that is, the dependence between choice and quantity decision is reflected by this function. The error-dependence technique handles dependence by allowing for correlations in the error terms of choice and quantity models. A major advantage of the single utility approach is that it enables researchers to estimate structural parameters and metrics of economic interest (e.g., compensating variation). The proposed model based on the multiple discrete-continuous choice method is categorized as a single utility approach.

Mobile users' app usage decisions can be broadly broken down into two choices; which apps to select and how extensively to consume them. Because multiple discrete-continuous choice models tackle both problems within a single utility maximization framework, they are appropriate for analyzing our mobile app and web time-use data. Kim et al. (2002) propose a translated nonlinear, addictive utility model wherein a parsimonious specification provides both corner and interior solutions under the simultaneous purchase of multiple product varieties. A multiple discrete-continuous choice model formulated by Bhat (2005, 2008) extends single discrete-continuous frameworks (e.g., Chiang 1991; Chintagunta 1993; Dubin and McFadden 1984; Hanemann 1984) to include handling multiple discreteness in demand and resolve the heteroscedasticity and correlations that arise from unobserved characteristics. Among various applications, multiple discrete-continuous choice models have frequently been employed in analyzing time-use data. Bhat (2005) scrutinizes time-use allocation decisions among several discretionary activities on weekends. Drawing from Bhat's multiple discrete-continuous time-use model, Spissu et al. (2009) probe into within-subject variations over a 12-week sample period for six broad activity categories along with another activity. Luo et al. (2013) incorporate dynamic components into a multiple discrete-continuous choice model to examine how consumers allocate time to a portfolio of leisure activities over time.

In the present study, we develop a unique structural model of app selection and time-use decision by incorporating a factor analytic structure into a multiple discrete-continuous choice framework. The vectors of individual-level baseline utilities and satiation parameters are modeled as functions of observed mobile user characteristics and a small number of unobservable user-specific factors. In the literature, factor analytic structures are combined with probit or logit models, whose principal objective is to understand inter-brand competition by pictorially depicting the locations of competing brands on a perceptual map (Chintagunta 1994; Elrod and Keane 1995). Our approach methodologically extends the multiple discrete-continuous choice models by allowing for correlations in both the baseline utilities and satiation levels of various mobile app categories. The correlations are taken into account in a parsimonious manner by using factor analytic approaches.

Empirical Background and Data Description

Panel Data on Mobile App and Web Time-Use

This section presents an overview of the empirical background behind our data. We collected large-scale panel data comprising the mobile app and website time-use histories provided by Nielsen KoreanClick, a market research company that specializes in consumers' Internet and mobile usage. Audience measurement is designed to gauge the proportion of users in a given audience and how long they remain attentive, usually in relation to television viewership (e.g., Nielsen ratings), but also with respect to increasing traffic on websites and mobile application platforms. Nielsen KoreanClick maintains a panel of mobile app users with Android operating system-based devices in Korea. These users are aged 10 to 70 and are selected by stratified sampling.[4] Android is the dominant operating system of mobile devices worldwide, accounting for 67.5% of the global market. In Korea, nearly 93% of smartphones are powered by the Android platform (Yonhap News 2014).

After individuals voluntarily agree to serve in the panel, they are asked to download and install a meter application from Nielsen KoreanClick in their mobile devices.[5] The participants are rewarded points for installing the meter app, and the incentive points can be accumulated and redeemed for gift cards. The app runs in the background and collects data on the panel members' use of mobile apps and the mobile web, even when they are not connected to the Internet.[6] The meter app regularly transmits encrypted log files to a server via a secure cellular connection or Wi-Fi. We also acquired individual user-level demographics, such as age, gender, monthly income, and education.

Between March 5 and July 1, 2012 (17 weeks), we collected data on 1,366 panel members who used mobile apps and the web throughout the sampling period. Our data incorporates individual-level weekly information on the types and names of mobile apps and websites, as well as on duration of visits. Nielsen KoreanClick classified the mobile content under 14 activity categories; communication, game, map and navigation, entertainment, lifestyle, personal finance, music and radio, photo, portal, schedule and memo, social networking, utility, video, and combined mobile web activities.[7] The panel members used 11,548 apps and visited 8,043 websites (see Appendix A for details).[8] The apps in our sample include not only top global mobile apps such as Facebook, YouTube, Twitter, and Skype, but also top local mobile apps such as Kakao Talk, Naver, and Cyworld.

Our data contain 23,222 (1,366 users × 17 weeks) app choice occasions. Column 1 of Table 1 shows that the apps most frequently used by the panel members are communication apps (99.4%), followed by schedule/memo apps (98.8%), utility apps (97.8%), and photo apps (90.0%). The least frequently accessed applications are the entertainment apps (38.0%). Column 2 of Table 1 reveals that the smartphone users in our sample devoted an average of 12 hours and 4 minutes every week (approximately 2 hours every day on average) to consuming content via their mobile devices.[9] Weekly consumption on mobile apps surpasses that on the mobile web. A more specific illustration is provided in Figure 1. The users spent the largest amount of time (26%) on communication apps (e.g., mobile messengers), followed

[4]To check the robustness of our results, we excluded users whose age is less than 20 years old or greater than 50 years old. The sample size reduced to approximately 85% of the original sample. Results show that our main results remain robust even when excluding the users in young or old groups. We did not include the results of this subsample analysis in the paper to conserve space, but they are available upon request from the authors.

[5]Nielsen's metering app collects an exact start time when a user opens an app and measures how long s/he is actively using it until the app is closed or another app is activated. So it captures the engaged time in apps by measuring the amount of time a user actively consumes an app content. Further, a distinctive advantage of this measurement approach over the previous metering method is that the metering app can effectively measure the usage time of communication and news apps, which are often used for short bursts of time (e.g., 10 seconds).

[6]Mobile web refers to the collective term for websites accessed from mobile devices by using browsers. Thus, this term is often used interchangeably used with "mobile browser."

[7]Google Play is a leading app market based on the Android operating system. Notably when publishing a new app or a new version of an existing app on Google Play, app developers self-select one or more appropriate app categories; however, they are not required to go through the verification process. In some cases, therefore, the app categories reported by app developers are incorrect or inconsistent. To address this issue, Nielsen KoreanClick performed a thorough, manual reclassification to ensure that a certain app is classified under a single, primary app category. We used Nielsen Korean Click's categorization in our empirical analysis. If the categorization of apps were arbitrary, deriving meaningful results from the empirical analysis would be difficult. Our empirical analysis shows highly significant and meaningful results (refer to the "Results" section), thus endowing empirical validity to the categorization. An alternative categorization can be adopted in the proposed empirical framework. We performed an empirical analysis using the individual app-level data set in the "Applications of Proposed Approaches" section.

[8]The number of mobile websites visited was aggregated to the domain level. That is, multiple URLs with the same domain name were counted as one. For example, two different URLs with the common domain names (https://www.google.com/maps/preview and https://www.google.com/calendar/render) were treated as one website when we counted the number of websites visited.

[9]The mobile app and web usage amounts in our Korean sample resemble closely those in the U.S. market. According to Flurry (2013), a global leader in mobile analytics solutions, the average U.S. mobile consumer spends an average of 2 hours and 38 minutes per day on smartphones and tablets, and 80% of that time (2 hours and 7 minutes) is spent inside apps and 20% (31 minutes) is spent on the mobile web. This helps enhance the external validity of our substantive findings. However, our proposed framework can be readily applied to different data from other geographical users and different sample periods.

Table 1. Choice and Time Use According to App Categories

Categories	Choice	Time Use	
		Hours per Week	Percent
Outside Option (other activities)	100.0%	155.83	92.8%
Communication	99.4%	3.15	1.9%
Game	63.9%	1.53	0.9%
Map/Navigation	67.6%	0.21	0.1%
Entertainment	38.0%	0.26	0.2%
Lifestyle	67.4%	0.29	0.2%
Personal Finance	60.2%	0.29	0.2%
Music/Radio	67.0%	1.21	0.7%
Photo	90.0%	0.31	0.2%
Portal	74.9%	0.64	0.4%
Schedule/Memo	98.8%	0.67	0.4%
Social Network	72.3%	0.81	0.5%
Utility	97.8%	0.53	0.3%
Video	77.0%	0.66	0.4%
Web	88.3%	1.61	1.0%
Total		168.00 (24 hours × 7 days)	100.00%

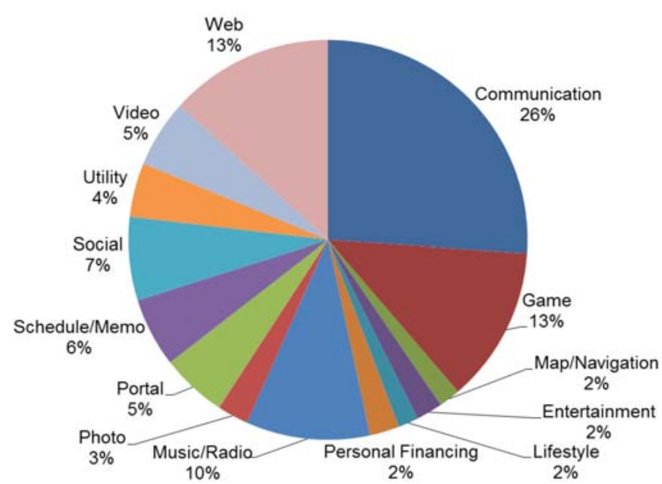

Figure 1. Time Use According to App Categories Excluding Outside Option

by the mobile web (13%), game apps (13%), music and radio apps (10%), social apps (7%), and schedule/memo apps (6%). In the "Results" section, we show that our findings on app category baseline utilities and satiation levels, derived using the proposed model differ from those reported in Table 1 and Figure 1.

Model-Free Evidence of Dependence Between Mobile Content Choice and Time-Use Decisions

As mobile users increasingly access the mobile web and various kinds of apps, their choices become interdependent. Figure 2 indicates that all of the users accessed at least two

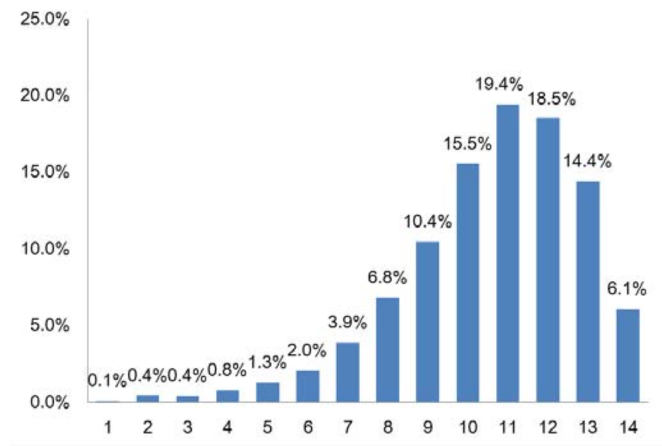

Figure 2. Distribution of the Number of Jointly Used App Categories

categories of mobile content during a given week. Approximately 98.3% of the users accessed more than four categories of mobile content in a given week. These descriptive findings on the joint use of multiple mobile content categories strengthen the validity of our econometric model, in which we incorporated multiple-discrete choices into continuous time-use decisions.

Drawing inferences on time-use decisions across multiple app categories through simple methods is often challenging. We did not observe usage time on app categories that were not selected by the panel members. Our weekly data indicates that only 6.1% of usage was devoted to all 14 categories of mobile content. Employing simple metrics instruments (e.g., a correlation matrix) therefore necessitates aggregating the observed weekly data into a monthly or quarterly series or discard observations with zero-time use. To attribute zero time use to non-app use, a correlation matrix of app choice incidence can be employed using dummy variables that take the value of 1 if an app is used and 0 otherwise. Similarly, a correlation matrix of app time-use quantity can be established by assigning non-incidence with a zero value. These approaches are inferior to the proposed method because they do not fully leverage available information.

The correlation matrix of app choice incidence variable and the correlation matrix of app time-use quantity variable (see Appendix B, Tables B1 and B2) indicate that the observed relationships among app use incidences and app use time are mostly positive but marginal. We found substantial positive relationships among communication, utility, and schedule/memo categories. However, we could not find any substantial negative correlation. In the "Results" section, we demonstrate that the findings derived with the proposed model drastically differ from what the model-free correlation matrix reveals, indicating that simple methods can generate misleading results in the evaluation of correlation across mobile content categories. We discuss our modeling approach in detail below.

Econometric Model

In this section, we present our proposed model to estimate the baseline utility and satiation levels of different categories of mobile web and apps while allowing for user heterogeneity and cross-app use interdependence even when the number of app categories is large. We then discuss how we identify our demand system.

