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# Quantifying the Dynamic Sales Impact of Location-Based Mobile Promotion Technologies

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## Abstract

Location-based mobile promotion (LMP) is believed to trigger spontaneous and impulsive purchases. This field study quantifies the dynamic impact of LMP, using aggregated daily mobile movie promotions and purchase data from over 3 million real-world users of a large mobile service provider. The developed multivariate time-series models confirm that LMP has a significant contemporaneous impact on movie ticket sales. Surprisingly, Bayesian vector autoregressive results also suggest that LMP has significant immediate (next day) and cumulative impacts on sales over the next 9 days. The immediate and cumulative impacts account for 66% of the total effects. These findings suggest that without considering the dynamic effects, practitioners and researchers may substantially under-estimate the value of LMP.

**Keywords:** Mobile computing, mobile promotion, advertising, dynamic long-term impact, and location-based mobile promotion.

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## 1. Introduction

Recent developments in mobile communication technologies present businesses with a new marketing channel of mobile promotion. Mobile promotion proffers personalized communication opportunities for businesses to connect with targeted consumers (Scharl, Dickinger, and Murphy 2005). While mobile promotion takes many forms, e.g. banner ads on mobile websites (Goh, Chu, and Soh 2008), the vast majority of mobile promotions are delivered through short message service (SMS) due to cost considerations and cross-device compatibility (Mirbagheri and Hejazinia 2010; Wouters and Wetzels 2006). Statistics show that more than 84 percent of the U.S. population owns mobile devices (Skeldon 2011). The growth of mobile services has been remarkable in Africa, Asia, and Europe as well (Kim et al. 2010).

Two unique features of mobile technologies distinguish mobile promotion from traditional marketing tools. First, mobile technologies increase consumer accessibility. A mobile user can be reached anywhere and anytime. Given this accessibility, mobile devices have become one of the most employed and important personal devices in consumers' daily lives (Tsirulnik 2010). Consumers pay significantly more attention to messages delivered through mobile devices than traditional channels (billboard, TV, print, and Internet). Not surprisingly, businesses increasingly embrace mobile platforms as a novel marketing tool (Friedrich et al. 2009; Laszlo 2009).

Second, mobile technology is location-sensitive. Mobile technology not only allows businesses to expand their reach to consumers but also enables businesses to obtain information on consumers' whereabouts. With this information, businesses can deliver personalized marketing messages specific to a consumer's location and surrounding environment. As such, mobile promotion represents an excellent tool to implement *real-time marketing*, a term coined by Oliver, Rust, and Varki (1988) that entails meeting "customer needs at the time and place they want it" (Bruner and Kumar 2007). Not all mobile promotions capitalize on the location sensitivity feature of mobile technology. Many mobile promotions are broadcast in ways that do not differentiate recipients. This study focuses on a specific type of mobile promotion: location-based mobile promotion (LMP). LMP refers to promotions customized for recipients' geographic positions and received on mobile communication devices. LMP is delivered automatically to a consumer when he or she is within the vicinity of the promoting business.

While LMP has been recognized as a new tool to deliver real-time marketing, whether and to

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what degree it affects actual product sales has received limited attention in the literature. The few studies that appraise the sales effect of LMP, either focus on its immediate impact on sales (Butcher 2011; Ververidis and Polyzos 2002) or do not differentiate between immediate and dynamic effects on sales (Molitor et al. 2012). Such focus may be due to the fact that LMP intends to target customers at the right location in real time. However, this focus implicitly assumes that real-time marketing equates to impulsive, spontaneous purchases, and overlooks the fact that LMP may also trigger need-recognition and initiate planned purchase processes that could take time to materialize. Honing only on the instant effect of LMP is echoed in practice as well, where LMP is often considered a tool to draw spontaneous store visits and purchases (Carr 2012), and promotions delivered through LMP often expire on the same day (Finocchiaro 2010).

