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The Dynamics of Consumer Engagement with Mobile Technologies

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Abstract. While important insights about the customer engagement concept have been gleaned in recent literature, little remains known regarding the nature and dynamics characterizing customers' engagement with mobile devices, particularly from a longitudinal perspective. Therefore, the objective of this paper is to examine how customer engagement with mobile technology is related to purchase behaviors over time as a dynamic iterative process. A unique database addressing customers' mobile engagement and purchase behaviors is used for the analysis. The results from a vector autoregressive (VAR) model suggest that customer mobile disengagement, where consumers abandon an app, has a strong negative long-term effect on purchase behaviors. However, purchase behaviors can alleviate the level of disengagement. The study, therefore, provides novel findings pertaining to the dynamic interrelationship between customers' engagement with new digital media and purchase behaviors, and therefore it has important scholarly and managerial implications.

Keywords: engagement • disengagement • mobile devices • mobile apps • VAR model

1. Introduction

Approaches and tools for managing customer interactions have evolved rapidly over the last two decades (Hoffman and Fodor 2010, Kaplan and Haenlein 2010). A driver of this rapid shift resides in the emergence and proliferation of modern information and communication technologies (ICTs), which serve as platforms facilitating interactions with and among consumers (Brodie et al. 2013, Hoffman and Novak 1996, Trusov et al. 2009, Wiertz and Ruyter 2007). Examples include personal computing devices, the Internet, social media platforms, mobile devices, and mobile applications. These technologies have spawned numerous new ways for companies to interact with consumers (Kaplan and Haenlein 2010, Men and Tsai 2013), which are also subject to continuous innovation and evolution. The technologies also produce a digital record of many interactions, creating big data sets.

Among these emerging technologies, branded mobile applications and mobile optimized websites (hereafter referred to as "mobile apps") used on smartphones and tablets are changing the ways in which customers interact with brands. According to Nielsen (2015), U.S. smartphone users spend around 37 hours 28 minutes while accessing an average of 26.7 apps each month. Gartner (2014) predicts that by 2017, mobile apps will be downloaded more than 268 billion times generating revenues in excess of USD 77 billion. These trends suggest how deeply mobile media have penetrated smartphone users' daily lives. Their broad accessibility, ease of use, and ubiquitous nature make apps powerful tools facilitating customer engagement and empowerment (Tarute et al. 2017), thereby assisting individuals to proactively cocreate their own, as well as each other's, brand-related experiences (De Valck et al. 2009, Hollebeek et al. 2014, Nambisan and Baron 2007, Prahalad and Ramaswamy 2004). Correspondingly, Tarute et al. (2017) posited "mobile [to be] the new face of engagement."

There is a growing body of research testing how the use of mobile media affects subsequent purchases (Bellman et al. 2011, Wang et al. 2015, Kim et al. 2015). While the number of studies is currently small, there is a growing consensus that branded mobile app adoption and use positively affect subsequent purchases, confirming that developing mobile contact points can be an effective strategy for firms seeking to engage, cocreate with and, ultimately, retain customers (Tarute et al. 2017, Baxendale et al. 2015). Most contemporary firms are concerned with the strategic enhancement of customer loyalty and lifetime value (Rust et al. 2004). Traditionally, the specific types of activities deployed to achieve such objectives, including advertising and other promotional tools, tend to be relatively costly in nominal terms (Kaplan and Haenlein 2010, Mangold and Faulds 2009). Engaging customers on mobile devices, by contrast, constitutes a potentially cost-saving alternative (after recovering development costs), which may be used toward the achieving of broader strategic organizational objectives.

Previous research on mobile marketing, however, has focused on a one-way relationship between mobile use and outcomes such as purchase. We posit that the relationship is more complicated and multidimensional. Using a mobile app certainly exposes customers to a brand and thereby increases the likelihood of purchase and use of the service, but the relationship could go the other way as well: a customer who uses a service and derives value from it may seek out the app and use it. For example, someone who flies often with an airline may download and use the airline's app because it conveniently provides flight status, allows the customer to select seats, etc. Use of the app may, in turn, increase the customer's loyalty (i.e., future ticket purchases) with the airline. Thus, there is a dynamic, iterative relationship where purchases cause app use, which causes additional purchases, which causes more app use, and so on. Rather than being unidirectional, the relationship is symbiotic, where app use and purchase mutually sustain and reinforce each other. Moreover, there is a possibility that the app will disappoint the user by not providing sufficient value, breaking the symbiosis. When this occurs, it is of interest to know whether purchases are affected. For example, can a disappointing experience with an app cause a customer to reduce the purchase of some service?

The fact that there are few empirical studies that examine the relationship between customers' mobile engagement and their purchase behaviors, and none that model the dynamic interplay between engagement, purchase, and consumption, provides the impetus for the present, longitudinal investigation. Extending Van Ittersum et al. (2013), we hypothesize that multiple variables iteratively affect one another over time. Correspondingly, we adopt a vector autoregressive (VAR) model to analyze this iterative, longitudinal set of processes. We also examine customer mobile *disengagement*, as reflected by individuals' discontinued use of a focal mobile app or website (Hollebeek et al. 2014, Peck and Malthouse 2011), which has not received any empirical scrutiny.

This large-scale, longitudinal investigation into customers' mobile engagement directly responds to the calls in the literature (Brodie et al. 2011; Hollebeek 2011a, b; Hollebeek 2012; Leeflang 2011; MSI 2016) and provides novel insights into this emerging area. Further, by investigating the dynamic interrelationship between customers' mobile engagement, purchase and consumption behaviors, this study also directly responds to the calls from Van Doorn et al. (2010) and Hollebeek et al. (2014) for further exploration of customer engagement-based causal relationships within broader nomological networks. In addition, investigation into customer engagement fits within the broader theoretical strands of literature addressing service-dominant (S-D) logic and relationship marketing (Palmatier et al. 2009; Vargo and Lusch 2004, 2008; Brodie et al. 2011).