Proposed Model

Consumer Utility Function

We observe which app categories are chosen and how much time is spent on each selected app category in our data. Accordingly, we describe a mobile user's behavior by virtue of a multiple discrete-continuous choice process. Compared to discrete choice models (i.e., Logit or Probit models) and continuous dependent variable models, multiple discrete-continuous choice models can handle more effectively both discrete and continuous natures of observed data within a single utility-based framework. Because of this advantage, multiple discrete-continuous choice models have successfully been applied in several academic fields, including marketing, transportation, and economics (Bhat 2008; Hendel 1999; Kim et al. 2002). In this paper, we extend Bhat's (2008) multiple discrete-continuous extreme value (MDCEV) framework. We specify the latent utility of mobile content usage as follows:

$$U_{ht} = \tfrac{1}{\alpha_0} \cdot \exp(\varepsilon_{h0t}) \cdot q_{h0t}^{\alpha_0} + \sum_{j=1}^{J} \tfrac{1}{\alpha_{hjt}} \cdot \mu_{hjt} \cdot \left\{ \left(q_{hjt} + 1\right)^{\alpha_{hjt}} - 1 \right\} \quad (1)$$

where $h = 1, \ldots, H$ denotes individual mobile users, $j = 0$ and $j = 1, \ldots, J$ denote an outside option (activities other than mobile content use) and mobile content use categories, respectively, and $t = 1, \ldots, T$ denotes time period (weeks). q_{hjt} ($j = 0, \ldots, J$) is time allocated to alternative j by user h in time period t. This specification is referred to as "alpha-profile" in the literature (for further details on model specification and other possible specifications, see Bhat 2008). ε_{hjt} is a user-, alternative-, and time-specific random term associated with the outside option.[10] μ_{hjt} represents the "baseline marginal utility" (the marginal utility when none is consumed) of alternative j in time t by user h. When a user decides which category to use first, categories with large value of μ_{hjt} have higher probabilities of being selected compared to those with small μ_{hjt}. Also, it can be interpreted as a measure of "perceived quality" because higher values of μ_{hjt} mean that the alternative confers higher levels of utility from any level of consumption, all else equal.

In addition, α_0 and α_{hit} are referred to as satiation parameters in that they determine how the marginal utility of alternative j changes as their consumption quantity increases. It is noteworthy that the satiation parameter captures the marginal rate of substitution among different options within a given time period and does not capture any dynamic effects.[11] To illustrate the role of the satiation parameter, let us assume that there are only two choice options—the outside option ($j = 0$) and alternative 1 ($j = 1$) – and that the satiation parameters are fixed to one (i.e., $\alpha_0 = 1$ and $\alpha_{h1t} = 1$). Then, the utility function (1) becomes $U_{ht} = \exp(\varepsilon_{h0t}) \cdot q_{h0t} + \mu_{h1t} \cdot q_{h1t}$. The marginal utilities of the outside option and the alternative 1 are equal to $\exp(\varepsilon_{h0t})$ and μ_{h1t}, respectively. It should be noted that the marginal utility values do not change with consumption quantities, resulting in a linear indifference curve (see case (a) in Figure 3). In this case, user h allocates all her time to the category with the highest perceived quality. If $\exp(\varepsilon_{h0t}) > \mu_{h1t}$ ($\exp(\varepsilon_{h0t}) < \mu_{h1t}$), as shown in Figure 3(a), the user can attain the highest level of utility by spending all her time for the outside option (alternative 1) and thus select the outside option (alternative 1) only. That is, $q_{h0t} = Q$ and $q_{h1t} = 0$ ($q_{h0t} = 0$ and $q_{h1t} = Q$). Note that this linear indifference curve implies that the two alternatives are perfect substitutes.

Now, let us consider a more realistic case where $\alpha_0 < 1$ and $\alpha_{hit} < 1$. Then the utility function (1) shows diminishing marginal utility. As α_{hit} decreases, the utility function in alternative j shows more concave patterns, and higher satiation occurs at a lower value of q_{hit}. Due to this diminishing marginal utility, multiple alternatives can become comparable to each other and they will be chosen together rather than only one option is selected (see case (b) in Figure 3). In this case, user h consumes the outside option and alternative 1 by $q_{h0t} = \hat{q}_{h0t} > 0$ and $q_{h1t} = \hat{q}_{h1t} > 0$, respectively.

According to Bhat (2008), U_{ht} becomes a proper utility function when $u_{hjt} > 0$ and $\alpha_{hjt} < 1$ for $j = 1, \ldots, J$. To ensure that the baseline utility is nonnegative and the satiation parameter is less than 1 regardless of the model parameter values, we specify the baseline utility parameter μ_{hjt} and the satiation parameter α_{hjt} as the following:

$$\begin{aligned} \mu_{hjt} &= \exp\left(\beta_{hjt} + \varepsilon_{hjt}\right), \text{ for } j = 1, \ldots, J \\ \alpha_{hjt} &= 1 - \exp\left(\lambda_{hjt}\right), \text{ for } j = 1, \ldots, J \end{aligned} \quad (2)$$

ε_{hjt} represents idiosyncratic elements in utility. Both ε_{h0t} and ε_{hjt} are known to decision makers, but unknown to researchers. We assume that these follow Type-I Extreme Value distribution.

User Heterogeneity, Dynamics, and Correlation among Mobile Web and App Categories

For user-, alternative-, and time-specific β_{hjt}, we specify the factor analytic structure

$$\begin{aligned} \beta_{ht} = \bar{\beta} + \Xi_\beta \cdot t + \Sigma_\beta \cdot SD_{ht} \\ + \Pi_\beta D_h + \Gamma_\beta \psi_h + \Lambda_\beta \upsilon_h \end{aligned} \quad (3)$$

where a ($J \times 1$) vector $\beta_{ht} = [\beta_{h1t}, \beta_{h2t}, \ldots, \beta_{hJt}]'$ and $\bar{\beta}$ is a ($J \times 1$) constant vector. t is time index ($t = 1, \ldots, T$) and Ξ_β is a ($J \times J$) vector of time trend coefficients. A ($J \times 1$) vector $SD_{ht} = [SD_{h1t}, SD_{h2t}, \ldots, SD_{hJt}]'$ and SD_{hjt} takes the value of one if the alternative j is selected at t-1 and takes the value of

[10]The utility function can be classified as a generalized variant of the translated constant elasticity of substitution (CES) utility function. This specification assumes additively separable utility. We discuss a limitation of this model specification in detail later in the "Conclusions." Note that the utility specification of the outside option (the first term in the right hand side of (1)) is different from those of the other alternatives and this is for the utility function to capture that the outside option is always consumed.

[11]We capture dynamic effects in mobile app choice and usage with structural state dependence and common time trends. We elaborate on these in the next section.

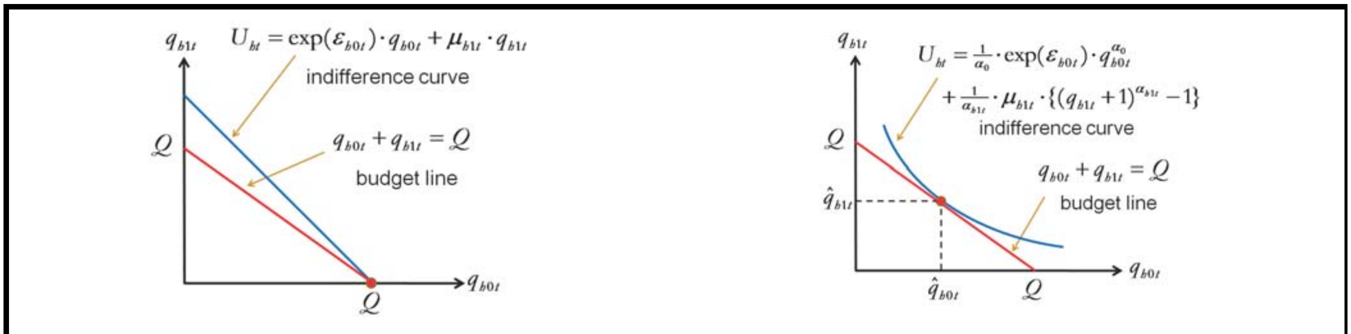

Figure 3. An Example of How Diminishing Marginal Utility (Satiation) Affects Multiple Discrete Choices

zero otherwise. Σ_β is a ($J \times J$) diagonal matrix of the state-dependence coefficients. D_h is the ($K \times 1$) vector of observed demographic variables of user h and Π_β is a ($J \times K$) coefficient matrix. Γ_β is a ($J \times F$) factor loading matrix and ψ_h is a ($F \times 1$) vector of orgthogonal Gaussian factors ($\psi_h \sim N(0, I_F)$). Λ_β is a ($J \times J$) diagonal matrix and υ_h is a ($J \times 1$) vector of independent unit-variance Gaussian random variables ($\upsilon_h \sim N(0, I_J)$). The proposed specification decomposes dynamics and heterogeneity in mobile content choice utility into five parts: (1) time trend; (2) structural state dependence; (3) demographic influence; (4) common factor; and (5) specific factor.

The first is the category-specific time trend in baseline utility captured by $\Xi_\beta \cdot t$. The impact of category-specific time trend is the same for all mobile users and thus this captures the influences of common demand shifter (e.g., common high demand for weather apps in storm seasons). A mobile user's prior app choice and usage experience typically influence her decision in the future. In our model, we capture this using the lagged choices SD_{hjt}. Unlike the time trend, this dynamic effect is individual specific and is referred to as "structural state dependence" in the literature. Structural state dependence can be positive or negative, in which cases they are called "inertia" (Jeuland 1979) and "variety seeking" (McAlister 1982), respectively. Variety seeking comes into play when consumers get bored with the same choice over time. Inertia could result from satisfaction obtained from the choice, learning and reinforcement effect, and/or decision makers' need to routinize behavior so as to minimize the cost of thinking. Several empirical studies have reported that ignoring dynamics in consumer choice can result in biased estimates. Also, it is reported that structural state dependence, along with unobserved heterogeneity, captures most of the observed temporal dynamics in consumers' product choices (Keane 1997; Seetharaman 2004).

The influence of demographic variables on the app baseline utility is captured by $\Pi_\beta D_h$ in (3). The remaining variations in the baseline utility is captured by parsimonious common factors. In factor analysis literature, ψ_h is referred to as a "common factor." F elements in ψ_h influence all J elements in β_{ht}. We can understand the main characteristics of the factors by interpreting the factor loading matrix Γ_β. Also, it should be noted that, along with $\Sigma_\beta \cdot SD_{ht}$ and $\Pi_\beta D_h$, these common factors generate correlations in β_{ht}. The last term in equation (3), $\Lambda_\beta \upsilon_h$, is referred to as a "specific factor." Unlike ψ_h, the j^{th} element in υ_h influences β_{hjt} only.

The factor analytic structure is of interest in our empirical setting for a number of reasons. First, a factor model allows us to estimate category similarity in unobserved attributes (Elrod and Keane 1995). We can potentially interpret the factors as inherent mobile users' traits. Moreover, the user-specific factor estimates can be used for targeting purposes. Second, the factor model introduces correlations in the latent baseline utilities across app categories with relatively few parameters. This characteristic is particularly useful in our context to alleviate the concern for dimensionality issues inherent in estimating unobserved heterogeneity and their interdependence when the number of app categories (i.e., alternatives) is large. We can reduce the number of parameters required to estimate a full covariance matrix in a linearly scalable manner while remaining highly flexible and minimizing loss of information. Because of these major advantages, researchers have applied factor analytic structure in random coefficient Logit or Probit models (Elrod and Keane 1995; Hansen et al. 2006; Singh et al. 2005). A key methodological contribution of our proposed model is that it extends factor analytic structure to multiple discrete-continuous choice models.

From equation (3), we can derive the following covariance matrix of β_{ht}:

$$Cov(\beta_{ht}) = \Sigma_\beta \Theta_{SD} \Sigma'_\beta + \Pi_\beta \Omega_D \Pi'_\beta + \Gamma_\beta \Gamma'_\beta + \Lambda_\beta \Lambda'_\beta \tag{4}$$

where Θ_{SD} and Ω_D are covariance matrices of SD_{ht} and D_h, respectively. The variance decomposition of equation (4) allows us to quantify the relative contribution of each part. For example, the proportion of variation in β_{hjt} explained by observed demographic variables is (j^{th} diagonal element of $\Pi_\beta \Omega_D \Pi_\beta'$)/($j^{\text{th}}$ diagonal element of $Cov(\beta_{ht})$).