In this field study, we put this assumption to a rigorous empirical test with daily aggregated product sales data from over 3 million users of a large mobile service provider. We endeavor to quantify the dynamic impact of LMP with not only its contemporaneous (real-time) effects on product sales but also immediate (next day) and cumulative (delayed) effects on product sales over time. We developed the extended vector auto regressive (VARX) models and employed Bayesian vector autoregressive methods to rigorously gauge the dynamic effects of LMP.

We find that the impact of LMP is not limited to contemporaneous effects. It also has a significant immediate and long-term impact on product sales. Our analyses indicate that the effect of LMP may last for up to nine days. The immediate and long-term effects account for more than half of the total sales effect of LMP. Thus, LMP not only attracts spontaneous and impulsive purchases, but also creates product awareness for future purchase considerations.

The rest of the paper is organized as follows. We first review the mobile promotion and LMP literature. We then present a theoretical framework on how LMP influences consumers' impulsive buying and planned buying behavior. After that, we present a time-series analysis of the relationship between LMP and sales using daily aggregated data from over three million users of a major mobile service provider. We conclude with a discussion of the implications based on our findings.

## **2. Conceptual Background**

### **2.1. Characteristics of Mobile Technology and Real-Time Marketing**

Mobile technology has a number of unique characteristics compared with traditional information and communication technology. Similar to traditional information technologies, it can store

information, run applications, and connect and communicate with other information sources and people. The unique characteristics of mobile technology comprise its higher accessibility and location sensitivity (Nysveen et al. 2005; Ghose, Hann, and Goldfarb 2012).<sup>1</sup>

The combination of accessibility and location sensitivity makes location-based mobile promotion an ideal channel for real-time marketing. As mentioned previously, the goal of real-time promotions is to meet individualized consumer needs at the time and place they want it (Oliver, Rust, and Varki 1988). Importantly, real-time marketing recognizes that customer needs change constantly over time and place (McKenna 1999). Mobile technology allows businesses to obtain real-time location-specific information on consumers and deliver personalized marketing messages unique to a customer's location and time.

The research on LMP is nascent. Table 1 presents the related literature and clarifies how the current study differs from previous studies. First, while a few recent studies have considered the sales effect of LMP, they mostly examine immediate sales without considering the dynamic effect. Such an approach does not consider the possibility that LMP can motivate need recognition which leads to future purchases. Second, prior studies use lab experiment (Soroa-Koury and Yang 2010; Ghose, Ipeiritis, and Li 2012; Brunner and Kumar 2007; Zhang and Mao 2008) or clickstream data to assess the impact of LMP. Few of them validate the *actual* sales impact.

**Table 1. Extant Literature on Mobile Promotion**

<b>Reference</b>	<b>Dependent Variable</b>	<b>Data</b>	<b>Product and Technology</b>	<b>Dynamic, Cumulative Impact</b>
<i>This study</i>	<i>Actual Sales</i>	<i>Sales data</i>	<i>LMP</i>	<i>Yes</i>
Ghose, Hann, and Goldfarb 2012	Mobile browsing	Clickstream data	LMP	No
Molitor, Reichhart, and Spann 2012	Coupon clicking and redemption	Clickstream data	LMP	No

<sup>1</sup>Accessibility refers to the ease of access to the device and information. Accessibility stems from the small form factor and instant connectivity to information sources. Due to its small size, users can carry the device anytime and anywhere (Junglas and Watson 2006), referred to as mobility, portability, or ubiquity. The benefit of instant connectivity is the access to real-time information (Varnali and Toker 2010), particularly information not stored on the local device. Connectivity also implies easy information dissemination and sharing with other people (Nysveen et al. 2005). Location sensitivity refers to the ability of the device to identify its geographic location, a unique feature of mobile technology based on a global positioning system (Xu et al. 2009-10; Xu et al. 2011). It allows for personalization of commercial information that could be highly relevant, targeted, and valuable for users (Gidofalvi, Larsen, and Pedersen 2008).