2. Literature Review and Conceptual Development

2.1. The Emerging Use of Mobile Devices as an Engagement Tool

Mobile media represent a relatively new way of communicating with customers (Kim et al. 2013, 2015) and may be viewed as an interactive advertising sub-form (Bellman et al. 2011). Wang et al. (2016) discuss how mobile apps and platforms can serve as a new and innovative advertising channel. Mobile media are characterized as being portable, personal, interactive, multimodal, and converged (Larivière et al. 2013, Bruns and Jacob 2014). With their portable and personal nature, mobile media have great potential to be a pull promotional tool, i.e., the consumer chooses to download an app considered relevant and subsequently decides when, where, and how often to use it (Bellman et al. 2011). The interactive, multimodal, and converged nature of mobile media allows consumers to have deeper cognitive processing of relevant information. In addition, sticky apps that provide value relevant to customers help them build a habit of using the apps on a regular basis (Wang et al. 2015). In sum, the unique characteristics of mobile devices facilitate a high level of customer engagement with them and the brand (Calder and Malthouse 2008, Kim et al. 2013), which ultimately affects purchase behavior (Kim et al. 2015).

2.2. Conceptualizing Customer Mobile Engagement Behavior

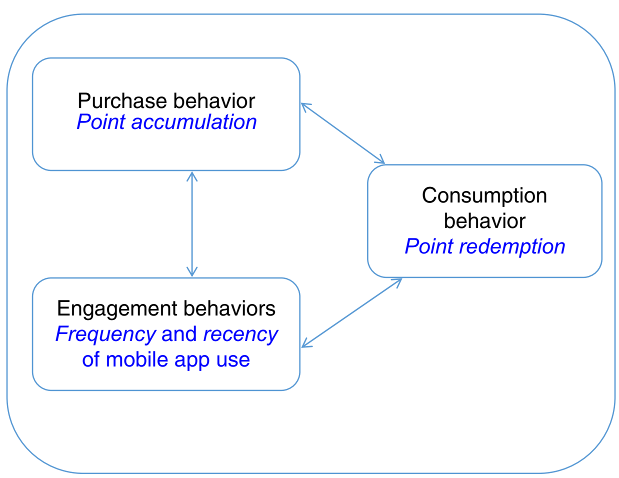
Brodie et al. (2011, p. 260) suggest that engagement occurs by virtue of *interactive, cocreative customer experiences* with a focal agent/object (e.g., a brand) in specific service relationships and that varying context-dependent conditions generate differing customer engagement levels. Furthermore, they suggest that it exists as a *dynamic, iterative process* within service relationships that cocreates value. Other authors have highlighted the particular importance of the directly observable, *behavioral* dimension underlying the engagement concept. Specifically, this has been referred to as *customer engagement behaviors* (CEBs) (Jaakkola and Alexander 2014, Van Doorn et al. 2010, Verleye et al. 2013). Van Doorn et al. (2010, p. 253) define CEBs as "customers' behavioral manifestation toward a brand or firm, beyond purchase, resulting from motivational drivers." The conceptual ambit of CEBs includes a broad array of behaviors, including word-of-mouth activity, writing reviews, and customers' focal branded mobile-related behaviors (e.g., log-ins and check-ins, which represent the particular CEBs examined in this study). Based on these conceptualizations, we define mobile engagement behavior as *customers' interactive experience with the focal branded mobile media*. CEBs are expected to affect particular customer- and firm-based variables, including the development of specific attitudes, and the attainment of focal financial outcomes (Van Doorn et al. 2010).

Additionally, extending the work of Van Doorn et al. (2010), Verleye et al. (2013), and Jaakkola and Alexander (2014), we study *customer disengagement*, which is indicated when a customer who was formerly engaged, stops performing CEBs. O'Brien and Toms (2008, p. 944) state, "Disengagement occurred when participants made an internal decision to stop the activity, or when factors in the participants' external environment caused them to cease being engaged." Likewise Brodie et al. (2013, p. 110) state that "'Termination' represents a state of more permanent disengagement, and as such, refers to the conclusion of a consumer's engagement with a particular brand community." In the case of mobile apps, disengagement is indicated by discontinued use of check-ins and logins. Peck and Malthouse (2011, pp. 230–232) discuss psychological motivations for disengaging with a media product such as a mobile app and identify several experiences including information overload, poor or annoying design, and poor-quality content (Calder and Malthouse 2004). Our focus is on the observable manifestation, discontinued use.

2.3. The Dynamic Interrelationship Between Customer Mobile Engagement, Purchase, and Consumption Behaviors

While the Brodie et al. (2011, p. 260) definition emphasizes that engagement is a "dynamic, iterative process," there has been little research that models it as such. Figure 1 gives our conceptual model showing how the different variables interact (Maslowska et al. 2016, Pfisterer and Roth 2015). We begin our discussion with the purchase and consumption boxes. Purchase behaviors end in a transaction where (usually) money is exchanged for the service or product, while consumption involves using whatever was purchased for its intended purpose. Sometimes purchase and consumption occur more or less concurrently, such as paying for a bus fare (purchase) and then riding to the destination (consumption), or eating dinner at a restaurant (consumption) and paying the bill (purchase). In other situations the purchase experience happens prior to consumption, e.g., one could purchase season theater tickets but not attend shows (consumption) for several months. It is not uncommon for the purchase of an airline ticket to happen weeks or even months before the actual flight (consumption). One could purchase a month of Netflix or health club service today but watch movies or work out (consumption) throughout the month. The purchaser might also forget or become too busy to watch or to work out, in which case a transaction has occurred without any consumption. One might also read news stories on websites or listen to music on a streaming service, both examples of consumption, without paying. They may eventually purchase a subscription or buy the album at a later time, illustrating how consumption can happen before purchase. These examples illustrate how purchase and consumption can be different behaviors in various service settings, how one can occur without the other, and also how one may be antecedent to the other.

Figure 1. Conceptual Model of Customer Engagement/Disengagement



Now consider the role of engagement behaviors, including those with mobile media. As the airline example in the introduction illustrated, it is easy to construct examples showing how CEBs can cause, or be caused by, purchase and consumption. One may purchase skis from REI, and then want to download the REI Snow Report app for information about snow conditions. Using the app could enhance the "consumption" of the skis and lead to purchases of other accessories at REI, such as winter clothing. Reading a favorable consumer review of a restaurant, which is considered an engagement behavior by Muntinga et al. (2011), may cause someone to visit it. A consumption experience may cause diners to write their own reviews, another CEB.

Now consider the role of mobile disengagement. When mobile media fail to provide value for customers, they will stop using it. More generally, a customer could become engaged with any environment designed to facilitate CEBs, such as a company-sponsored discussion forum focused on a software product (e.g., the Microsoft Office discussion forum). A poor purchase or consumption experience could cause a customer to cut all ties with the brand, including an app or discussion forum. Likewise, a poorly designed, bug-prone or worthless app in terms of fulfilling a customer's goals may cause the customer to discontinue using it. The more important questions are whether (1) abandoning an app could affect subsequent purchase or consumption of the service itself and (2) whether favorable purchase and consumption episodes can cause a customer to re-engage with the app and other CEBs (i.e., decrease disengagement).