Further, the value of user-, alternative-, and time-specific satiation parameter α_{hjt} is determined by λ_{hjt}. Similar to equation (3), we specify the following factor analytic model structure to λ_{hjt}:

$$\begin{aligned}\lambda_{ht} &= \bar{\lambda} + \Xi_\lambda \cdot t + \Sigma_\lambda \cdot SD_{ht} \\ &+ \Pi_\lambda D_h + \Gamma_\lambda \varphi_h + \Lambda_\lambda v_h\end{aligned} \tag{5}$$

where a $(J \times 1)$ vector $\lambda_{ht} = [\lambda_{h1t}, \lambda_{h2t}, \ldots, \lambda_{hJt}]'$ and $\bar{\lambda}$ is a $(J \times 1)$ constant vector. Ξ_λ, Σ_λ, and Π_λ are $(J \times 1)$, $(J \times J)$, and $(J \times K)$ coefficient matrices, respectively. Γ_λ is a $(J \times F)$ factor loading matrix and φ_h is a $(F \times 1)$ vector of orthogonal Gaussian factors ($\varphi_h \sim N(0, I_F)$). Λ_λ is a $(J \times J)$ diagonal matrix and v_h is a $(J \times 1)$ vector of independent Gaussian random variables ($v_h \sim N(0, I_J)$). The covariance matrix of λ_{ht} can be decomposed as follows:

$$\begin{aligned}Cov(\lambda_{ht}) &= \Sigma_\lambda \Theta_{SD} \Sigma_\lambda' + \Pi_\lambda \Omega_D \Pi_\lambda' \\ &+ \Gamma_\lambda \Gamma_\lambda' + \Lambda_\lambda \Lambda_\lambda'\end{aligned} \tag{6}$$

Model Estimation and Identification

Constrained Utility Maximization and Estimation

We derive our demand system by applying the Kuhn-Tucker method to the latent utility of mobile content use specified in equation (1). By solving the Kuhn-Tucker conditions for constrained utility maximization, we obtain demand functions wherein a mixture of corner solutions and interior solutions are a product of the underlying utility structure. The Lagrangian for the constrained utility maximization problem is given by

$$\begin{aligned}L_{ht} &= \tfrac{1}{\alpha_0} \cdot \exp(\varepsilon_{h0t}) \cdot q_{h0t}^{\alpha_0} + \sum_{j=1}^{J} \tfrac{1}{\alpha_{hjt}} \cdot \mu_{hjt} \cdot \\ &\left\{ (q_{hjt} + 1)^{\alpha_{hjt}} - 1 \right\} + \delta_{ht} \left(Q - \sum_{j=0}^{J} q_{hjt} \right)\end{aligned} \tag{7}$$

where δ_{ht} is the Lagrange multiplier, and Q denotes total amount of time given to each mobile user (i.e., 168 hours per week). The Kuhn-Tucker first order conditions can be derived as follows:

$$\begin{aligned}&\mu_{hjt} \cdot (q_{hjt} + 1)^{\alpha_{hjt} - 1} - \delta_{ht} = 0, \text{ if } q_{hjt} > 0 \\ &\mu_{hjt} \cdot (q_{hjt} + 1)^{\alpha_{hjt} - 1} - \delta_{ht} < 0, \text{ if } q_{hjt} = 0\end{aligned} \tag{8}$$

and $\exp(\varepsilon_{h0t}) \cdot q_{h0t}^{a_0 - 1} - \delta_{ht} = 0$ since the outside option is always consumed (i.e., time used for activities other than mobile app and web uses is nonzero). We use the expression for δ_{ht} from the first-order condition for the outside option to eliminate the Lagrange multiplier from (7) and then take log in both sides, so the Kuhn-Tucker conditions for the interior and corner solutions can be written, respectively, as

$$\begin{aligned}&\beta_{hjt} + (\alpha_{hjt} - 1) \cdot \ln(q_{hjt} + 1) + \varepsilon_{hjt} = \\ &\quad (\alpha_0 - 1) \cdot \ln(q_{h0t}) + \varepsilon_{h0t}, \text{ if } q_{hjt} > 0 \\ &\beta_{hjt} + (\alpha_{hjt} - 1) \cdot \ln(q_{hjt} + 1) + \varepsilon_{hjt} < \\ &\quad (\alpha_0 - 1) \cdot \ln(q_{h0t}) + \varepsilon_{h0t}, \text{ if } q_{hjt} = 0\end{aligned} \tag{9}$$

From this Kuhn-Tucker first order condition, we derive the following probability that any M of the J alternatives are chosen (for details, see Chapter 4 of Bhat 2008):

$$\begin{aligned}&P_{ht}(q_{h0t}, q_{h1t}, \ldots, q_{hMt}, 0, 0, \ldots, 0) \\ &= \int_{\Theta_h} M! \cdot \left(\prod_{j=0}^{M} \frac{1 - \alpha_{hjt}}{q_{hjt} + \tau_j} \right) \cdot \left(\sum_{j=0}^{M} \frac{q_{hjt} + \tau_j}{1 - \alpha_{hjt}} \right) \\ &\cdot \frac{\prod_{i=0}^{M} e^{V_{hit}}}{\left(\sum_{j=0}^{J} e^{V_{hjt}} \right)^{M+1}} dF(\Psi_h)\end{aligned} \tag{10}$$

where $V_{h0t} = (\alpha_0 - 1) \cdot \ln(q_{h0t})$, $V_{hjt} = \beta_{hj} + (\alpha_{hjt} - 1) \cdot \ln(q_{hjt} + 1)$ for $j = 1, \ldots, J$, $\tau_0 = 0$, and $\tau_j = 1$ for $j = 1, \ldots, J$. Ψ_h is a vector of common factors and specific factors in α_{hjt} and β_{hjt} (ψ_h, υ_h, φ_h, and v_h) and $F(\Psi_h)$ is a joint distribution function of Ψ_h. We use Monte Carlo simulation methods to calculate the probability (10) and estimate the model parameters by maximizing a likelihood function derived from equation (10) (for details, see Keane 1993). To compute the integrals in the likelihood function, we generate random normal draws for ψ_h, υ_h, φ_h, and v_h from their distributions, and then take averages of computed integrands. In our application, we use 100 Halton draws. The resulting estimator becomes a simulated maximum likelihood (SML) estimator. This procedure is the same as maximum likelihood except that simulated probabilities are used instead of the exact probabilities (see Appendix C for detailed instructions on model estimation). Researchers (e.g., Keane 1993) have articulated thoroughly the properties of SML (i.e., its consistency, efficiency, and asymptotic normality).

Identification

Bhat (2008) discusses the identification issues of general multiple discrete-continuous choice models and shows the empirical identifiability of "alpha-profile" specification, which is adopted in the proposed model. A distinctive feature of our model is that it incorporates the Gaussian factor analytic structure into a multiple discrete-continuous choice model. It should be noted that our Gaussian factor specification is the most general and widely used specification (Elrod and Keane 1995; Hansen et al. 2006; Singh et al. 2005), but other distributional assumptions also can be used. For the identification of model parameters, appropriate restrictions on factor loading matrices are required. Following Singh et al. (2005) and Hansen et al. (2006), we impose a standard triangular restriction on a loading matrix. It is widely known that this approach imposes the minimum restriction for the parameter identification. Specifically, with two factors, one of the elements in the second column of factor loading matrix is restricted to be equal to zero. With three factors, a 3×3 submatrix of factor loading matrix is lower triangular. We estimate zero-, one-, two-, three-, and four-factor versions of the model specified in equations (3) and (5).[12] The log-likelihood values for the zero-, one-, two-, three-, and four-factor models are, -176,152, -174,366, -173,784, -172,662, and -172,589, respectively. To determine the number of factors, we use the Bayesian Information Criterion (BIC). The BIC values for the zero-, one-, two-, three-, and four-factor models are 355,452, 352,120, 351,195, 349,192, and 349,265, respectively. In our case, the three-factor model is chosen.[13] The estimation results of the other specifications are available upon request. Accordingly, we report and discuss the results for the three-factor model below.

Results

Baseline Utility and Satiation Levels for Mobile Web and App Categories

Tables 2 and 3 show the estimates for the baseline utility parameters ($\bar{\beta}$, Ξ_β, Σ_β, and Π_β) and the satiation parameters ($\bar{\lambda}$, Ξ_λ, Σ_λ, and Π_λ), respectively. The results in Table 2 indicate that mobile users' baseline utility for utility apps is the highest and their baseline utility for personal finance apps is the lowest among the various mobile web and app categories. The highest baseline utility for utility apps can be attributed to the routine use of utility apps such as alarm clock apps. The lowest baseline utility for personal finance apps suggests that they remain a niche market. It should be noted that as $\bar{\beta}$ increases the baseline utility increases. The sign for $\bar{\beta}$ estimates for all types of mobile content is negative due to the relatively higher utility of outside options (e.g., mobile users spend more than 155 hours weekly—approximately 22 hours daily—engaging in activities other than mobile content use), which is normalized to zero for model identification ($\beta_{h0} = 0$). We can also interpret the degree of baseline utility in terms of $\bar{\mu}$ because the sign of the estimates is reversed. However, the relative magnitude of estimates remains unchanged after the exponential transformation specified in equation (2). Furthermore, among several demographic variables, age, gender, and education account for substantial heterogeneity in baseline utilities across mobile users. For example, senior users show a lower intrinsic preference for entertainment, social network, photo, and game apps in comparison with young users. In addition, women exhibit a higher intrinsic preference for photo and communication apps and a lower intrinsic preference for entertainment apps in comparison with men. Users with high education exhibit lower baseline utilities in most categories. Moreover, although users exhibit inertia in their app choices in all categories, they show stronger tendencies of inertial use of personal finance, game, and social network apps than other app categories, indicating that users have routinized their choices for these app categories. Finally, despite their small effect size, there is an increasing time trend of baseline utility for all app categories.

Table 3 suggests that the satiation level is the highest in the portal search app category and the lowest in the communication app category. As $\bar{\lambda}$ increases, the satiation effect also increases. The highest satiation for portal search apps implies that users access these apps quickly (e.g., having a quick search using mobile apps). In contrast, the lowest satiation for communication apps suggests that users tend to continue communicating via mobile apps without growing tired of them. Further, there exists substantial user heterogeneity in terms of satiation levels. For example, as age increases, satiation with music/radio and communication apps increases, while satiation with personal finance, map/navigation, and schedule/memo apps simultaneously decreases. In addition, women show significantly lower satiation levels for photo, social network, and communication apps than men do. Users with high education show significantly higher satiation levels regarding entertainment, communication, and social networking apps. Moreover, although users exhibit inertia in their app consumption in all categories, they show stronger tendencies of inertial use of portals search and game apps and

[12]The zero-factor has no common factor and thus the correlations among random shocks are all set to zero.

[13]Unfortunately, we were unable to estimate a model with the full variance-covariance matrix and use it as an additional benchmark. The estimation of the variance-covariance of dimension of 14 in random coefficients seems almost impossible because of empirical difficulties. As the number of factors increases, the estimated variance-covariance matrix approaches the unstructured full variance-covariance matrix. We observe that the BIC of four-factor model is higher than that of three-factor model. This indicates that the selected three-factor model is arguably better than a full variance-covariance model in describing the data adequately without using too many parameters.

Table 2. Estimates for Baseline Utility Parameters

	Constant ($\bar{\beta}$)	Demographic Variables(Π_β)							State Dependence	Time Trend
		Age 30's	Age 40's & over	Female	Income Mid-class	Income Upper-class	Education High-School Graduates	Education University Graduates		
Communication	**-20.05**	**-0.31**	**-0.21**	**0.30**	-0.02	0.05	-0.05	**-0.09**	**0.82**	**0.013**
	(0.29)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.12)	(0.003)
Game	**-21.87**	**-0.15**	**-0.35**	0.02	**-0.13**	**-0.20**	-0.04	**-0.17**	**1.80**	**0.011**
	(0.27)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.003)
Map/Navigation	**-21.17**	**-0.38**	**-0.42**	0.01	-0.03	0.02	**-0.22**	**-0.13**	**1.06**	**0.008**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.02)	(0.002)
Entertainment	**-21.94**	**-0.40**	**-0.58**	**-0.11**	**-0.09**	**-0.15**	**-0.20**	**-0.31**	**1.70**	**0.015**
	(0.27)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.03)	(0.003)
Lifestyle	**-21.44**	**-0.25**	**-0.30**	**0.13**	-0.02	**-0.08**	**-0.32**	**-0.22**	**1.35**	**0.009**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.02)	(0.003)
Personal Finance	**-22.20**	**-0.29**	**-0.36**	**0.12**	0.00	0.01	-0.02	0.03	**1.87**	**0.016**
	(0.27)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.003)
Music/Radio	**-21.15**	**-0.51**	**-0.61**	**0.10**	-0.03	**-0.06**	**-0.19**	**-0.33**	**1.22**	**0.010**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.02)	(0.003)
Photo	**-20.46**	**-0.29**	**-0.45**	**0.33**	**-0.06**	-0.04	**-0.24**	**-0.25**	**0.77**	**0.014**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.002)
Portal	**-21.38**	**-0.14**	**-0.22**	**0.13**	**-0.07**	-0.06	**-0.17**	**-0.19**	**1.18**	**0.013**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.002)
Schedule/Memo	**-20.07**	**-0.20**	**-0.11**	**0.13**	**-0.10**	-0.03	-0.02	-0.02	**0.59**	**0.008**
	(0.28)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.08)	(0.003)
Social Network	**-21.69**	**-0.33**	**-0.57**	**0.18**	-0.05	-0.03	**-0.14**	**-0.19**	**1.76**	**0.023**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.003)
Utility	**-19.79**	**-0.36**	**-0.35**	0.04	**-0.07**	**-0.10**	-0.06	**-0.24**	**0.52**	**0.008**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.003)
Video	**-21.03**	**-0.15**	**-0.24**	0.04	-0.05	**-0.07**	-0.06	**-0.17**	**0.85**	**0.016**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.02)	(0.002)
Web	**-20.96**	**-0.23**	**-0.27**	0.03	**-0.06**	**-0.08**	-0.08	**-0.17**	**1.11**	**0.006**
	(0.27)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.002)

Note: Standard errors in parentheses. Bold: significant at the .05 level. Following Bhat (2008), α_0 is bounded between 0 and 1. The estimated value α_0 of is -5.77 with a standard error of 0.02. To code discrete demographic variables, we use the following as a reference level: we use age 20's or less for age and male for gender, respectively. For monthly income, we create two dummy variables, mid-class ($3,000–$5,000) and upper-class ($5,000 or over), and we use lower-class ($3,000 or less) as a reference level. Similarly, for education, we create two dummy variables, high school graduates and university graduates, and we use students (elementary, middle-and-high school students, university students) as a reference level.

