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How many, how often, and how new? A multivariate profiling of mobile app users

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ABSTRACT

Despite enormous demand for and explosive growth of mobile phone apps in recent years, few studies have been conducted to arrive at a multi-faceted valuation of app users. Our paper addresses this important gap in literature. Drawing on Household Production Theory and Hedonic and Utilitarian Consumption Theory, we investigate how mobile app users behave in the dimensions of possession quantity, usage Frequency, and acquisition Recency. We propose a multivariate model to examine these behaviors jointly and calibrate it using data from a survey of app users. We take a Bayesian MCMC computational approach for model calibration. The results are consistent with our theoretically derived expectations. The significance of the findings is discussed.

1. Introduction

In recent years, consumers have adopted smartphones with great enthusiasm. According to digital marketing research company emarketer.com, the total number of smartphone users in the US has reached 193.9 million in October 2015. Smartphone has also achieved a penetration rate of 77.9% in the US mobile market (ComScore Reports October, 2015). Worldwide, the number of active smartphone users is expected to surpass 6.1 billion by 2020, more than 70% of the total population in the world (Ericsson Mobility Report).

As smartphones become more mainstream, the usage of mobile applications, programs designed specifically to add functionality to mobile handsets and are able to interact directly with the technical features of the phone (Chiem et al., 2010), has been immensely prevalent (Ludwig, 2012). Portio Research (Whitfield, 2013) estimates that by the end of 2017, 4.4 billion people worldwide will use mobile applications in their mobile devices. More importantly, revenue from the sale of apps, in-app purchases and subscriptions across smart phones and tablets will reach an astonishing $189 billion by 2020 (Statistics and facts about mobile app usage, 2015).

Consequently, companies have also quickly adopted mobile marketing strategy to engage consumers in two-way interactions that increase brand loyalty and overall consumer satisfaction. Mobile marketing is “a set of practices that enables organizations to communicate and engage with their audience in an interactive and relevant manner through any mobile device or network” (MMA, 2009). The instituting and maintenance of mobile apps have become a vital part of mobile marketing strategy of many companies who want to expose app users to brands in innovative and effective ways.

Many studies on mobile apps have been conducted in different academic areas. For example, Azfar et al. (2016a) looked at how 30 popular social apps can help forensic investigators to identify the personally information stored by the apps. They also extended the research and developed a taxonomy for the forensic investigators to get personal information from the productivity apps (Azfar et al., 2016b). These apps are, thus, a rich source of digital evidence. Researchers also find that security mechanisms in mobile platforms and apps can complicate the forensic acquisition of data. D’Orazio and Choo (2016) presented techniques to circumvent security mechanisms and facilitate collection of artefacts from cloud apps. Azfar et al. (2016c) also examined the 10 most popular free voice over internet protocol (VoIP) apps and analyzed the communications to determine whether these apps are encrypted. In addition, there are some other studies aiming at understanding of the app users on their attitudes and behaviors toward security consciousness about using apps (e.g., Imgraben et al., 2014).

Surprisingly, however, existing Marketing literature is very limited in understanding the important group of mobile app users, despite the fact that mobile apps play a central and critical role in stimulating and

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advancing mobile marketing. Who are these users? How do they behave regarding obtaining, retaining, and using apps? Are these behaviors related, and what are their influencers? These vital questions remain largely unanswered. In particular, few studies have been conducted to access and profile app users in a multi-faceted manner.

Our paper addresses this gap in literature. While traditional valuation of customer centers on RFM analysis (e.g., Recency, Frequency, and Monetary value), we draw on Household Production Theory and Hedonic and Utilitarian Consumption Theory to investigate how mobile app users behave in the aspects of possession Quantity, usage Frequency, and acquisition Recency. We propose a multivariate model to examine these behaviors jointly and calibrate it using data from a survey of app users. We take a Bayesian MCMC computational approach for model calibration. The results are consistent with our theoretically derived expectations: all the three components of app users' value are influenced by the generalized Household Production process. Hedonic and utilitarian preferences, on the other hand, play limited roles in determining how many apps to possess, how often to use them, and how recently they are obtained. Further, the three components are not always in accordance with one another.

In the next section, we discuss the literature on relevant concepts. Section three describes our data while section four explains our model. In section five we present and discuss our empirical results. Section six concludes with managerial implications of our findings and directions for additional research.

2. Literature review

2.1. Valuation of app users: RFQ model

Marketing scholars have produced an abundant body of research on mobile marketing. Although these studies cover a wild range of topics such as the role of mobile technology adoption in consumer purchase decision processes (Shankar and Balasubramanian, 2009) and the trends in mobile marketing (Shankar et al., 2010), the majority of them have focused on mobile advertising and promotion, that is, how companies can utilize mobile device to communicate with their customers. Researchers have found that overall, mobile advertising and promotion are quite effective. For instance, consumers accept the concept of mobile coupons rapidly (Dickinger and Kleijnen, 2008), often use apps for quick access to location-based information (Grewal and Levy, 2016), are influenced by environment cues identified by mobile devices (Andrews et al., 2015; Luo et al., 2014), and, in searching information, weigh benefits owing to device mobility over increased search costs due to decreased screen size (Ghose et al., 2013).