Although increased purchases have been mostly discussed as a consequence of engagement (Van Doorn et al. 2010), the effect of engagement on purchase behaviors does not necessarily fully describe the relationship between the two concepts. For example, Gummerus et al. (2012) note that customer engagement with a brand community may develop as a result of preexisting brand loyalty, which is further strengthened by the positive experience customers have taking part in the community activities. Analogously, Brodie et al. (2013) suggest that a number of designated engagement consequences (including brand loyalty) may act as antecedents to subsequent engagement behaviors, thus reflecting the dynamic, iterative nature of the engagement process.

3. Research Design

3.1. Data

The main objective of this study is to examine how CEBs with a mobile app and purchase/consumption behaviors influence each other over time. To achieve this objective, we utilize a data set sourced from LoyaltyOne in Canada. Each member enrolled in the program is provided a membership card that can be swiped at various sponsors across a number of categories, including grocery stores, petrol stations, drug stores, home improvement stores, and financial services. Within each category, only a single sponsor is used (e.g., for gasoline, Shell represents the only supplier of points, etc.).

When customers swipe their card at a sponsor location, they receive *points* approximately proportional to their purchase amount, and LoyaltyOne receives a payment from the sponsor in return for the points issued. Thus, the loyalty program earns revenue when the consumer goes to a sponsor and accumulates points by swiping the card. The loyalty program intends for members to purchase from sponsors, rather than nonsponsoring firms. Accumulating points is the *purchase behavior* of interest to the loyalty program, since it is directly linked to its revenues. Consumers are entitled to redeem their points for a variety of rewards ranging from merchandise (e.g., televisions, blenders, mixers, etc.), travel, gift certificates, or instant cash. Such rewards are the tangible value the company provides to the consumer, and therefore are expected to represent consumers' main reason to enroll in the loyalty program; that is, with customers being motivated to accumulate points with a view to receiving a future reward (Blau 1964). Redemption is how members "consume" the loyalty program's service. Drawing an analogy with our earlier examples, just as a consumer enrolled in the loyalty program AMC Stubs accumulates points while purchasing a movie ticket at AMC theaters, redeeming these points at a future date for a free ticket at AMC is how consumers derive value from the loyalty program.

LoyaltyOne developed a branded mobile app and launched it in February 2012, which allows customers (i.e., loyalty program members) to undertake specific CEBs, including *logging in* to check their point balances, browse potential reward items, keep track of their purchase histories, and progress toward the attainment of particular rewards (including by emailing details regarding particular rewards to a specified address), find sponsors nearby, and *check-in* at sponsors. Consumers can share their check-in information on specific social networking sites (e.g., Facebook), helping to inform their family and friends where they shop, or to keep a record of specific locations they have visited. It is important to note that consumers are unable to make purchases by using this app. The app was introduced as an additional brand touch point primarily to stimulate CEBs such as log-ins and check-ins. This is consistent with the definition of CEBs, as customers' interactions with theapp do not directly relate to purchase (Van Doorn et al. 2010, MSI 2016).

Table 1. Descriptive Statistics

	Recency of app use	*Frequency* of app use	*Points accumulated*	*Points redeemed*	*Age*	*Tenure*
Mean	17.41	0.0088	22.70	19.40	37.40	9.58
SD	14.55	0.1112	134.56	342.61	12.22	6.29
Min	0.00	0.0000	0.00	0.00	12.10	0.00
Max	54.00	6.9027	42,894.00	122,933.00	78.17	20.91

The loyalty program provided us with daily transactional information reflecting individuals' usage with the mobile app, *point accumulation*, and *redemption* for 548,569 customers from February 7, 2012, to February 12, 2013. We selected a simple random sample of 10% (i.e., 54,858) of the customers for the analysis. We then aggregated the available information on CEBs, i.e., *recency* and *frequency* of app usage, as well as their *point accumulation* and *redemption* at the weekly level for 54 weeks, thus resulting in a total of 2,962,332 customer–week observations for analysis.

3.2. Measures

We compute two measures of CEBs, namely the *frequency* and *recency* of customers' usage of the app. *Frequency* is computed using the total number of log-ins and check-ins carried out by a customer every week and is a direct measure of a consumer's cumulative behavioral engagement with the app. Higher *frequency* values suggest greater CEBs with the app. *Recency* is measured using the number of weeks elapsed since a customer's most recent app activity and directly measures whether a customer has become disengaged with the app. Large values of *recency* indicate that the customer has likely abandoned the app.

We calculate the total number of *points accumulated* each week by a customer as a measure of purchase behavior. As explained in Section 3.1, the study is conducted in the context of a loyalty program. Therefore, we also calculate the total number of *points redeemed* each week by a customer as a measure of consumption behavior.

3.3. Descriptive Statistics

Summary descriptive statistics for the final sample are shown in Table 1. Overall, the statistics suggest that, on average, customers use the app less than once a week. The average time between two consecutive uses was 17.7 weeks, while the number of weekly *points accumulated* equals, on average, 22.7 points, with average weekly *redemption* equaling 19.4 points. However, the standard deviation and range (i.e., max − min) for these variables are substantial. Additionally, we included individuals' *age* and *tenure* (defined as the number of years in the loyalty program) as demographic variables. The average age reported in our sample was 37.4 years and the average loyalty program membership tenure was 9.5 years.

For the analysis, we log-transformed values of these measures based on the observed right skewed counts and outliers. Specifically, the log transformation symmetrizes the distributions, reduces the influence of outliers, and stabilizes their variance. Since the minimum value for each of the four focal variables is zero and the logarithm of zero is not defined, we increased the value of each variable by one prior to the transformation. The correlations between the log-transformed variables are also reported in Table 2.