Table 3. Estimates for Satiation Parameters

		Demographic Variables (Π_β)								
	Constant ($\bar{\lambda}$)	**Age 30's**	**Age 40's & over**	**Female**	**Income Mid-class**	**Income Upper-class**	**Education High-School Graduates**	**Education University Graduates**	**State Dependence**	**Time Trend**
Communication	**2.38**	**0.42**	**0.56**	**-0.22**	-0.03	-0.03	**0.24**	**0.23**	**-0.70**	**-0.013**
	(0.09)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.09)	(0.001)
Game	**3.34**	**-0.06**	0.02	0.03	**0.14**	**0.07**	0.02	**0.09**	**-1.57**	**-0.012**
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.002)
Map/Navigation	**4.80**	-0.05	**-0.21**	**0.20**	**-0.08**	-0.04	**0.17**	0.02	**-0.80**	**-0.016**
	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.002)
Entertainment	**4.15**	**0.30**	**0.11**	**0.14**	0.04	-0.04	**0.25**	**0.36**	**-1.22**	**-0.019**
	(0.06)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.06)	(0.05)	(0.04)	(0.003)
Lifestyle	**5.03**	0.02	**-0.14**	0.03	0.04	0.12	-0.02	-0.05	**-0.96**	**-0.013**
	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.002)
Personal Finance	**4.87**	**-0.40**	**-0.46**	**0.05**	0.00	-0.19	0.08	0.05	**-1.04**	**-0.005**
	(0.05)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.002)
Music/Radio	**3.68**	**0.59**	**0.67**	0.03	0.00	**-0.06**	**-0.13**	0.02	**-1.45**	**-0.026**
	(0.05)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.003)
Photo	**4.44**	**0.19**	**0.30**	**-0.47**	**0.06**	**0.15**	**0.19**	**0.18**	**-0.72**	**-0.012**
	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.002)
Portal	**5.56**	**0.23**	**0.41**	-0.01	**-0.08**	**-0.07**	**0.18**	-0.02	**-2.55**	**-0.029**
	(0.05)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)	(0.002)
Schedule/Memo	**4.15**	**-0.08**	**-0.18**	**0.09**	0.01	**0.04**	-0.03	0.02	**-0.81**	**-0.012**
	(0.07)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.07)	(0.001)
Social Network	**3.68**	**0.30**	**0.49**	**-0.39**	0.03	**0.20**	**0.15**	**0.19**	**-1.19**	**-0.010**
	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)	(0.002)
Utility	**4.19**	**0.14**	**0.24**	**0.09**	**0.05**	**0.14**	**0.14**	-0.01	**-0.94**	**-0.004**
	(0.06)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.002)
Video	**4.43**	**0.18**	**0.19**	0.04	**0.06**	0.03	**-0.14**	**-0.12**	**-1.27**	**-0.026**
	(0.05)	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.002)
Web	**3.97**	**0.13**	**0.50**	**-0.09**	**-0.06**	**-0.08**	**0.19**	**0.12**	**-1.87**	**-0.010**
	(0.05)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.03)	(0.04)	(0.002)

Note: Standard errors in parentheses. Bold: significant at the .05 level. To code discrete demographic variables, we use the following as a reference level: we use age 20's or less for age and male for gender, respectively. For monthly income, we create two dummy variables, mid-class ($3,000–$5,000) and upper-class ($5,000 or over), and we use lower-class ($3,000 or less) as a reference level. Similarly, for education, we create two dummy variables, high school graduates and university graduates, and we use students (elementary, middle-and-high school students, university students) as a reference level.

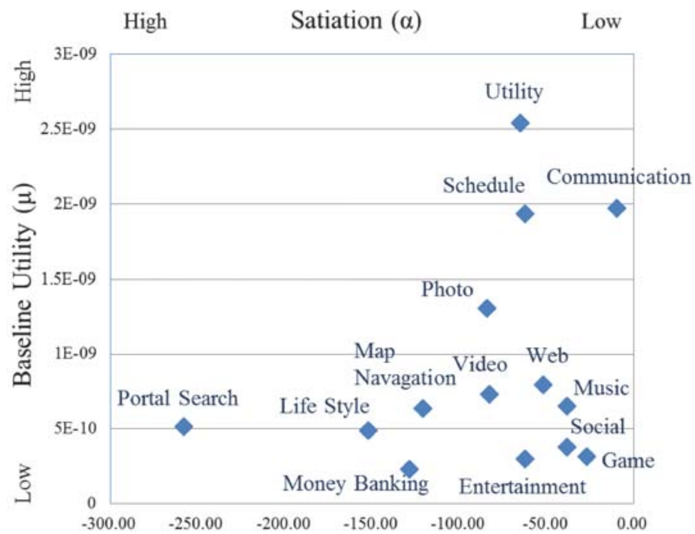

Figure 4. Mapping App Categories According to Baseline Utility and Satiation

mobile web than other app categories, indicating that users have formed their consumption habit for these app categories. Finally, despite their small effect size, there is a decreasing time trend of satiation towards all app categories. We can also interpret the degree of satiation in terms of $\bar{\alpha}$. However, unlike $\bar{\mu}$, $\bar{\alpha}$ decreases as $\bar{\lambda}$ increases after the exponential transformation in equation (2). Consequently, a lower $\bar{\alpha}$ represents a higher satiation level.

In Figure 4, we map mobile web and app categories according to their mean baseline utility and satiation levels, $\bar{\mu}$ and $\bar{\alpha}$. The four quadrants of the scatterplot provide intriguing insights into the multiplicity of mobile content in terms of its choice and time use. For example, the top-right, quadrant *I*, represents mobile content that is used widely as well as extensively, including utility, communication, and schedule apps. Furthermore, we can distinguish among the apps with the similar level of baseline utility: low satiation apps from high satiation counterparts. For example, baseline utility levels are similar to each other for apps in quadrant *III* (portal search and life style apps) and quadrant *IV* (photo, map/navigation, personal finance, social, music, video, entertainment, game apps, and mobile web). However, satiation levels are greater in the former than in the latter.

Variance Decomposition for Mobile Web and App Categories

Tables 4 and 5 present the estimation results for common factors (Γ_β and Γ_λ) and specific factors (Λ_β and Λ_λ). In addition, in the last four columns of Tables 4 and 5, we decompose the overall variations in baseline utilities and satiations for mobile web and app categories into variations attributed to the state dependence, demographic variables, common factors, and specific factors. Interpretation of the factors is based on estimated factor loading matrices and variance decompositions. For the baseline utility, the first factor loads with positive signs for all app categories. In contrast, the second factor loads with positive signs for communication, game, map/navigation, entertainment, and schedule/memo apps, and a large positive factor score indicates high baseline utility for these app categories. Finally, the third factor loads with negative signs for communication, game, map/navigation, utility, and video apps, and a large negative factor score indicates low baseline utility for these app categories. The variance decomposition reveals that, on average, 34% of variation in the baseline utility can be explained by state dependence and 1% by demographic variables while 41% by common factors and remaining 23% by specific factors. In marketing literature, researchers assert that demographic variables often serve as poor predictors of consumer brand preferences that are estimated on scanner panel data (Singh et al. 2005). Echoing this, our result indicates that the proportion of variation explained by demographic variables is small.

For the satiation parameters, we find that the first factor loads strongly with positive signs for most app categories except for game and entertainment apps. The second factor loads with negative signs for most app categories except communication, photo, and social network apps, capturing uniformly lower

Table 4. Baseline Utility Factor Estimates and Variance Decomposition

	Estimates				Variance Decomposition			
	Common Factor			Specific Factor	State Dependence	Demo-graphic	Common Factor	Specific Factor
Communication	**0.07**	**0.02**	**-0.02**	**0.03**	0.04	0.07	0.01	0.87
	(0.01)	(0.01)	(0.01)	(0.01)				
Game	**0.05**	**0.03**	**-0.04**	**0.59**	0.65	0.00	0.31	0.04
	(0.01)	(0.01)	(0.01)	(0.02)				
Map/Navigation	**0.05**	**0.02**	**-0.02**	**0.82**	0.25	0.00	0.69	0.06
	(0.01)	(0.01)	(0.01)	(0.01)				
Entertainment	**0.05**	**0.03**	**0.00**	**1.14**	0.33	0.00	0.62	0.05
	(0.01)	(0.01)	(0.01)	(0.02)				
Lifestyle	**0.04**	0.01	**0.02**	**0.76**	0.39	0.00	0.55	0.05
	(0.01)	(0.01)	(0.01)	(0.03)				
Personal Finance	**0.07**	0.00	0.00	**0.76**	0.58	0.00	0.39	0.02
	(0.01)	–	–	(0.01)				
Music/Radio	**0.05**	0.02	0.00	**1.17**	0.18	0.00	0.74	0.08
	(0.01)	(0.01)	–	(0.02)				
Photo	**0.06**	-0.01	-0.01	0.00	0.32	0.02	0.00	0.66
	(0.01)	(0.01)	(0.01)	(0.03)				
Portal	**0.05**	0.02	-0.01	**1.10**	0.18	0.00	0.80	0.02
	(0.01)	(0.01)	(0.01)	(0.02)				
Schedule/Memo	**0.04**	**0.02**	0.00	**0.15**	0.12	0.04	0.44	0.40
	(0.01)	(0.01)	(0.01)	(0.01)				
Social Network	**0.06**	0.00	0.00	**0.06**	0.85	0.01	0.00	0.14
	(0.01)	(0.01)	(0.01)	(0.02)				
Utility	**0.04**	0.01	**-0.03**	**0.16**	0.06	0.02	0.27	0.65
	(0.01)	(0.01)	(0.01)	(0.01)				
Video	**0.06**	0.00	**-0.03**	**0.14**	0.72	0.03	0.11	0.14
	(0.01)	(0.01)	(0.01)	(0.02)				
Web	**0.03**	0.02	0.01	**0.80**	0.16	0.00	0.80	0.04
	(0.01)	(0.01)	(0.01)	(0.01)				

Note: Standard errors in parentheses. Bold: significant at the .05 level. The second common factor estimate for personal finance apps and the third common factor estimates for personal finance and music/radio apps are set to zero for the purposed of identification.

Table 5. Satiation Factor Estimates and Variance Decomposition

	Estimates				Variance Decomposition			
	Common Factor			Specific Factor	State Dependence	Demo-graphic	Common Factor	Specific Factor
Communication	**0.32**	**0.07**	**-0.15**	0.05	0.01	0.49	0.49	0.01
	(0.01)	(0.01)	(0.01)	(0.06)				
Game	0.01	**-0.37**	**-0.17**	**0.21**	0.88	0.01	0.04	0.07
	(0.01)	(0.01)	(0.01)	(0.07)				
Map/Navigation	**0.32**	**-0.18**	**-0.23**	0.05	0.39	0.07	0.53	0.01
	(0.01)	(0.01)	(0.01)	(0.07)				
Entertainment	0.01	**-0.56**	**-0.03**	0.08	0.68	0.10	0.20	0.01
	(0.01)	(0.01)	(0.01)	(0.09)				
Lifestyle	**0.45**	**-0.59**	**-0.17**	0.03	0.23	0.01	0.76	0.00
	(0.01)	(0.01)	(0.01)	(0.07)				
Personal Finance	**0.49**	0.00	0.00	0.03	0.51	0.10	0.39	0.00
	(0.01)	–	–	(0.07)				
Music/Radio	**0.28**	**-0.29**	0.00	0.11	0.66	0.12	0.20	0.02
	(0.01)	(0.01)	–	(0.07)				
Photo	**0.56**	**0.18**	**-0.05**	**0.28**	0.08	0.19	0.59	0.14
	(0.01)	(0.01)	(0.01)	(0.06)				
Portal	**0.48**	**-0.16**	**0.12**	**0.25**	0.70	0.02	0.24	0.04
	(0.01)	(0.01)	(0.01)	(0.07)				
Schedule/Memo	**0.36**	**-0.11**	**-0.40**	0.04	0.04	0.04	0.91	0.01
	(0.01)	(0.01)	(0.01)	(0.06)				
Social Network	**0.68**	**0.29**	**0.16**	0.05	0.30	0.13	0.56	0.00
	(0.01)	(0.01)	(0.01)	(0.07)				
Utility	**0.41**	**-0.33**	**-0.44**	0.08	0.06	0.05	0.87	0.02
	(0.01)	(0.01)	(0.01)	(0.06)				
Video	0.45	-0.89	0.52	0.03	0.42	0.01	0.57	0.00
	(0.01)	(0.01)	(0.01)	(0.09)				
Web	**0.21**	**-0.20**	**0.17**	**0.15**	0.72	0.11	0.12	0.04
	(0.01)	(0.01)	(0.01)	(0.06)				

Note: Standard errors in parentheses. Bold: significant at the .05 level. The second common factor estimate for personal finance apps and the third common factor estimates for personal finance and music/radio apps are set to zero for the purposed of identification.

(higher) levels of usage with a large positive (negative) factor score. The third factor also loads with negative signs for most app categories except for portal search, social network, video apps, and mobile web. The variance decomposition denotes that 41% of variation in satiation parameters is explained by state dependence. In contrast, 10% of the variation is accounted for by demographic variables and 46% by common factors while the remaining 3% by specific factors. While only a small variation is accounted for by demographic variables, a large variation is explained by state dependence, which indicates that satiation is a routinized behavior. Thus it is difficult to predict a user's app satiations based on her demographic information. Instead, individual level historical information may be required for reliable prediction.