Nonetheless, few researchers in mobile marketing have assessed the value of the mobile phone app users, despite the fact that the latter is the subject of, and the medium for, all mobile marketing actions. In fact, in the mobile commerce context, the term "consumer value" is interpreted by many researchers not as a quality that is intrinsically incorporated into consumer behavior, but as a utility perceived by consumers from using product offerings (Koo, 2009; Penttinen et al., 2010). In other words, it is mainly treated as a driving factor for using products such as the apps. The assessment of mobile app users seems to be largely neglected by marketing scholars, despite the fact that it is an important concept in customer relationship management (CRM).

In CRM, marketing managers traditionally use Recency, Frequency, and Monetary value (RFM) information to predict customer value and behavior (Hoekstra and Huizingh, 1999). A scoring process used to determine which customers to target in order to maximize profit, the RFM model is purely behavior-based, in which "Recency" refers to how recent is the last purchase by the customer, "Frequency" the number of purchases, and "Monetary" the total amount spent. In its simplest form, the model classifies customers into groups based on these behavioral variables. Mailing or other marketing communication programs are then prioritized based on the scores of different RFM groups (Bult and Wansbeek, 1995; Hughes, 1996; Yeh et al., 2009).

The model has undergone several modifications in the literature. Qualitatively, the definition of RFM is often customized to fit into the research context. For example, Hsieh (2004) examined bank customers by considering Recency as the average time distance between the day of making a charge and the day of paying the bill, Frequency as the average number of credit card purchase made, and Monetary as the amount of consumption spent during a yearly time period. In a study on telecommunication customers, Li et al. (2008) defined Recency as the most recent traffic time that lasts for 3 h with its network flow exceeds the threshold, Frequency as the usage counts over 7 weeks, and Monetary as the ratio between monthly-network-rental to monthly-network-traffic. While investigating members of private travel vacation clubs in America, Lumsden et al. (2008) tied Recency to the year in which the member booked the most recent vacation, Frequency to the number of vacations via the number of years spent in the club, and Monetary to the average spending per vacation. As another example, Chan (2005) defined Recency as the online auction customer's total bid period, Frequency the total number of bids, and Monetary the final bid price.

On the other hand, the model has also been quantitatively developed for better scoring. For example, Marcus (1998) used the number of purchases (F) and the average purchase amount (A) to construct a two-dimensional matrix model to capture the CLV (customer lifetime value). Some researchers have used the model in conjunction with other techniques such as Clustering and Association Rule Mining for consumer segmentation (Sohrabi and Khanlari, 2007; Wu et al., 2009; Namvar et al., 2010; Mo et al., 2010; Li et al., 2011). Other researchers have proposed Weighted RFM models where each R, F, M measure is multiplied by different weights according to the type of business and customer so that intuitive judgments on a specific measure are enabled (Liu and Shih, 2005a, 2005b; Sohrabi and Khanlari, 2007).

In addition, literature has expanded the RFM models by considering many additional variables. Yeh et al. (2009) selected targets for direct marketing from a database using a modified RFM model, namely RFMTC, by adding two parameters, e.g., time since first purchase (T) and churn probability (C). Chiang (2011) introduced a RFMDR model to examine online shoppers, where D represents discount-price product and R represents the return cost. Chang and Tsai (2011) proposed a GRFM model (for group RFM analysis) to take into account the characteristics of the purchased items. Also, Timely RFM (TRFM) was proposed to deal with the product periodicity, e.g., to analyze different product demands in different times (Birant, 2011). Recently, Zhang et al. (2015) demonstrated the deficiency in RFM as a basis for summarizing customer history (data compression) and extended the framework to include clumpiness (C) by a metric-based approach.

Furthermore, researchers have also used newly identified measures to substitute the existing RFM components. Examples include RML (Recency, Monetary, and Loyalty) in transaction environment research and RFR (Recency, Frequency, Reach) in social graph research (Birant, 2011). In particular, a RFD (Recency, Frequency, Duration) model was proposed to consider visit duration for the website visitors. Yan and Chen (2011) used RFD to estimate how much a user "likes" to use an application. Cardone et al. (2012) used the RFD score to monitor and quantify IMS-enabled mobile service usage. Hingorani et al. (2014) applied a RFD (Recency, Frequency, and Duration) model to make recommendations of apps to the users.

In light of prior research, we propose a RFQ model, in lieu of the traditional RFM model, to capture the value of app users. In our model, Q represents "Possession Quantity", and is defined as the number of apps obtained and installed in the user's smart phone. We use this measure to replace "Monetary" because the majority of mobile phone apps today are free of charge. As such, possession Quantity has become a more important measure of value than monetary spending. For example, one app user with a possession of many free apps can be much more valuable to mobile marketing practitioners than another