3.4. Model Specification

Based on the conceptual model shown in Figure 1, we expect *frequency*, *recency*, *point accumulation*, and *redemption* to represent a dynamic, iterative process (Brodie et al. 2011, Maslowska et al. 2016). Correspondingly, we employ

Table 2. Bivariate Correlations of Log-Transformed Variables

	Recency of app use	*Frequency* of app use	*Points accumulated*	*Points redeemed*	*Age*	*Tenure*
Recency of app use	1.000	−0.547	−0.076	−0.011	0.068	0.065
Frequency of app use		1.000	0.081	0.017	−0.031	−0.023
Points accumulated			1.000	0.089	0.199	0.204
Points redeemed				1.000	0.040	0.046
Age					1.000	0.578
Tenure						1.000

Note. All correlations are significant with $p < 0.01$; number of subjects 54,858; total number of observations 2,962,332.

Table 3. Results (p-Values) from Pairwise Granger Causality Test Using 10 Lags of Log-Transformed Variables

	Response variable			
Explanatory variable	*Recency*	*Frequency*	*Points accumulated*	*Points redeemed*
Recency	—	0.00	0.00	0.00
Frequency	0.00	—	0.00	0.00
Recency	0.00	0.00	—	0.00
Points redeemed	0.39	0.00	0.00	—

a VAR model to account for the dynamic nature of interactions between the four variables studied. Before constructing a VAR model we conduct various pretests.

We first test for simultaneity between the focal variables by using the pairwise *Granger causality test* (Granger 1969, Hanssens and Schultz 2001). The null hypothesis assumes that adding lagged values of X does not improve Y's prediction. For each pair, we conducted the test varying the number of lags of the independent variable from two to ten, attaining consistent results irrespective of the number of lags introduced. The pairwise Granger causality test results shown in Table 3 reveal the presence of simultaneity between the variables in our framework ($p < 0.01$), with the exception of the effect of customers' *points redeemed* on the *recency* of their usage of the mobile app. Therefore, we construct a full VAR to quantify the dynamic interaction among *points accumulated*, *points redeemed*, *frequency*, and *recency* of app use.

An evolving variable has an infinite variance and suggests the presence of permanent effects, while a stationary variable has a finite variance and suggests the existence of temporary effects. Testing for stationarity, therefore, is critical since inferential statistics can be computed only for variables with a finite variance (Granger and Newbold 1974). The null hypothesis of a *unit root test* is that a variable has a unit root (i.e., the variable is "evolving"). In the event that a variable has a unit root, a common solution is to use the first differenced value of the variable in the model. Alternatively, the variable can be used in its current form; that is, in levels, for the estimation. We conducted the unit root test for panel data as suggested by Im et al. (2003) and reject the null hypothesis for each of the four focal variables ($p < 0.01$). The results, therefore, suggest that we are able to utilize the values of the variables in levels for the estimation.

Based on the results outlined in the previous subsection, we specify a VAR model where the log-transformed variables of customers' *recency* of the mobile app use (lnR), *frequency* of the mobile app use (lnF), *point accumulation* though monetary purchases (lnM), and *point redemption* (lnC) for individual i in week t is influenced in a dynamic fashion through $j = 1, \ldots, p$ lags of the endogenous variables. For the nth ($n = 1, 2, 3, 4$) response variable, parameters b_{nm}^{j} capture the effect of the jth lag of the mth ($m = 1, 2, 3, 4$) endogenous variable and parameters γ_{nh} capture the effects of the $h = 1, 2$ exogenous variables of age and tenure. We also include a vector of intercepts A_n and assume the error terms ϵ_{nt} are distributed as MVN$(0, \Sigma)$. The VAR system can be written as follows:

$$\begin{pmatrix} \ln R_{it} \\ \ln F_{it} \\ \ln M_{it} \\ \ln C_{it} \end{pmatrix} = \begin{pmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{pmatrix} + \sum_{j=1}^{p} \begin{pmatrix} b_{11}^{j} & b_{12}^{j} & b_{13}^{j} & b_{14}^{j} \\ b_{21}^{j} & b_{22}^{j} & b_{23}^{j} & b_{24}^{j} \\ b_{31}^{j} & b_{32}^{j} & b_{33}^{j} & b_{34}^{j} \\ b_{41}^{j} & b_{42}^{j} & b_{43}^{j} & b_{44}^{j} \end{pmatrix} \begin{pmatrix} \ln R_{i,t-j} \\ \ln F_{i,t-j} \\ \ln M_{i,t-j} \\ \ln C_{i,t-j} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \\ \gamma_{41} & \gamma_{42} \end{pmatrix} \begin{pmatrix} \ln age_{it} \\ \ln tenure_{it} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{pmatrix}. \tag{1}$$

4. Results

The number of lags p to be included in the model was decided based on several criteria (Gredenhoff and Karlsson 1999), including the Schwarz information criterion (BIC), Akaike information criterion (AIC), and final prediction error (FPE). We consistently found across each of these criteria that, while their values decrease significantly when one lag of the endogenous variables is included, there is little change with additional lags. Consequently, we estimate a VARX(1) model containing *age* and *tenure* as exogenous variables, and one lag of the endogenous variables.

Given the dynamic nature of our model, the estimated parameters are not easy to interpret independently (Sims 1980). Consequently, following Sims and Zha (1999) we calculate impulse response functions (IRFs). The IRFs capture both the direct and indirect effects of a shock to one of the variables on the other variables in the dynamic system. However, it is important to note that the focal variables pertaining to CEBs, and *point accumulation* and *redemption* are log-transformed; hence, the IRFs obtained are also log-transformed. However, it is desirable to obtain the IRFs for each variable in the customary units of measurement; that is, without the log-transformation, thus facilitating interpretation and the development of actionable managerial recommendations.

A common approach to remove the log transformation is to simply take the exponential. However, Ariño and Franses (2000) demonstrate that this approach leads to biased forecasts, and hence propose an alternative method to obtain the forecasts of the response variables without log-transformations under the assumption of normally distributed error terms. Wieringa and Horváth (2005) employ this approach and explain, using a marketing application, how to obtain the level-impulse response. We follow their methodology and refer the reader to these studies for further detail.