Correlation across Mobile Web and App Categories

Tables 6 and 7 present the correlation matrices for the baseline utility and satiation parameters across mobile web and app categories. Table 6 hints that people who use communication apps (e.g., mobile messengers) also frequently use photo apps (e.g., Instagram). This result indicates that com-

Table 6. Correlation Matrix for Baseline Utility Parameters

	Communication	Game	Map/Navigation	Entertainment	Lifestyle	Personal Finance	Music/Radio	Photo	Portal	Schedule/Memo	Social Network	Utility	Video	Web
Communication		**0.14**	**0.20**	**0.13**	**0.19**	**0.15**	**0.22**	**0.74**	**0.14**	**0.65**	**0.32**	**0.66**	**0.33**	**0.15**
Game	**0.14**		**0.07**	**0.12**	**0.09**	**0.05**	**0.08**	**0.19**	**0.06**	**0.12**	**0.14**	**0.17**	**0.17**	**0.06**
Map/Navigation	**0.20**	**0.07**		**0.08**	**0.11**	**0.10**	**0.09**	**0.22**	**0.06**	**0.15**	**0.12**	**0.19**	**0.15**	**0.06**
Entertainment	**0.13**	**0.12**	**0.08**		**0.11**	**0.06**	**0.10**	**0.17**	**0.06**	**0.12**	**0.14**	**0.18**	**0.15**	**0.06**
Lifestyle	**0.19**	**0.09**	**0.11**	**0.11**		**0.12**	**0.09**	**0.24**	**0.07**	**0.16**	**0.16**	**0.19**	**0.16**	**0.06**
Personal Finance	**0.15**	**0.05**	**0.10**	**0.06**	**0.12**		**0.06**	**0.17**	**0.06**	**0.12**	**0.13**	**0.13**	**0.12**	**0.05**
Music/Radio	**0.22**	**0.08**	**0.09**	**0.10**	**0.09**	**0.06**		**0.24**	**0.06**	**0.17**	**0.15**	**0.23**	**0.16**	**0.06**
Photo	**0.74**	**0.19**	**0.22**	**0.17**	**0.24**	**0.17**	**0.24**		**0.16**	**0.51**	**0.42**	**0.60**	**0.41**	**0.17**
Portal	**0.14**	**0.06**	**0.06**	**0.06**	**0.07**	**0.06**	**0.06**	**0.16**		**0.11**	**0.10**	**0.12**	**0.12**	0.02
Schedule/Memo	**0.65**	**0.12**	**0.15**	**0.12**	**0.16**	**0.12**	**0.17**	**0.51**	**0.11**		**0.24**	**0.51**	**0.27**	**0.12**
Social Network	**0.32**	**0.14**	**0.12**	**0.14**	**0.16**	**0.13**	**0.15**	**0.42**	**0.10**	**0.24**		**0.30**	**0.26**	**0.09**
Utility	**0.66**	**0.17**	**0.19**	**0.18**	**0.19**	**0.13**	**0.23**	**0.60**	**0.12**	**0.51**	**0.30**		**0.35**	**0.16**
Video	**0.33**	**0.17**	**0.15**	**0.15**	**0.16**	**0.12**	**0.16**	**0.41**	**0.12**	**0.27**	**0.26**	**0.35**		**0.11**
Web	**0.15**	**0.06**	**0.06**	**0.06**	**0.06**	**0.05**	**0.06**	**0.17**	0.02	**0.12**	**0.09**	**0.16**	**0.11**	

Note: Bold: significant at the .01 level.

Table 7. Correlation Matrix for Satiation Parameters

	Communication	Game	Map/Navigation	Entertainment	Lifestyle	Personal Finance	Music/Radio	Photo	Portal	Schedule/Memo	Social Network	Utility	Video	Web
Communication		0.00	**0.30**	**0.42**	**0.15**	**-0.19**	**0.32**	**0.87**	**0.37**	**0.49**	**0.75**	**0.57**	**0.22**	**0.34**
Game	0.00		**0.10**	**0.18**	**0.21**	**0.16**	**0.16**	-0.02	**0.13**	**0.09**	-0.01	**0.16**	**0.23**	**0.12**
Map/Navigation	**0.30**	**0.10**		**0.39**	**0.57**	**0.38**	**0.27**	**0.35**	**0.43**	**0.75**	**0.29**	**0.70**	**0.50**	**0.21**
Entertainment	**0.42**	**0.18**	**0.39**		**0.33**	**0.12**	**0.32**	**0.36**	**0.32**	**0.44**	**0.35**	**0.46**	**0.33**	**0.20**
Lifestyle	**0.15**	**0.21**	**0.57**	**0.33**		**0.58**	**0.42**	**0.09**	**0.41**	**0.60**	0.03	**0.73**	**0.70**	**0.30**
Personal Finance	**-0.19**	**0.16**	**0.38**	**0.12**	**0.58**		**0.21**	**-0.19**	**0.23**	**0.31**	**-0.20**	**0.38**	**0.47**	**0.15**
Music/Radio	**0.32**	**0.16**	**0.27**	**0.32**	**0.42**	**0.21**		**0.18**	**0.29**	**0.25**	**0.16**	**0.43**	**0.45**	**0.28**
Photo	**0.87**	-0.02	**0.35**	**0.36**	**0.09**	**-0.19**	**0.18**		**0.36**	**0.57**	**0.82**	**0.51**	**0.16**	**0.25**
Portal	**0.37**	**0.13**	**0.43**	**0.32**	**0.41**	**0.23**	**0.29**	**0.36**		**0.47**	**0.31**	**0.52**	**0.42**	**0.19**
Schedule/Memo	**0.49**	**0.09**	**0.75**	**0.44**	**0.60**	**0.31**	**0.25**	**0.57**	**0.47**		**0.47**	**0.86**	**0.53**	**0.23**
Social Network	**0.75**	-0.01	**0.29**	**0.35**	0.03	**-0.20**	**0.16**	**0.82**	**0.31**	**0.47**		**0.40**	**0.10**	**0.19**
Utility	**0.57**	**0.16**	**0.70**	**0.46**	**0.73**	**0.38**	**0.43**	**0.51**	**0.52**	**0.86**	**0.40**		**0.68**	**0.38**
Video	**0.22**	**0.23**	**0.50**	**0.33**	**0.70**	**0.47**	**0.45**	**0.16**	**0.42**	**0.53**	**0.10**	**0.68**		**0.33**
Web	**0.34**	**0.12**	**0.21**	**0.20**	**0.30**	**0.15**	**0.28**	**0.25**	**0.19**	**0.23**	**0.19**	**0.38**	**0.33**	

Note: Bold: significant at the .01 level.

munication apps and photo apps might be frequently used together as complements.[14] Table 7 shows correlations in satiation levels. People who spend a great deal of time on social apps (e.g., Facebook) also spend a significant amount of time on communication apps (e.g., WhatsApp) and photo apps (e.g., Instagram), which suggests that social, communication, and photo apps might be economic complements to each other. For example, many users take a picture or video, use Instagram to choose a filter to transform its look and feel, and post it to Facebook or share it on WhatsApp. In contrast, people who use social network apps infrequently use personal finance apps, which indicates that social network and personal finance apps might be economic substitutes.

Applications of Proposed Approaches

In this section, we illustrate the applications of our proposed model and findings in several areas, including mobile competitive analysis, mobile user targeting, and mobile media planning.

Mobile Competitive Analysis

Our proposed model provides a general empirical framework to analyze the usage data on various emerging IT artifacts as well as the app time usage data. To illustrate this vital strength, we conduct an app-level analysis using the proposed model to investigate mobile users' popular app choices and time usage decisions. We consider the most popular nine apps (in terms of total usage time) and all of the other mobile content use excluding the top-nine apps as a single combined, "Others," option. A similar specification can be applied for a mobile competitive analysis when a manager wants to understand the nature of competition between her/his company and key competitors in the mobile market.

We chose a total of 10 options for the sake of the tractability of the model; however, we can increase the number of options at the expense of the computational time required to identify and to estimate the parameters of the model. Table 8 lists the selected 10 apps with their key descriptive statistics. Column 2 of Table 8 shows that users accessed Kakao Talk (a communication app) most frequently (95.83%), while they accessed Rule the Sky (a game app) least frequently (3.78%). Column 5 of Table 8 shows that, excluding outside options, users spent the most time (18.38%) using Kakao Talk, followed by Naver (3.64%), Kakao Story (3.00%), Tiny Farm (1.66%), and Facebook (1.57%). In addition, the top-nine apps account for 33% of the total mobile content use and the "Others" category accounts for the remaining 67%.

We use the same specification for the model estimation as in the app category-level analysis. Results exhibited in Appendix D show the estimates for the baseline utility and satiation parameters, respectively.

Table 9 shows the correlation matrix for the baseline utility for the top nine apps and the remaining, combined other apps. We find that people who use the Naver app also frequently use its competing portal search Daum's app. Moreover, people who use the Kakao Talk app also frequently use Kakao Story, a social networking app developed by Kakao Talk. Table 10 shows the correlation in the satiation levels. We find that people who spend a great deal of time on Facebook also spend a lot of time on Kakao Talk, which is similar to our empirical findings based on the category-level analysis.

Now we illustrate the strategic value of our findings summarized in the correlation matrices in developing optimal mobile content portfolios. Companies can build and maintain an optimal mobile content portfolio by making internally and/or buying external mobile websites and apps. The results of the correlations for the app choices and app time use exhibited in Tables 9 and 10 provide useful and actionable guidelines and insights for this fundamental issue. The results of the correlation in app time use satiation reported in Table 10 demonstrate that some apps are used more extensively when they are used together rather than separately. Therefore, a company should acquire apps that complement its focal app in terms of time use to maximize the consumption of the combined apps. For example, due to strong positive correlations in consumption among photo, communication, and social network apps, a company can maximize the customers' time spent on its portfolio of apps by combining these app categories together. Facebook's recent acquisition of WhatsApp and Instagram is a good manifestation of this case.

Mobile User Targeting: App Time-Use Prediction

Previous research has frequently used demographics or preference estimates based on individual-level panel data for new

[14]The positive correlation in baseline utility can be explained by not only inherent complementary relationship among apps but also some external reasons for simultaneous use. For example, in the case of product purchase decisions, bundle promotions (e.g., buy one get one free) can result in correlated demand. When mobile users decide which app to use, the decision is less likely to be influenced by external factors compared to other purchase or choice decisions. Thus, we believe that the inherent complementarity plays the major role in our context.

Table 8. Selected Apps and Summary Statistics

App	Category	Choice	Time Use: Hour	Time Use: Percent	Time Use: Percent excld. outside option
Outside option (other activities)		100.00%	155.67	92.66%	—
KakaoTalk	Communication	95.83%	2.27	1.35%	18.38%
Naver	Portal Search	46.35%	0.45	0.27%	3.64%
Kakao Story	Social	59.14%	0.37	0.22%	3.00%
RuleTheSky	Game	3.78%	0.16	0.10%	1.31%
Facebook	Social	27.07%	0.19	0.12%	1.57%
TinyFarm	Game	5.51%	0.21	0.12%	1.66%
Mellon	Music and Radio	11.03%	0.17	0.10%	1.41%
Daum	Portal Search	13.84%	0.14	0.08%	1.13%
YouTube	Video	29.21%	0.08	0.05%	0.64%
Others		100.00%	8.29	4.94%	67.25%
Total			168.00	100.00%	100.00%

Table 9. Correlation Matrix for Baseline Utility Parameters: App-Level Analysis

	Kakao Talk (Comm.)	Naver (Portal)	Kakao Story (Social)	RuleTheSky (Game)	Facebook (Social)	TinyFarm (Game)	Mellon (Music/Radio)	Daum (Portal)	YouTube (Video)	Others
Kakao Talk		**0.12**	**0.26**	**0.11**	**0.19**	**0.13**	**0.19**	0.04	**0.20**	**0.23**
Naver	**0.12**		**0.11**	0.04	**0.13**	**0.05**	**0.07**	**0.27**	**0.07**	0.01
Kakao Story	**0.26**	**0.11**		**0.06**	**0.09**	**0.06**	**0.08**	0.04	**0.15**	**0.07**
RuleTheSky	**0.11**	0.04	**0.06**		**0.05**	**0.11**	0.03	0.01	-0.01	**-0.12**
Facebook	**0.19**	**0.13**	**0.09**	**0.05**		**0.06**	**0.20**	**0.05**	**0.09**	**0.09**
TinyFarm	**0.13**	**0.05**	**0.06**	**0.11**	**0.06**		**0.12**	0.01	0.01	0.03
Mellon	**0.19**	**0.07**	**0.08**	0.03	**0.20**	**0.12**		0.02	**0.10**	**0.18**
Daum	0.04	**0.27**	0.04	0.01	**0.05**	0.01	0.02		**0.09**	**0.12**
YouTube	**0.20**	**0.07**	**0.15**	-0.01	**0.09**	0.01	**0.10**	**0.09**		**0.30**
Others	**0.23**	0.01	**0.07**	**-0.12**	**0.09**	0.03	**0.18**	**0.12**	**0.30**	

Note: Bold: significant at the .01 level.

customer prediction (e.g. Rossi et al. 1996). In addition, researchers and practitioners have developed regression-based scoring models to predict customers' future behaviors (e.g. Bolton 1998; Malthouse and Blattberg 2005). The purpose of these approaches is to use the measurements of customers' prior behavior as predictors of their future behavior. Similarly, in direct marketing literature, it is a common practice to summarize customers' prior behavior in terms of their recency (time of most recent purchase), frequency (number of prior purchases), and monetary value (average purchase amount per transaction) (RFM method; Fader et al. 2005). However, when there are no detailed information on prior transactions or behaviors, all these established methods are difficult to apply. In such a case, an average consumer's category usage pattern over multiple categories can be used instead. We can obtain this information from the estimated correlation matrix of the proposed model.