Soroa-Koury and Yang 2010	Intention	Survey	Mobile promotion in general	No
Xu, Oh, and Teo 2009	Intention	Lab experiment	LMP	No
Brunner and Kumar 2007	Attitude towards LBA	Survey	General location ads	No
Xu, Teo, Tan, and Agarwal 2009	Intention	Lab experiment	LMP	No
Goh, Chu and Soh 2008	Response to mobile display ad	Clickstream data	Mobile display ads (varying location)	No

## 2.2. Impulsive Buying and Real-Time (Contemporaneous) Effects of LMP

Impulsive buying refers to consumers' experience of "a sudden and unplanned urge that is immediately gratifying or acting on an impulse without careful deliberation of the negative or long-term consequences" (Mishra and Mishra 2010; Sengupta and Zhou 2007). This definition suggests two key elements in the activation of impulsive buying: (1) the trigger of a sudden and unplanned consumption urge, and (2) the psychological state that allows the desire to instantly fulfill the consumption needs to outweigh various inhibiting factors. Since the goal of real-time marketing in general and LMP in particular is to deliver highly relevant marketing messages to consumers at the right time and right place, LMP influences both elements of impulsive buying.

First, the delivery of a highly relevant LMP could remind a consumer of his/her needs and trigger the "sudden and unplanned urge" to fulfill these needs. The more relevant an LMP is, the more likely it triggers this urge. Second, physical proximity, temporal proximity, and social comparison may each reduce the inhibiting factor and lead to impulsive buying (Hoch and Loewenstein 1991). The first two mechanisms directly relate to LMP. When a user is close to the consumption object both physically and temporally, the denial of consumption would cause a sense of psychological deprivation (Hoch and Loewenstein 1991). This deprivation increases desire and impatience, and consequently stimulates purchase behavior (Ainslie 1975; Mischel 1974; Loewenstein 1988). Moreover, Luo (2005) finds that social influence can significantly increase the urge to purchase. Since mobile devices are heavily used for online social interactions, LMP could further strengthen this impulsive urge to purchase.

## 2.3. Planned Buying and Delayed (Immediate, Cumulative) Effects of LMP

Theoretically, LMP can influence not only impulsive buying but also consumers' planned buying behavior. The consumer purchase process involves five stages: problem recognition, information

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search, evaluation of product options, purchase decision, and post-purchase support (Engel and Kollat 1978; Kotler 2002). LMP may have a significant effect on each of these stages. At the problem recognition stage, LMP could remind a consumer of the need for consumption and trigger the planned buying behavior process. In the information search stage, LMP allows promotion messages to be stored in a mobile phone, which facilitates users' access to and recall of promotion information. In the evaluation and decision-making stage, LMP enables consumers to easily share information with and solicit opinions from friends and family members (Clemons, Gao, and Hitt 2010; Zhang, Hui, and Hou 2011). It also allows scheduling and instant coordination with relevant others. In the purchase stage, LMP saves users time and travel costs by providing instant online purchases with special discounts. In the post-purchase stage, LMP provides easy access to the scheduled event through directions and location searches. It also provides a way to interact with customers to help diminish cognitive dissonance (Kotler 2002). These reasons suggest that LMP could facilitate consumer decision-making in planned buying behavior, thereby creating immediate and cumulative sales effects.

#### **2.4. Substitute and Complementary Relationships between LMP and Other Mobile Promotions**

Managers often adopt multiple forms of mobile promotions to reach consumers. This raises an important question on the relationship between different forms of mobile promotions. Prior studies on firms' marketing efforts suggest that the relationship among multiple marketing efforts could be either complementary or substitute. For example, Godes et al. (2005) ask whether firms' management of social interactions is a complement or a substitute to firms' traditional advertising effort. Chen and Xie (2005) show that online consumer reviews can have substitutive and/or complementary effects on firms' advertising effort. Shankar and colleagues have suggested the critical importance of mobile-based promotions in multi-channel settings. They point out possible complementary effects of using LMP and other traditional promotional practices (Shankar and Balasubramanian 2009; Shankar et al. 2010) because retailers can promote relevant information (such as the store's location, price, and coupon) to consumers near their stores via mobile phones. Recently, Ghose, Goldfarb, and Han (2013, p. 2) reported significant user-behavior differences between mobiles and personal computers in terms of search costs and local activities. Thus, the degree to which LMP complements or substitutes other promotional forms (e.g. non-location based mobile promotions or mobile-linked instant message-based promotions as explained in Section 3 below) in their impact on sales purchases remains an empirical question.