An IRF for each level is defined as the difference of the level forecasts of the shocked system, and the level forecasts of the nonshocked system (Wieringa and Horváth 2005). To understand the dynamic effects, we applied a shock by increasing the average value of one of the focal variables (e.g., *recency*) by 20% (we have tried other shock levels and found similar conclusions); followed by the computation of the IRF for the other three variables as the difference of their level forecasts in the shocked system, and the level forecasts of a nonshocked system. In this case, the IRF of *points accumulated* k weeks after the shock was applied to *recency* is calculated as $\mathrm{IRF}(k \mid X_t) = \hat{X}^s_{t+k\mid X_t} - \hat{X}_{t+k\mid X_t}$ where $\hat{X}_{t+k\mid X_t}$ is the level forecast of *points accumulated* at period $t+k$, and $\hat{X}^s_{t+k\mid X_t}$ is the level forecast of *points accumulated* assuming *recency* is shocked at time t. The response functions for *points redeemed* to a shock in *recency*, too, can be calculated in a similar manner. Further, we shocked the other variables in the model one at a time and computed the differences in the level forecasts of the shocked system and the level forecasts of the nonshocked system for the other three variables, thus obtaining a complete set of IRFs. To obtain the confidence intervals for the IRFs, we performed a bootstrap where we resampled the errors 1,000 times, and then reestimated the level responses.

A 20% shock generates an increase over the average value of each endogenous variable by the following amounts (Table 1): an increase of 0.002 in the *frequency* of customers' mobile app use, an additional 4.5 *points accumulated*, approximately 4 additional *points redeemed*, and approximately 3 additional weeks of lapsed use for *recency*. We summed the IRFs obtained over time to capture the "net effects" of a shock on other variables in the system. Since the variables pertaining to *frequency* and *recency* have different units of measurement from those pertaining to *point accumulation* and *redemption*, we cannot use the IRFs or net effects to compare their relative effects. Therefore, we also calculated a measure without units, namely elasticities at time period k, using the formula

$$\mathrm{Elasticity}_{Y\mid X} = \frac{\partial(\sum_{k=1}^{K} Y_{t+k})}{(\sum_{k=1}^{K} Y_{t+k})}\frac{X_t}{\partial X_t}, \tag{2}$$

where Y is the response variable and X is the shocked variable. In the interest of brevity, we report the net effects (Table 4) and elasticities (Table 5) for three particular time periods. We term the net effects and elasticities one week from the shock (i.e., $t+1$) as "immediate effects," 20 weeks from the week of the shock as "medium-term effects," and 40 weeks from the week of the shock as "long-term effects."

Before proceeding to the results, we briefly summarize the steps in the estimation process:

1. Estimate Equation (1) using the least squares approach;
2. use the estimated parameters and draw residuals from $\mathrm{MVN}(0, \Sigma)$ to estimate the level forecasts of the non-shocked system 1,000 times for the next 40 weeks following Wieringa and Horváth (2005);
3. shock each focal variable by 20% of its average value at time t and compute the level forecasts of the shocked system for the next 40 time periods 1,000 times using the same bootstrapped residuals as in step 2;
4. compute the mean IRF as the difference of the level forecast of the shocked system and the level forecast of the non-shocked system and corresponding error bands;
5. calculate the mean "net effect" for time period $t+k$ as the sum of the IRF until time period k and also corresponding error bands; and
6. calculate the elasticities using the formula in Equation (2).

Figure 2 plots the IRFs for the four focal variables employed in the study. In each plot, the blue line represents the average accumulated IRF, while the green and red lines represent the 95% upper and lower confidence limits, respectively. The top row of three plots displays the response of *frequency*, *points accumulated*, and *points redeemed* to a shock in *recency*; the second row displays the response of *points accumulated*, *points redeemed*, and *recency* to a shock in *frequency*; the third row shows the response of *frequency*, *points redeemed*, and *recency* to a shock in *points accumulated*; and the final row shows the response of *frequency*, *points accumulated*, and *recency* to a shock in *points redeemed*.

The first row of IRF plots shows that an increase in the value of *recency* results in less *frequent* use of the app, fewer *points accumulated*, as well as fewer *points redeemed* in the next period. These plots also reveal that the effects of a shock to *recency* on all other three variables endure for a considerable amount of time. These results suggest that the longer customers have abandoned an app, the harder it will be to get them to use it again. In addition, *accumulation* and *redemption* behaviors also decline.

Figure 2. IRF Plots (with 95% Confidence Intervals)