To add a specific context to our application, we aimed to identify a segment with extensive social network app use. We

Table 10. Correlation Matrix for Satiation Parameters: App-Level Analysis

	Kakao Talk (Comm.)	Naver (Portal)	Kakao Story (Social)	RuleTheSky (Game)	Facebook (Social)	TinyFarm (Game)	Mellon (Music/Radio)	Daum (Portal)	YouTube (Video)	Others
Kakao Talk		**0.22**	**0.48**	**-0.28**	**0.53**	**-0.20**	**0.17**	**0.25**	**0.15**	**0.46**
Naver	**0.22**		**0.07**	0.03	**0.37**	-0.01	0.01	**0.33**	**0.10**	**0.37**
Kakao Story	**0.48**	**0.07**		**-0.23**	**0.13**	-0.01	**0.12**	-0.01	**0.06**	0.04
RuleTheSky	**-0.28**	0.03	**-0.23**		0.00	**0.34**	**-0.10**	**0.11**	-0.01	0.01
Facebook	**0.53**	**0.37**	**0.13**	0.00		**-0.12**	0.03	**0.62**	**0.23**	**0.85**
TinyFarm	**-0.20**	-0.01	-0.01	**0.34**	**-0.12**		**-0.12**	0.03	-0.04	**-0.12**
Mellon	**0.17**	0.01	**0.12**	**-0.10**	0.03	**-0.12**		-0.05	0.00	-0.02
Daum	**0.25**	**0.33**	-0.01	**0.11**	**0.62**	0.03	-0.05		**0.19**	**0.70**
YouTube	**0.15**	**0.10**	**0.06**	-0.01	**0.23**	-0.04	0.00	**0.19**		**0.24**
Others	**0.46**	**0.37**	0.04	0.01	**0.85**	**-0.12**	-0.02	**0.70**	**0.24**	

Note: Bold: significant at the .01 level.

divided our 17 week sample data into an estimation period (first 9 weeks) and a holdout prediction period (last 8 weeks). We first estimated the proposed model using the estimation period data and obtained a correlation matrix of satiation parameters. The correlation matrix for satiation parameters is very similar to the pattern based on the full 17 week data (see Appendix B, Tables B1 and B2).[15] The left panel of Figure 5 visualizes the correlation pattern in satiation parameters on two-dimensional space using a multidimensional scaling (MDS) technique.[16] Using the same MDS technique, the right panel of Figure 5 depicts the correlation pattern in app use time as a benchmark against which the performance of the proposed approach is compared. Social network, photo, and communication apps are closely located in both plots of Figure 5. This indicates that heavy photo and communication app users are also characterized as heavy social network app users. Accordingly, we used the photo and communication app use time during the estimation period to infer the potential targets of extensive social network app use during the prediction period. It should be noted that we are not using past usage behavior of the focal category (i.e., social network) as in a typical RFM approach. Our strategy was to use the photo and communication app usage histories instead.

Table 11 shows the performance of the proposed targeting strategy. First, we divided the app users by the photo app use time in the estimation period. The average social network app use time of the top 50% is 1.58 and the bottom 50% is 0.52 during the prediction period. The average use time for all users is 1.03 and this is what we can expect when we use a random targeting strategy. When we select 50% of the users based on their photo app use time during the estimation period, the average social network app use time during the prediction period is longer by 53% than that of a randomly selected group. That is, the gain is 53%. Similarly, when we select 50% of the users based on their communication app use time during the estimation period, the gain is 43% in comparison with a random targeting strategy.

Additionally, the left panel of Figure 5 indicates that there exist strong correlations in satiation parameters between video and lifestyle apps and among schedule, utility, and map/navigation apps, respectively. However, these meaningful relationships do not show up on the right panel or the correlation matrix based on app use time. The last three columns of Table 11 show the performance of the same targeting applications based on these strong positive correlations in the aforementioned satiation parameter estimates. All of these applications show substantial gains in comparison with the random targeting strategy, which confirms the validity of the proposed targeting strategy. Moreover, this clearly illustrates a distinctive advantage of the proposed method over the simple model-free approaches.

[15]The main findings from the estimation results using the first nine weeks are the same as those from the full data. The results are available on request from the authors.

[16]Multidimensional scaling (MDS) is a means of visualizing the level of similarity of individual objects (categories in our case) of a dataset. An MDS algorithm aims to place each object in N-dimensional space such that the between-object distances are preserved as well as possible. As in our application, two-dimensional (N = 2) is the most frequently used option since it allows an easy graphical interpretation. We use the SPSS Proxscal package.

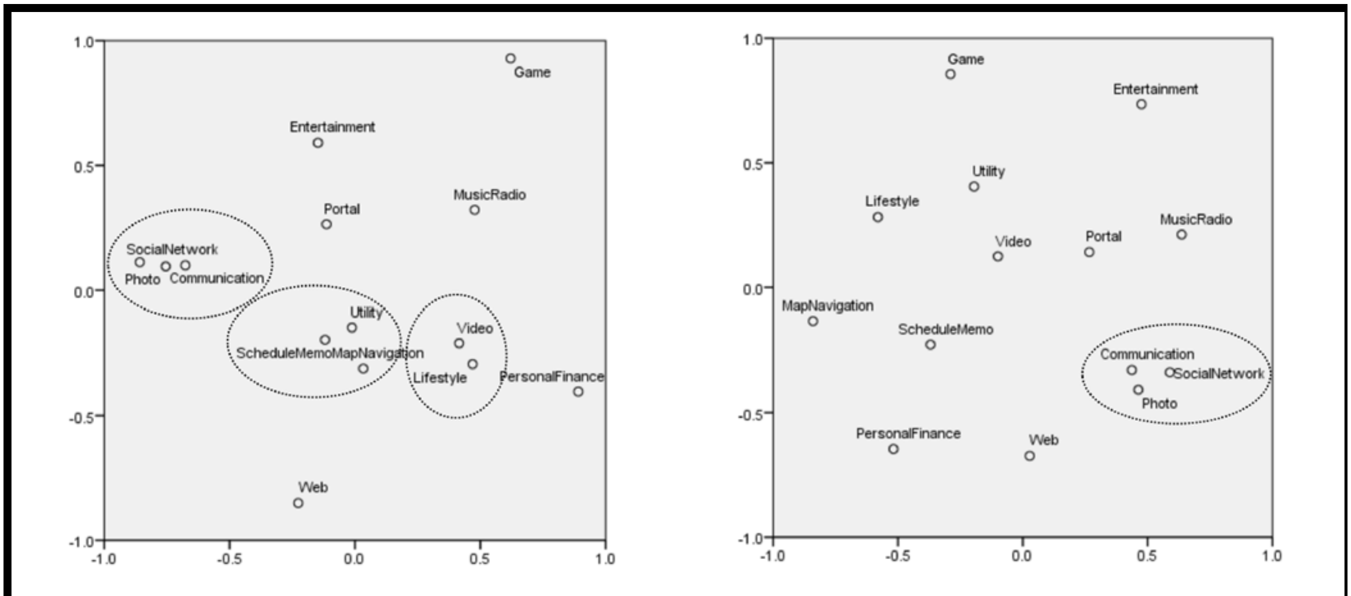

Figure 5. A Two-Dimensional MDS Representation of Correlation Matrices of Satiation Parameters (Left) and App Use Time as a Benchmark (Right)

Table 11. Result of Heavy User Targeting Application

Target Category		Social Network	Social Network	Lifestyle	Schedule	Schedule
Sorting Variable		Photo	Communication	Video	Utility	Map/Navigation
Use Time	Top 50%	1.58	1.48	0.27	0.94	0.92
	Bottom 50%	0.52	0.57	0.17	0.68	0.72
	Average	1.03	1.03	0.21	0.81	0.81
Gain		53%	43%	30%	17%	14%

Mobile Media Planning

This section illustrates the usefulness of the proposed model in optimal mobile media planning. To be specific, we developed a method that optimally selects mobile advertising vehicles and determines the share of advertising impressions that should be purchased to maximize one's objective function. We first applied the proposed model in predicting individual mobile users' app consumption, after which we used the resultant usage distribution as a component in the broader problem of optimal advertising vehicle selection.

To the best of our knowledge, the proposed media selection method is the first general framework for mobile media. The proposed framework is based on continuous app usage time and ad exposure time. By contrast, existing media planning models for online, TV, or print media are based on discrete counts of ad exposure (e.g., Danaher et al 2010). Continuous exposure time provides more precise information and is more appropriate for measuring emerging forms of mobile ads (e.g., video ads with varying run times) than the discrete counting of ad exposure.

The first step in any media scheduling method is to develop reliable estimates of potential audience size. For this purpose, we used the proposed multiple discrete-continuous choice model. In existing methods for online, TV, and print media, simple count data models, such as Poisson or negative binomial models, are adopted. Compared with these count data models, the proposed model enables us to easily incorporate a rich set of explanatory variables (i.e. demographic variables, state dependence, factor analytic structure).

Resolution of a Mobile Advertising Planner's Optimization Problem

Here, we present our mobile media planning framework. We focused on mobile media advertising scheduling for display ads given that our objective is to reach a target group via visual advertisements. For expositional simplicity, we considered one period (one week) and drop time subscript t, but the proposed approach can be extended to a multi-period case in a straightforward manner. c_j denotes the cost of advertising on app j; c_j is the cost per-hour of exposure; q_{hj} is the time spent (in hours) on app j by mobile user h in a week. We can compute q_{hj} using our proposed model (Equations 1–4). Let $s_j (0 \leq s_j \leq 1)$ denote the share of time purchased for an ad at app j. s_j is the media planner's decision variable. That is, a media planner's goal is deciding optimal $\{s_j\}_{j=1,\ldots,J}$ with the aim of maximizing her objective function while remaining within budget. We formally write down the optimization problem as follows:

$$\begin{aligned} &\text{maximize} \quad \sum\nolimits_{h=1}^{H} R\left(q_{h1} \cdot s_{1,\ldots,} q_{hJ} \cdot s_J\right) \\ &\text{subject to} \quad \sum\nolimits_{j=1}^{J} \left(\left(\sum\nolimits_{h=1}^{H} q_{hj}\right) \cdot s_j \cdot c_j\right) \leq B, \\ &\qquad\qquad \text{and } 0 \leq s_j \leq 1 \end{aligned} \tag{11}$$

where $R(\cdot)$ is a media response function, and B is an advertising budget. Several response functions have been proposed for media planning, but we focused on two popular response variants: a linear function and a square-root function. The linear function assumes a simple and naive response function as follows:

$$\begin{aligned} &R\left(q_{h1} \cdot s_1, \ldots, q_{hJ} \cdot s_J\right) = \\ &q_{h1} \cdot s_1 + q_{h2} \cdot s_2 + \cdots + q_{hJ} \cdot s_J \end{aligned} \tag{12}$$

When this response function is used, a media planner simply maximizes the total exposure time. Alternatively, Rust and Leone (1984) propose the following square-root response function:

$$R\left(q_{h1} \cdot s_1, \ldots, q_{hJ}\right) = \sqrt{\sum\nolimits_{j=1}^{J} q_{hj} \cdot s_j} \tag{13}$$

This response function assumes that exposure suffers from diminishing returns.

Illustration

The proposed method is elucidated using a specific example. Let us assume that a mobile media planner has three available mobile apps (App1, App2, and App3) for her advertising campaign. Let us also suppose that the target market comprises 1,000 mobile app users and that the media planner's budget for this campaign is \$350. The ad planner estimated the proposed multiple discrete-continuous choice model by using a representative app usage panel data set derived from the target market; thus, she knows the baseline utilities and satiation levels of these apps (summarized in Table 12). She also knows the per-hour cost of advertising on these apps. In this example, App1 can be characterized as a "high utility, low satiation" application, whereas App2 and App3 are "low utility, high satiation" apps. Using the given parameter values, we simulated 1,000 pseudo mobile users' app usage for a week and then determine the optimal solution that maximizes the ad planner's objective function. For numerical optimization, we used the Matlab's constrained nonlinear optimization routine.

Table 13 reports the optimal schedules for the three apps. We first assumed that no correlation exists among the baseline utility parameters and among the satiation parameters (first three rows in Table 13). The predicted total app usage times are 795, 141, and 138 hours for App1, App2, and App3, respectively. When the linear response function is used, buying a 44% share of time on App1 or spending the entire ad budget on App1 is an optimal decision. The linear response function simply maximizes the total exposure time. Given that App1 exhibits the lowest cost, this result is unsurprising. The next row in Table 13 lists the optimal schedule for the square-root response function, which assumes diminishing returns on exposure. Note that the costs of App2 and App3 are more expensive than that of App1. However, buying 28% and 27% shares of time on App2 and App3, along with App1, is the optimal schedule. This optimality is ascribed to the fact that under the square-root response function, short ad exposure to many audience members is better than long exposure to a small group of people. The optimal ad schedule implies that allocating the ad budget to the more expensive App2 and App3 enables us to reach more audiences and reduce the overexposure.