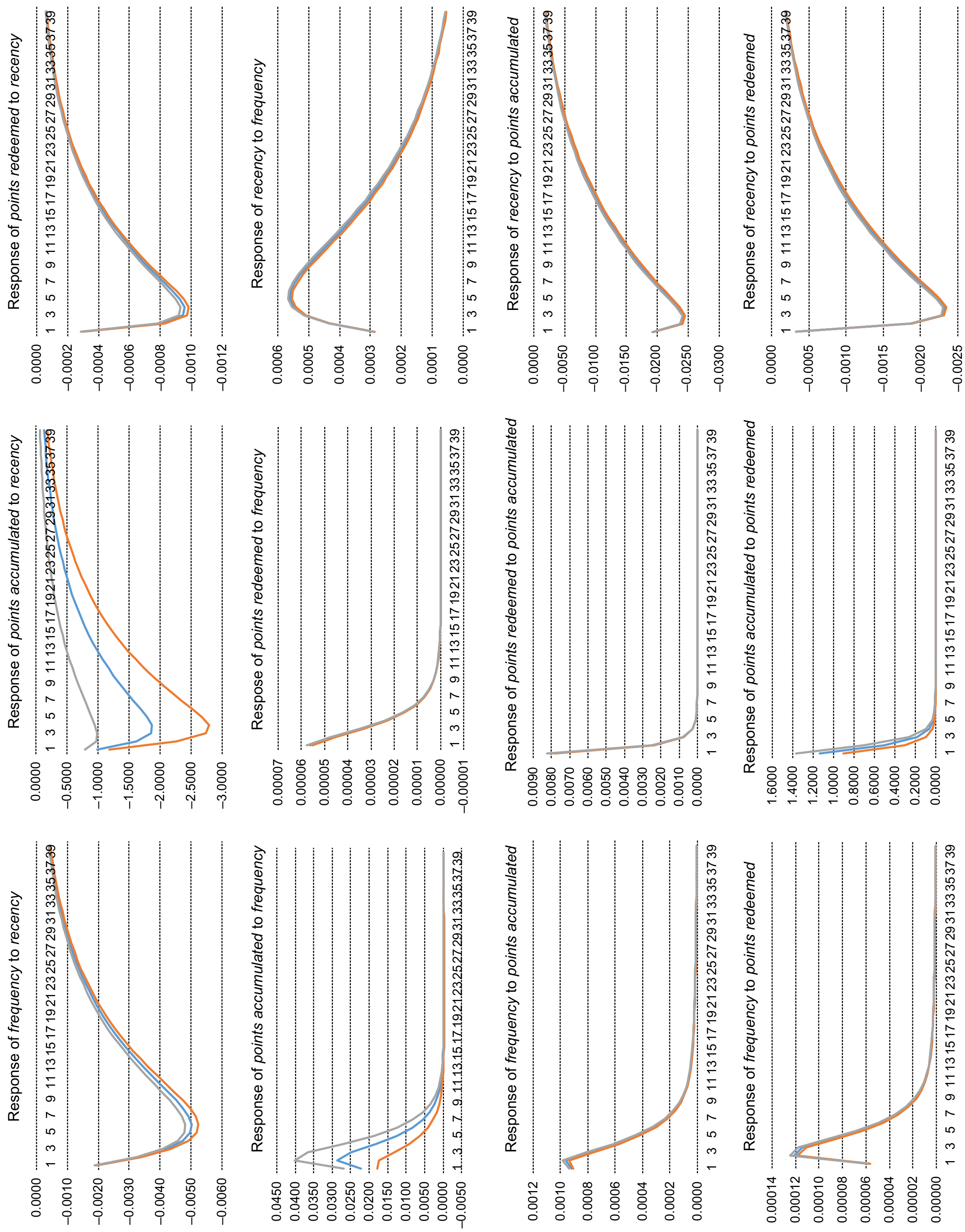


Table 4. Accumulated IRF: Net Effects of a 20% Increase in the Shocked Variable

Shocked variable	Response variable	Immediate ($t+1$)	Medium-term ($t+20$)	Long-term ($t+40$)
Recency	*Frequency*	−0.0019 [−0.0019, −0.0019]	−0.0719 [−0.0750, −0.0688]	−0.0915 [−0.0956, −0.0875]
	Points accumulated	−0.9834 [−1.1841, −0.7826]	−23.8639 [−35.2563, −12.4715]	−29.4673 [−43.6736, −15.2610]
	Points redeemed	−0.0003 [−0.0003, −0.0003]	−0.0123 [−0.0126, −0.0120]	−0.0153 [−0.0157, −0.0149]
Frequency	*Points accumulated*	0.0223 [0.0177, 0.0269]	0.1288 [0.0749, 0.1826]	0.1272 [0.0741, 0.1803]
	Points redeemed	0.0001 [0.0001, 0.0001]	0.0002 [0.0002, 0.0002]	0.0002 [0.0002, 0.0002]
	Recency	0.0003 [0.0003, 0.0003]	0.0084 [0.0083, 0.0085]	0.0110 [0.0108, 0.0112]
Points accumulated	*Frequency*	0.0009 [0.0009, 0.0009]	0.0050 [0.0049, 0.0052]	0.0052 [0.0050, 0.0054]
	Points redeemed	0.00806 [0.0079, 0.0083]	0.01178 [0.0115, 0.0121]	0.01181 [0.0115, 0.0121]
	Recency	−0.0192 [−0.0193, −0.0192]	−0.3214 [−0.3262, −0.3167]	−0.4057 [−0.4129, −0.3985]
Points	*Frequency redeemed*	0.0001 [0.0001, 0.0001]	0.0006 [0.0006, 0.0007]	0.0007 [0.0006, 0.0007]
	Points accumulated	1.1343 [0.9028, 1.3659]	1.9302 [1.3608, 2.4996]	1.9356 [1.3636, 2.5077]
	Recency	−0.0003 [−0.0003, −0.0003]	−0.0302 [−0.0307, −0.0297]	−0.0388 [−0.0395, −0.0380]

Note. 95% confidence intervals in brackets.

The second row of IRF plots reveals that more *frequent* use of the app has a positive effect on the number of *points accumulated* (i.e., revenue to the company), as well as a small positive effect on the number of *points redeemed* and *recency* of the customer's last use of the app. While the effect of *frequency* on *points accumulated* and *points redeemed* seems to diminish after around 20 weeks, the effect on *recency* persists for a longer period of time. *Frequency* can therefore increase the level of disengagement with the app in future time periods.

The third row of IRF plots indicates that *accumulating* additional points results in more *frequent* use of the app and more *points redeemed*. It also results in reduced values of *recency*, i.e., higher level of engagement as fewer weeks elapse between two consecutive uses of the app by a customer. These results suggest that purchase behaviors can, in fact, influence customers to experience the app more frequently and with higher levels of engagement.

In the last row of plots, we observe that *redeeming* more points results in more *frequent* use of the app and more *points accumulated*. *Redeeming* more points also results in lower values of *recency*. At the same time, consumption also results in customers increasing their levels of engagement with the app and using it more frequently. The results, therefore, suggest that consumption has a positive effect on future purchase behavior, an outcome that loyalty programs typically desire. Furthermore, consumption as measured by redeeming points also results in consumers increasing their levels of engagement with the app and using it more frequently. These CEBs in turn can favorably influence future purchase behavior. Loyalty programs often do not encourage members to redeem points, because redemptions cost the program money. This result indicates that customers become better, more engaged customers after a redemption. These rewarding experiences influence future revenues directly and through favorable CEBs indirectly too.

The IRF plots for *points accumulated* and *points redeemed* are remarkably similar in that their effects on *frequency* and *recency* appear to last for a longer time than on each other. To summarize, the results are broadly consistent with what one would expect, and they validate the thesis proposing a dynamic, iterative model of CEBs (Brodie et al. 2011, Van Doorn et al. 2010), thus representing the first known empirical investigation.

To better understand the long-term effects and compare the magnitude of the effects of a shock to different variables over time, we examine the net effects and elasticities reported in Tables 4 and 5, respectively. We first inspect how *recency* of app use affects *points accumulated* and *points redeemed.* The medium- and long-term net

Table 5. Elasticities: Immediate, Medium-Term and Long-Term

Shocked variable	Response variable	Immediate ($t+1$)	Medium-term ($t+20$)	Long-term ($t+40$)
Recency	*Frequency*	−0.0544 [−0.3623, 0.2535]	0.7196 [−0.7162, 2.1555]	−0.1233 [−1.4820, 1.2354]
	Points accumulated	−0.0827 [−0.1044, 0.0610]	−1.2557 [−1.5070, −1.0045]	−2.7121 [−4.6779, −0.7462]
	Points redeemed	−0.0051 [−0.0172, 0.0070]	−9.4137 [−27.5343, 8.7068]	−0.3311 [−0.6145, −0.0478]
Frequency	*Points accumulated*	0.0019 [0.0014, 0.0024]	0.0100 [0.0074, 0.0125]	0.0192 [0.0035, 0.0350]
	Points redeemed	0.0010 [−0.0013, 0.0033]	0.1572 [−0.1453, 0.4596]	0.0045 [0.0006, 0.0084]
	Recency	0.00010 [0.00010, 0.00010]	0.0019 [0.0019, 0.0020]	0.0024 [0.0024, 0.0024]
Points accumulated	*Frequency*	0.0262 [−0.1220, 0.1744]	−0.0595 [−0.1691, 0.0501]	0.0029 [−0.0819, 0.0876]
	Points redeemed	0.1394 [−0.1896, 0.4683]	8.6545 [−7.9948, 25.3039]	0.2540 [0.0294, 0.4786]
	Recency	-0.0055 [−0.0055, −0.0055]	−0.0744 [−0.0754, −0.0734]	−0.0897 [−0.0911, −0.0882]
Points	*Frequency redeemed*	0.0016 [−0.0076, 0.0108]	−0.0072 [−0.0208, 0.0063]	0.0005 [−0.0099, 0.0109]
	Points accumulated	0.0954 [0.0703, 0.1205]	0.2448 [0.1673, 0.3223]	0.5495 [0.0552, 1.0439]
	Recency	-0.00010 [−0.0001, −0.0001]	−0.0069 [−0.0070, −0.0069]	−0.0085 [−0.0086, −0.0084]

Note. 95% confidence intervals in brackets.

effects (Table 4) of a shock to *recency* on *points accumulated* are significantly greater, relative to the immediate effect. In fact, the effect of *recency* on the number of *points accumulated* in the medium term ($|\xi| = 1.25$) and long term ($|\xi| = 2.71$) are "elastic" (Table 5). Higher values of *recency*, i.e., greater levels of disengagement, also have a negative effect on the number of *points redeemed.* The net effects shown in Table 4 also indicate that a decrease in the value of *recency* elicits a much smaller response from *points redeemed* than from *points accumulated*. The long-term elasticity (see Table 5) reveals that the effect of *recency* on *points redeemed* is, in fact, "inelastic" ($|\xi| = 0.33$).

The net effects of *frequency* on *points accumulated* and *points redeemed* are positive (Table 4), but the magnitude of both these effects appears to be relatively small. Further, the elasticities in Table 5 suggest that the effect of *frequency* on the number of *points accumulated*, as well as *points redeemed*, across all time periods is quite small and hence can be deemed "highly inelastic." To summarize, disengagement, measured in terms of *recency* of app use, has a stronger, long-term effect on ensuing *point accumulation* and *redemption* than *frequency* of app use.

We now examine the net effects of *point accumulation* and *redemption* behaviors on *recency* and *frequency* of the app use, respectively, and the corresponding elasticities. We observe from Table 4 that the long-term effect of *points accumulated* on *recency* is greater than the medium- and short-term effects, thus again suggesting the importance of accounting for the dynamic nature of the relationship between these two variables in the model. Further, the effect of *points redeemed* on *recency* continues to build over time, though to a much smaller extent than the effect of *points accumulated*. Comparing the elasticities shown in Table 5, we observe that the effect of *points accumulated* on *recency* is greater, relative to the effect of *points redeemed*. Similarly, the net effects of *points accumulated* and *points redeemed* on *frequency* of the app use continue to build over time, though to a much smaller extent than their effect on *recency*. Furthermore, the 95% confidence intervals for the corresponding elasticities include zero, suggesting that the effects are "highly inelastic."

Finally, from a loyalty program perspective, it is important to understand how the number of *points accumulated* and *points redeemed* affect one another over time. We find that the medium- and long-term net effects (Table 4) of the number of *points accumulated* on *points redeemed* are greater, relative to the immediate effect. Similarly, we find that that the medium- and long-term net effects of *points redeemed* on *points accumulated* are greater, relative to the corresponding immediate effect. Interestingly, a comparison of the elasticities (Table 5) suggests that the effect of the number of *points redeemed* on *points accumulated* is greater, as opposed to vice versa. This represents an important finding for loyalty programs, which are based on the premise that the offering of rewards incentivizes customers to remain loyal to a focal brand.

To summarize, the results obtained from our VAR model broadly reveal the following insights. First, the findings validate the existence of a dynamic, iterative customer engagement process comprising a number of focal CEBs, thus representing the first known empirical investigation into these dynamics. Second, the effects of *recency* on *point accumulation* and *redemption* are significant and perhaps much larger than advertising elasticities reported in prior research (i.e., Hanssens and Schultz 2001 observe that advertising elasticities are typically around 0.1). In other words, experiences that lead to higher levels of engagement with touch points such as mobile apps have a significant effect on desired marketplace outcomes. Further, greater levels of disengagement, as measured by larger values of *recency*, were found to generate fewer *points redeemed*, in turn generating fewer *points accumulated*. Third, increased *point accumulation* and *redemption* results in lower values of *recency*, i.e., greater level of engagement, of the app use. In other words, the findings suggest that greater levels of purchase and redemption behaviors result in greater engagement with the mobile app, which in turn further increases accumulation. Since *point redemption* was found to favorably affect *recency* of customers' usage of the mobile app, one way to get customers engaged with mobile apps is to stimulate their perceived value extracted from their experiences with the brand.

Overall, our findings suggest that the emerging brand touch point of mobile apps provides a powerful tool for fostering customer engagement behaviors that influence marketplace outcomes such as purchase behavior. Specifically, based on our findings, engaging customers with mobile apps represents not only a viable revenue-generating opportunity but also a way to reduce advertising and promotion costs. Savings accrue because the firm does not buy advertising media and instead utilizes its branded app to control the medium, grow its audience, and cocreate and distribute content. Nor must the firm reduce its margins through promotional tactics. Hence, despite the upfront investment required for the development of the mobile app, our findings show that the introduction of branded mobile apps is an effective tactic that fosters the development of desirable CEBs and other ensuing behaviors, including *point accumulation* and *redemption*, thus contributing to the development of customer brand loyalty and lifetime value. As such, the introduction of branded mobile apps represents a "game changer" for marketing communications.

5. Discussion

5.1. Contributions and Implications

While many firms engage their customers with specific digital touch points and tools, including mobile, little is known about the effectiveness of such approaches. The main contribution of this study is that it responds to this observed challenge and provides initial insights into the nature and dynamics characterizing the interrelationship between customers' specific mobile-related CEBs and purchase behaviors over time, while controlling for *point accumulation.* While the finding that customers' *point accumulation* and *redemption* behaviors drive their subsequent use of the mobile app may seem intuitive, our study is the first to rigorously investigate and quantify this particular association, thus providing a methodological contribution in customer engagement research.