To determine how correlation in utility influences the optimal media schedule, we assumed that the baseline utility of App1 is correlated with that of App2. Specifically, we added $Corr(\beta_{hApp1}, \beta_{hApp2}) = 0.7$ to the parameter values specified in Table 13 when we simulated the app use times. The correlation suggests that a mobile user who highly values App1 tends to accord App2 the same appreciation. This correlation generates marginal differences in app use times. When the linear response function is applied, spending all the ad budget on App1 is the optimal decision as in the no-correlation case. However, when the square-root response function is applied, the optimal schedule becomes the purchase of 35%, 15%, and 34% of time shares on App1, App2, and App3, respectively. This optimal schedule markedly differs from that under the square-root response function with no correlation. App2 and App3 are identical in terms of baseline utility and satiation, but the shares required for the optimal schedules on these apps are substantially dissimilar (15% versus 34%). This

Table 12. Baseline Utility, Satiation, and Cost of Considered Mobile Apps				
Apps	**Baseline Utility**	**Satiation**	**App Characteristic**	**Ad Cost ($/per hour)**
App1	$\beta_{hApp1} \sim N(-4, 1)$	$\alpha_{hApp1} \sim N(-7, 1)$	High Utility / Low Satiation	1
App2	$\beta_{hApp2} \sim N(-6, 1)$	$\alpha_{hApp2} \sim N(-9, 1)$	Low Utility / High Satiation	1.1
App3	$\beta_{hApp3} \sim N(-6, 1)$	$\alpha_{hApp3} \sim N(-9, 1)$	Low Utility / High Satiation	1.1
Others	$\beta_{hOthers} \sim N(-3, 1)$	$\alpha_{hOthers} \sim N(-6, 1)$	—	—

Table 13. Optimal Schedules for Three Available Apps				
	App1	**App2**	**App3**	**Response Function Value**
No Correlation				
Total App Use Time (hours)	795	141	139	
Optimal Schedule ()				
Linear Response Function	44%	0%	0%	350
Square-Root Response Function	33%	28%	27%	531.8
$Corr(\beta_{hApp1}, \beta_{hApp2}) = 0.7$				
Total App Use Time (hours)	791	143	141	
Optimal Schedule (s_j)				
Linear Response Function	44%	0%	0%	350
Square-Root Response Function	35%	15%	34%	530.6

variance is due to the correlation between App1 and App2. Because of such correlation, App1 users tend to frequently use App2, thereby causing overexposure, which is undesirable under the square-root response function. Consequently, App3 becomes a more appealing avenue for the ad campaign, and its share increases to 34%.

Conclusion

The dramatic growth of the mobile platform and device industry has resulted in an app-centric marketplace, ushering in the app-based mobile economy, which provides new opportunities and challenges for entrepreneurs, managers, and marketers across all online business segments. Although online consumers are increasingly migrating from web browsers to mobile apps for their commercial transactions and social interactions, little is known about how these users behave and make decisions with respect to their choices, consumption, and management of mobile apps in diverse categories. The absence of sound mobile app analytics based on a thorough methodological approach has impeded our comprehension of consumers' behavioral responses to the choice and usage of mobile apps.

This study developed a novel framework for mobile app analytics by using the theoretical concepts of utility and satiation, along with a structured method of factor analytic approach. Our work contributes to an emerging stream of literature on the economics of the mobile Internet and mobile marketing by being the first study to quantify the baseline utility and satiation levels of distinct mobile app categories. Using large-scale, individual-level panel data on mobile app and web time-use histories, we constructed a unique multiple discrete-continuous model of app selection and time-use decisions to more clearly elucidate usage interdependence and dynamics among diverse categories of mobile web and apps. The frameworks, mechanisms, and processes discussed in this study offer high flexibility and efficiency in estimating parameters, particularly when the number of choices is exceedingly large, a phenomenon that has increasingly become prevalent in big data analytics. Our analytical paradigm and comprehensive computational procedures can, therefore, enlighten developers and researchers as to the advancement of big data analytics in general and mobile app analytics in particular.

Data availability issues suggest that some caution is warranted with regard to the estimation of the proposed model. In certain cases, some consumers implement app selection, consumption decisions, and utility maximization as frequently as they wish (i.e., on a daily or hourly basis). Only weekly usage data were available for the analysis, thereby preventing us from further enhancing the precision in estimation. Future researchers can apply our proposed model to high-frequency data on the usage patterns of individual users. Another limitation of this study is that we did not observe consumers' app purchase behaviors. Future works should be directed toward an integrated model of app purchase and consumption, provided that they have individual user-level data on both app purchase and usage. We believe that consumers' mobile app usage decisions are influenced by the context and social network variables measuring which users are connected to which other users. Once these variables are observed, these can enter into the baseline utility and the satiation parameters as the demographic variables are incorporated in the current specification. Furthermore, for the sake of tractability, we postulated that the utility function is additively separable; thus the model cannot explicitly partial out complementarity or substitution from other factors (Bhat 2008). Lee et al. (2013) recently developed a direct utility model that circumvents this problem, but the improved version remains restricted to accommodating a relatively small number of options. Future research can focus on addressing this limitation of multiple discrete-continuous choice models. Notwithstanding the limitations of the current work, our utility theory-based structural model of app selection and consumption remains relevant to the future direction of mobile analytics.

Online businesses that depend heavily on apps for their growth are confronted with a new strategic and operational challenge that increases with the rising volume and complexity of users' app consumption. The findings reported in this study may help managers alleviate the adverse effects of such challenges through an enhanced understanding of app selection and usage behaviors. Our study also sheds light on direct implications for management, specifically with respect to how managers should allocate their advertising resources across app categories, which often complement or compete with one another. Our empirical results suggest that both positive and negative correlations exist in the baseline utility and satiation levels of mobile web and app categories. We also found that users' demographic variables and unobservable factors play important roles in explaining app selection and time-use decisions. These findings offer insights related to mobile user segmentation, targeting, and optimal media planning in the mobile app marketplace, thus empowering firms in identifying valuable consumers on the basis of differing needs, varying demographic characteristics, and idiosyncratic behavioral patterns.

As we transition into the mobile economy, the adoption of effective mobile app analytics becomes a key basis for competition in mobile-based markets. The number and complexity of mobile apps will rise above and beyond our prediction, and the radical growth of apps will continue to confound the intellect and challenge the inventiveness of practitioners. The ability to develop strong analytical prowess and the capability to drive significant business value from the insights brought forth by mobile app analytics should occupy the core of a firm's mobile strategy.

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BIG DATA & ANALYTICS IN NETWORKED BUSINESS

MOBILE APP ANALYTICS: A MULTIPLE DISCRETE-CONTINUOUS CHOICE FRAMEWORK

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Appendix A

Mobile Apps Used and Websites Visited by Panel Members in the Data

Table A1. Mobile Content Categories: Mobile Apps and Mobile Websites

Category		Count	Example
Communication	Mobile Messengers, Mobile Internet Phone, Email	241	Kakao Talk, Mypeople Messenger, Phone, GO SMS Pro, LINE, NateOn UC, LightSMS, Gmail, LightSMS, Viber, Skype
Entertainment	Book, Cartoon, Adults, Sports, Humor, Magazine	1,054	Naver Webtoon, Live Scores, TIViewer, T store Book, jjComics Viewer, Naver Books, Score Center
Game	Action, Adventure, Board, Puzzle, Racing, Role Playing, Shooting, Simulation, Sports	2,870	Rule The Sky, TinyFarm, Smurfs' Village, Shoot Bubble Deluxe, Hangame, 2012 Baseball Pro, Angry Birds Space, Jewels Star
Map and Navigation	Map, Navigation	340	T map, Google Maps, SeoulBus, Naver Maps, Olle Navi, Subway Navigation,
Lifestyle	Weather, News, Education, Restau-rants, Job, Health, Religion, Fashion	1,811	YTN News, MK News, SBS News, Weather, Bible, Newspapers, JobsKorea
Personal Finance	Banking, Stocks, Finance, Real Estate, Ecommerce	414	Smart Trading, M-Stock Smart, KB Star Banking, Auction Mobile, Coupang, Gmarket Mobile
Music and Radio	Radio, Music	341	Music Player, SKY Music, PlayerPro, Mnet, MyMusicOn, FM Radio, Soribada
Photo	Photo Gallery, Camera	297	Gallery, Camera, Cymera, Photo Editor, Instagram
Portal Search	Portal Site, Search Engine	74	Naver, Daum, NATE, Google Search, Junior Naver

Table A1. Mobile Content Categories: Mobile Apps and Mobile Websites (Continued)			
Category		**Count**	**Example**
Schedule	Scheduler, Memo, Alarm Clock	1,389	Address book, Alarm/Clock, Calendar, Memo, Polaris Office, Polaris Office, Docviewer
Social	Social Networking Service, Board, Blog, Microblog	165	Kakao Story, Facebook, Twitter, Naver Café, Daum Café, Cyworld, Naver Blog, Me2day
Utilities	Productivity, Decoration, Webhard, Widget, Firewall	2,125	Alarm Clock, Calculator, Voice Recorder, HD Browser, Dropbox, Battery Widget
Video	Multimedia, Broadcasting, Movie	290	TV, Youtube, MX Video Player, SKY Movie, Afreeca TV, T-DMB, PandoraTV
Mobile Web	Websites	8,043	Naver.com, Daum.net, Nate.com, Google.co.kr, ppomppu.co.kr, dcinside.com, facebook.com
Sum		19,591	

Appendix B

Correlation Matrices of App Choice Incidence and App Use Time

Table B1. Correlation Matrix of App Choice Incidence

	Communi-cation	Game	Map/ Navigation	Entertain-ment	Lifestyle	Personal Finance	Music & Radio	Photo	Portal	Schedule/ Memo	Social Network	Utility	Video	Web
Communication		**0.07**	**0.10**	**0.05**	**0.09**	**0.08**	0.00	**0.20**	**0.10**	**0.51**	**0.11**	**0.36**	**0.11**	**0.02**
Game	**0.07**		**0.06**	**0.17**	**0.10**	**0.05**	**0.08**	**0.10**	**0.09**	**0.10**	**0.10**	**0.12**	**0.13**	**0.06**
Map/Navigation	**0.10**	**0.06**		**0.11**	**0.18**	**0.17**	**0.13**	**0.14**	**0.14**	**0.12**	**0.08**	**0.14**	**0.13**	**0.06**
Entertainment	**0.05**	**0.17**	**0.11**		**0.16**	**0.08**	**0.15**	**0.09**	**0.12**	**0.06**	**0.12**	**0.08**	**0.13**	**0.05**
Lifestyle	**0.09**	**0.10**	**0.18**	**0.16**		**0.17**	**0.11**	**0.16**	**0.15**	**0.12**	**0.13**	**0.15**	**0.14**	**0.07**
Personal Finance	**0.08**	**0.05**	**0.17**	**0.08**	**0.17**		**0.06**	**0.11**	**0.13**	**0.11**	**0.11**	**0.14**	**0.11**	**0.06**
Music & Radio	0.00	**0.08**	**0.13**	**0.15**	**0.11**	**0.06**		**0.14**	**0.11**	**0.05**	**0.13**	**0.07**	**0.15**	**0.05**
Photo	**0.20**	**0.10**	**0.14**	**0.09**	**0.16**	**0.11**	**0.14**		**0.18**	**0.23**	**0.22**	**0.24**	**0.22**	**0.08**
Portal	**0.10**	**0.09**	**0.14**	**0.12**	**0.15**	**0.13**	**0.11**	**0.18**		**0.15**	**0.13**	**0.14**	**0.16**	**-0.03**
Schedule/Memo	**0.51**	**0.10**	**0.12**	**0.06**	**0.12**	**0.11**	**0.05**	**0.23**	**0.15**		**0.11**	**0.36**	**0.15**	**0.03**
Social Network	**0.11**	**0.10**	**0.08**	**0.12**	**0.13**	**0.11**	**0.13**	**0.22**	**0.13**	**0.11**		**0.12**	**0.15**	**0.05**
Utility	**0.36**	**0.12**	**0.14**	**0.08**	**0.15**	**0.14**	**0.07**	**0.24**	**0.14**	**0.36**	**0.12**		**0.16**	**0.05**
Video	**0.11**	**0.13**	**0.13**	**0.13**	**0.14**	**0.11**	**0.15**	**0.22**	**0.16**	**0.15**	**0.15**	**0.16**		**0.10**
Web	**0.02**	**0.06**	**0.06**	**0.05**	**0.07**	**0.06**	**0.05**	**0.08**	**-0.03**	**0.03**	**0.05**	**0.05**	**0.10**	

Note: Bold: significant at the .01 level.

Table B2. Correlation Matrix of App Use Time

	Communi-cation	Game	Map/ Navigation	Entertain-ment	Lifestyle	Personal Finance	Music & Radio	Photo	Portal	Schedule/ Memo	Social Network	Utility	Video	Web
Communication		**-0.02**	0.01	**0.02**	**0.04**	0.00	**0.13**	**0.37**	**0.10**	**0.11**	**0.27**	**0.12**	0.01	**0.05**
Game	**-0.02**		-0.01	**0.03**	**0.04**	-0.01	0.01	**-0.02**	0.01	0.00	-0.01	**0.06**	0.01	-0.01
Map/Navigation	0.01	-0.01		-0.01	**0.03**	0.01	0.00	0.00	0.00	**0.05**	-0.01	**0.04**	0.01	-0.01
Entertainment	**0.02**	**0.03**	-0.01		0.00	**-0.02**	**0.04**	**-0.02**	**0.08**	0.00	0.00	**0.02**	**0.02**	0.00
Lifestyle	**0.04**	**0.04**	**0.03**	0.00		0.06	**0.07**	0.01	**0.08**	**0.07**	0.01	**0.10**	**0.09**	**0.05**
Personal Finance	0.00	-0.01	0.01	**-0.02**	**0.06**		0.00	-0.01	**0.08**	**0.04**	**-0.02**	**0.05**	**0.10**	**0.05**
Music & Radio	**0.13**	0.01	0.00	**0.04**	**0.07**	0.00		**0.07**	**0.06**	**0.03**	**0.08**	**0.05**	**0.09**	**0.06**
Photo	**0.37**	**-0.02**	0.00	**-0.02**	0.01	-0.01	**0.07**		**0.09**	**0.04**	**0.31**	**0.09**	**0.02**	**0.09**
Portal	**0.10**	0.01	0.00	**0.08**	**0.08**	**0.08**	**0.06**	**0.09**		**0.04**	**0.09**	**0.06**	**0.11**	**0.09**
Schedule/Memo	**0.11**	0.00	**0.05**	0.00	**0.07**	**0.04**	**0.03**	**0.04**	**0.04**		0.01	**0.09**	**0.06**	0.01
Social Network	**0.27**	-0.01	-0.01	0.00	0.01	**-0.02**	**0.08**	**0.31**	**0.09**	0.01		**0.06**	**0.04**	**0.08**
Utility	**0.12**	**0.06**	**0.04**	**0.02**	**0.10**	**0.05**	**0.05**	**0.09**	**0.06**	**0.09**	**0.06**		**0.09**	**0.07**
Video	0.01	0.01	0.01	**0.02**	**0.09**	**0.10**	**0.09**	**0.02**	**0.11**	**0.06**	**0.04**	**0.09**		**0.09**
Web	**0.05**	-0.01	-0.01	0.00	**0.05**	**0.05**	**0.06**	**0.09**	**0.09**	**0.01**	**0.08**	**0.07**	**0.09**	

Note: Bold: significant at the .01 level.

Appendix C

Details on the Estimation and the Scalability of the Proposed Model

In this appendix, we provide a guideline for the estimation of the proposed model. The estimation follows the general steps of simulated maximum likelihood estimation. Below we outline each step of the procedure.

1. Determine initial values for all model parameters (α_0, $\bar{\beta}$, Ξ_β, Σ_β, Π_β, Γ_β, Λ_β, $\bar{\lambda}$, Ξ_λ, Σ_λ, Π_λ, Γ_λ, Λ_λ).

2. Draw H random values for each of ψ_h, υ_h, φ_h, and ν_h from the standard normal distribution. Note that H is the number of panel members in the data. Statistical packages usually provide random number generators and these can be used. However, we use the Halton draws to generate random numbers because it is known to improve the simulation performance. See Chapter 9 of Train (2009) for detailed discussion on this.

3. Using the parameter values and random numbers drawn in the previous step, calculate the following:

$$M! \cdot \left(\prod_{j=0}^{M} \frac{1-\alpha_{hjt}}{q_{hjt}+\tau_j} \right) \cdot \left(\sum_{j=0}^{M} \frac{q_{hjt}+\tau_j}{1-\alpha_{hjt}} \right) \cdot \frac{\prod_{i=0}^{M} e^{V_{hit}}}{\left(\sum_{j=0}^{J} e^{V_{hjt}} \right)^{M+1}}$$

   Note that this is the integrand in (10).

4. Repeat steps 2 and 3 many times and take averages of computed integrands. This average is the simulated likelihood for the given parameter values. In the model estimation, we repeat the process 100 times using the Halton draws to obtain the simulated likelihood.

5. Maximize the simulated likelihood value (computed through step 1 to step 4) by updating model parameters. GAUSS package is used for

this numerical maximization. Specifically, we use a quasi-Newton numerical optimization algorithm developed by Broyden, Fletcher, Goldfarb, and Shanno (BFGS). The BFGS algorithm is an iterative method for solving unconstrained nonlinear optimization problems. The BFGS method is one of the most popular quasi-Newton numerical optimization algorithms. Moreover, this algorithm is suited to problems with large numbers of variables and has proven to have good performance even for non-smooth optimization problems.

We have 23,222 observations (1366 users × 17 weeks) and 363 parameters to be estimated. The computation time of likelihood value (step 1 through step 4) is 6.82 seconds with a desktop PC running at 2.8 GHz. Note that, like many other packages, GAUSS supports multi-thread computing and we calculate the likelihood using eight threads with eight-core processor. Multi-threading can reduce the computing time almost linearly. If one use 16 thread with a 16-core processor running at the same speed, the computation time will be reduced by a half.

To see how computation time changes as the number of observations changes in our model, we reduce the number of observation by a half (n = 11,611). We find that the computation time is 2.97 second (44% of 6.82 seconds).

Currently, we consider 15 alternatives in the main model. The total estimation time of this model is about seven days. If the number of alternatives increases, the model parameters will increase almost linearly and we can expect the similar increase in the likelihood computation time. However, the number of iterations needed for the numerical optimization (step 5) will increase due to the elevated problem complexity, resulting in substantial increase in total estimation time. It seems that there are no general results specifying the relationship between the number of alternatives (or model parameters) and nonlinear optimization time.

We also want to direct interested researchers to Chandra Bhat's web page (http://www.caee. utexas.edu/prof/bhat/FULL_CODES.htm) where his GAUSS and R codes for MDCEV model and its variants are available along with technical notes.

Appendix D

Model Estimation Results in Mobile Competitive Analysis

The results in Table D1 show that mobile users' baseline utility for Kakao Talk (a communication app) is the highest and that their baseline utility for Rule the Sky (a game app) is the lowest among the top nine apps. Consistent with the descriptive findings, the baseline utility for Kakao Talk is the highest. Demographic variables account for the substantial heterogeneity in the baseline utilities for all mobile users. For example, older users exhibit a lower intrinsic preference for Kakao Talk (a communication app), Facebook (a social network app), Mellon (a music/radio app), and Naver (a portal search app). Moreover, although users exhibit inertia in their app choices in all apps, they show stronger tendencies of inertial use of game apps (Rule the Sky and TinyFarm). Finally, the baseline utilities for Naver, Kakao Story, and YouTube significantly increase over the sample period.

The results in Table D2 show that the satiation level is the highest for YouTube and the lowest for Tiny Farm among the popular apps. A game app (TinyFarm) shows the lowest satiation, and this finding is consistent with our results based on the app category-level data. We find that there is a substantial user heterogeneity in terms of satiation levels. For example, older users show significantly lower satiation levels for TinyFarm, but exhibit a significantly higher satiation level for Kakao Talk and Mellon. The state dependence coefficients are all significantly negative and this indicates that users show notably lower satiation levels (or longer usage time) this week if the app was used last week. This can be arguably interpreted as the learning reinforcement effect, and/or habituation in app use. The estimated time trend coefficient of TinyFarm is significant and positive, capturing mobile users' decreasing time allocation for TinyFarm over time. This might be explained by boredom with the same game over time.

Table D1. Estimates for Baseline Utility Parameters: App-Level Analysis

		Demographic Variables								
	Constant	**Age 30's**	**Age 40's & Over**	Femal e	**Income Mid-class**	**Income Upper-class**	**Education High School Graduate**	**Education University Graduate**	State Dependence	**Time Trend**
KakaoTalk	**-19.88**	**-0.30**	**-0.41**	**0.36**	**-0.13**	**-0.12**	-0.07	-0.04	**2.29**	0.007
	(0.40)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.07)	(0.06)	(0.07)	(0.004)
Naver	**-22.04**	**-0.21**	**-0.31**	**0.12**	**-0.08**	-0.04	**-0.27**	**-0.12**	**3.80**	**0.010**
	(0.39)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.07)	(0.06)	(0.04)	(0.004)
Kakao Story	**-21.21**	-0.06	**-0.41**	**0.22**	-0.06	**-0.12**	**0.18**	0.05	**2.65**	**0.007**
	(0.39)	(0.04)	(0.05)	(0.03)	(0.04)	(0.04)	(0.06)	(0.05)	(0.03)	(0.003)
RuleTheSky	**-25.14**	0.11	-0.09	**0.34**	**-0.29**	**-0.31**	0.11	-0.08	**6.49**	0.014
	(0.44)	(0.14)	(0.18)	(0.12)	(0.13)	(0.15)	(0.21)	(0.18)	(0.15)	(0.013)
Facebook	**-21.88**	**-0.73**	**-0.69**	**0.10**	0.04	0.03	**-0.45**	**-0.32**	**3.66**	0.003
	(0.39)	(0.06)	(0.06)	(0.04)	(0.05)	(0.05)	(0.08)	(0.06)	(0.05)	(0.005)
TinyFarm	**-24.32**	-0.17	**-0.55**	**0.21**	-0.05	-0.15	0.13	-0.01	**5.66**	0.014
	(0.41)	(0.10)	(0.13)	(0.08)	(0.09)	(0.11)	(0.14)	(0.10)	(0.10)	(0.010)
Mellon	**-22.12**	**-0.63**	**-0.90**	**0.12**	0.10	**0.17**	**-0.24**	**-0.40**	**3.17**	-0.001
	(0.39)	(0.07)	(0.08)	(0.05)	(0.06)	(0.07)	(0.10)	(0.07)	(0.05)	(0.006)
Daum	**-23.10**	0.01	-0.10	0.00	-0.09	-0.09	**-0.30**	**-0.23**	**4.52**	0.007
	(0.40)	(0.08)	(0.09)	(0.06)	(0.06)	(0.07)	(0.11)	(0.09)	(0.06)	(0.006)
YouTube	**-20.97**	-0.07	-0.09	**0.17**	0.00	**-0.12**	**-0.28**	**-0.26**	**1.29**	**0.009**
	(0.39)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.07)	(0.05)	(0.03)	(0.004)
Others	**-16.84**	-0.09	**-0.21**	0.05	**-0.12**	**-0.11**	**-0.38**	**-0.25**	–	0.002
	(0.39)	(0.05)	(0.06)	(0.04)	(0.05)	(0.05)	(0.08)	(0.06)	–	(0.002)

Note: Standard errors in parentheses. Bold: significant at the .05 level. The estimated value of α_0 is -5.37 (standard error: 0.19). The state dependence parameter of "Others" cannot be separately identified from its constant because the "Others" option is always selected by all users.

Table D2. Estimates for Satiation Parameters: App-Level Analysis										
		Demographic Variables							State Dependence	
	Constant	**Age 30's**	**Age 40's & Over**	Female	**Income Mid-class**	**Income Upper-class**	**Education High School Graduate**	**Education University Graduate**		**Time Trend**
KakaoTalk	**2.83**	**0.57**	**0.79**	**-0.31**	-0.04	**-0.08**	**0.44**	**0.42**	**-0.80**	**-0.010**
(Communication)	(0.08)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.07)	(0.002)
Naver	**4.15**	**0.14**	**0.11**	**-0.11**	**-0.13**	-0.03	**0.22**	**0.11**	**-1.18**	**-0.014**
(Portal)	(0.07)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)	(0.04)	(0.05)	(0.003)
Kakao Story	**4.48**	0.02	**0.40**	**-0.71**	0.06	**0.24**	**-0.22**	**-0.24**	**-0.55**	-0.002
(Social)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.003)
RuleTheSky	**2.74**	-0.19	**-0.56**	-0.07	0.10	**-0.22**	0.28	-0.20	**-1.14**	0.011
(Game)	(0.20)	(0.11)	(0.14)	(0.09)	(0.10)	(0.11)	(0.15)	(0.12)	(0.17)	(0.009)
Facebook	**3.92**	**0.36**	**0.40**	**-0.28**	0.03	**-0.11**	**0.39**	**0.51**	**-1.01**	-0.004
(Social)	(0.07)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.07)	(0.04)	(0.05)	(0.004)
TinyFarm	**2.06**	**-0.43**	**-1.04**	0.00	-0.02	-0.02	-0.01	0.01	**-0.47**	**0.014**
(Game)	(0.12)	(0.08)	(0.11)	(0.06)	(0.07)	(0.08)	(0.10)	(0.08)	(0.09)	(0.007)
Mellon	**4.46**	**0.50**	**0.80**	**-0.17**	-0.18	**-0.31**	**0.55**	0.22	**-1.62**	-0.017
(Music/Radio)	(0.13)	(0.12)	(0.14)	(0.08)	(0.10)	(0.12)	(0.19)	(0.12)	(0.09)	(0.010)
Daum	**4.23**	**-0.27**	-0.04	0.02	**-0.19**	**-0.18**	0.19	**0.36**	**-1.13**	**-0.023**
(Portal)	(0.11)	(0.08)	(0.08)	(0.06)	(0.06)	(0.07)	(0.11)	(0.09)	(0.08)	(0.006)
YouTube	**4.89**	-0.03	**0.23**	**-0.14**	0.05	-0.03	-0.11	0.06	**-0.90**	**-0.013**
(Video)	(0.07)	(0.06)	(0.07)	(0.05)	(0.05)	(0.06)	(0.09)	(0.07)	(0.04)	(0.005)
Others	**1.25**	**0.14**	**0.16**	0.01	0.00	0.02	-0.04	0.04	–	0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	–	(0.002)

Note: Standard errors in parentheses. Bold: significant at the .05 level. The state dependence parameter of “Others” cannot be separately identified from its constant because the “Others” option is always selected by all users.

References

Train, K. 2009. *Discrete Choice Methods with Simulation* (2nd ed.), New York: Cambridge University Press.