The second contribution is that we conceptualize, and empirically investigate, the novel term of customer disengagement. Specifically, while our findings indicated greater mobile-related CEBs, typically, to be beneficial to firms, a specific form of app-related customer disengagement, by contrast, was shown to have the potential to engender harmful effects for organizations and their marketing programs. To illustrate, while customers may feel engaged with a focal app in some respects (e.g., high perceived informational value of the app), individuals may simultaneously feel disengaged with the app in others (e.g., low user friendliness; app fails to provide the desired features, does not work on consumer's phone, or does not perform as expected, etc.). When an app's perceived disengaging features debilitate the user from achieving her goals, we expect the emergence of specific app-related customer disengagement, which ultimately leads to the customer's discontinued use of the app. Importantly, the study finds that customer disengagement has a sizeable long-term effect on purchase behaviors. This is an interesting and important result for the marketing community.

In addition to the stated scholarly contributions and implications, this research also offers a number of managerial implications. First, our investigation is important because if the association between specific mobile-related CEBs and ensuing purchase and consumption behaviors would not be significant, firms should cease, or at least reduce, investing their marketing resources in the development of mobile media designed to stimulate specific CEBs. Conversely, if a significant relationship between the stated dynamics does exist, CEBs not only provide a powerful tool for the strategic development of customer loyalty but can also reduce spending on traditional promotional forms, including advertising (assuming mobile media are relatively inexpensive to run subsequent to their initial development cost).

Drawing on dynamic models deploying actual customer engagement, purchase and consumption behaviors, we obtain evidence for the existence of a positive relationship between mobile-related CEBs and *point accumulation* and *redemption*, thus indicating a high strategic importance of firms' development and adoption of mobile media. Specifically, our findings provide evidence for a potential "game changing" nature regarding the specific ways for firms to engage their customers, thus directly addressing firms' core strategic decision making on their mobile strategies. We expect this research to provide important insights facilitating managers' decision making regarding the development of specific new media strategies and tactics. Specifically, our research may help practitioners answer questions such as "given the heightened number of brand touch points resulting from customers' adoption of focal branded mobile media, to what extent do their specific mobile-related CEBs affect ensuing purchase behaviors over time?" and "how does customer disengagement with mobile media affect ensuing purchase behaviors?"

Our findings, broadly, provide a cautionary note for managers undertaking traditional advertising investments into their brands, which not only typically represent a relatively costly form of marketing communications lacking personalization, but also are predominantly based on an assumed one-way transmission of the promotional message from the firm to (prospective) customers culminating, ultimately, in the attainment of particular market outcome metrics. However, in the emerging digital era, (prospective) customers and firms are increasingly intertwined in sets of dynamic, interactive two-way exchanges and the undertaking of specific CEBs and customer disengagement (Hoffman and Novak 2012). As such, the ways to optimally execute specific marketing communications is changing. Hence, by providing managers with new strategic insights regarding key dynamics characterizing particular CEBs and customer disengagement, our findings provide an impetus for practitioners to reassess the effectiveness of their specific strategic brand touch points in driving important organizational objectives, including customer acquisition and retention.

Further, we also find customers' *point accumulation* and *redemption* to affect their subsequent use of the branded mobile app, thus providing a further managerial contribution of our work. Based on this finding, we highlight the importance of firms' strategic adoption of integrated marketing communications (IMC) exhibiting synergy or consistency across organizational marketing communications, including those employed at point of purchase, as well as those related to the adoption of specific mobile media. Finally, we find that mobile-related customer disengagement exerts a negative effect on customers' future purchases with the firm. A major implication arising from this finding is that firms need to have a clear understanding of specific customers' (or customer segments') perceived engaging and disengaging attributes of specific mobile media prior to launching it, as well as undertaking careful monitoring regarding the performance of particular apps.

5.2. Limitations and Future Research

While the study makes important contributions, we acknowledge it is also subject to certain limitations. First, our measures of CEBs are limited to addressing customers' specific behavioral expressions of engagement, thus rendering customer manifestations of their specific cognitive and emotional engagement with our studied mobile app largely implicit. While the study of customers' engagement behaviors has provided highly valuable findings, future research may wish to more explicitly incorporate specific cognitive and emotional engagement facets in their research designs.

Second, while we investigate engagement and disengagement with our selected app, it is important to understand and isolate their drivers (Brodie et al. 2011, Malthouse and Calder 2011). To illustrate, the cognitive and emotional drivers of engagement may differ, conceptually, from those that drive disengagement. For example, while engagement may occur based on a high perceived entertainment value of a focal app, disengagement may result from customers' perceived difficulty in operating the app (as stated). Therefore, it is necessary to better understand the specific drivers of both to design more effective apps in the future.

Third, the focal firm of this study did not carry out any significant targeted marketing campaigns during the time period that we had data for. However, future studies could include variables pertaining to firms' targeted advertising and communications campaigns at different points in time and examine how these variables affect engagement with the mobile app.

Fourth, our investigation was limited to a single branded mobile app. More research is required that investigates mobile app-related behaviors in different contexts, including within or across particular product categories, brands, or different countries or cultures. Specifically, based on consumers' distinct cross-cultural preferences for interacting with particular promotional content (Nakata 2009), their mobile-related preferences are also expected to differ across cultures, although insights into this area remain nebulous in the literature to date. Although we provide an initial investigation into disengagement, future studies should extend and validate our present findings across other contexts.

Fifth, while we explored specific CEBs with a focal branded mobile app, insights regarding CEBs with other emerging digital touch points and tools, including social media, QR codes and specific wearable components, as well as the integration of focal mobile apps and other touch points, remain limited to date. Future research may, therefore, wish to investigate the nature and dynamics characterizing these developments.

Despite these limitations, this study helps us further our understanding of the relationship between customer (dis)engagement with emerging digital platforms such as mobile apps and behaviors that occur in the marketplace. The results from a longitudinal analysis of a unique data set unearth interesting and important insights on (dis)engagement and its relationship with other brand-related and purchase-related behaviors. This study is, therefore, an ideal stepping-stone for future work on (dis)engagement and its role in influencing the relationship between firms and their consumers.

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