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In this study, we analyze the inter-dependent relationship between different forms of mobile promotions. It is critical for managers to understand how different forms of mobile promotions depend on each other and whether using one form of mobile promotions mirrors the underlying relationships in the inter-dependent real-world. For example, managers may wish to know whether they should use more or less non-location based mobile promotions after heavily relying on LMP. Also, it is useful for managers to know whether the inter-dependent relationship between mobile promotions and mobile-linked instant message-based promotions is positive, negative, or non-significant, after accounting for the sales impact of each type of mobile promotion. Further, we assess managerial decisions in these contexts by treating each day's mobile promotion volume as endogenous and analyze the complete, dynamic effect between LMP, other forms of mobile promotions, and sales purchases in a fully endogenous modeling system of equations (Dekimpe and Hanssen 1999; Luo et al. 2013).

### **3. Data of the Field Study**

#### **3.1. Research Context**

Our dataset is obtained from one of the world's largest mobile service providers in China through a field study. The company (which wishes to stay anonymous) launched a mobile promotion business in cooperation with major movie theatre chains to deliver text movie promotions to customers' mobile devices and mobile-linked IM applications. The mobile promotion business is unique in that, to use the discount code featured in the promotion message, customers must make the purchase through a designated mobile application. Payment will be automatically posted to the customer's mobile service account or deducted from the customer's deposit if the customer has a prepaid account with the service provider. This feature allows us to directly measure sales induced by mobile promotion.

The company provides LMP via short text-messages (SMSs). The message is the same for all customers and provides a discount code for all the movies showing in the designated movie theatre. LMP is sent to a randomly selected set of users whose mobile device is within the 200-meter range of the microcell that covers a given movie theatre.<sup>2</sup> The user receives the location-based mobile promotion via SMS. The LMP message contains information on movies that will be shown in the

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<sup>2</sup> A microcell is a cell in a mobile phone network served by a low power cellular base station (tower), covering a limited area such as a mall. The typical range of a microcell has a radius of fewer than 200 meters.

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theater and a link to the mobile app through which consumers can purchase movie tickets. The customer base of the movie mobile promotion business is over 3,200,000 users.

Among the 3,200,000 users, about 200,000 belong to a movie fan club initiated by the mobile service provider. We did not include the movie fan club members in our data as we recognize that movie fan club members would be significantly more responsive to location-based mobile movie promotions because they are more interested in watching movies in general. This movie-fan-club bias, if not controlled for, would confound the results regarding the sales impact of location-based mobile promotions. To remove this bias, our strategy is to use responses only from the non-movie-fan-club mobile users in data analyses because they are less likely to purposefully go to the movie theater, a priori, compared with the movie-fan-club members. Thus, to more clearly identify the dynamic impact of location-based mobile promotions, we track the responses of the 3 million non-movie-fan-club users. We recognize that a small percentage of non-movie-fan-club users may have already planned to attend a movie, in which case mobile promotions provided them with discounts but not necessarily increased sales for the movie theatre. While our data is not able to quantify the magnitude of this effect, we notice that this effect exists only in the contemporary term. Its implication is that our estimation of the contemporary effect could be higher than the actual sales impact, while underestimating the actual immediate and dynamic effect of mobile promotion. Put it differently, the immediate and dynamic effects identified in our analysis is likely to be the lower bound of the actual effects.

Besides LMP, the company has two other types of mobile promotion. First, Behavior-based Mobile Promotion (BMP) enables the mobile service provider to use behavior-based targeting in sending out SMS promotions. The targeting algorithm identifies and randomly selects users who had responded to previous mobile movie promotions and purchased movie tickets via the mobile application in the past three months. Second, Mobile-linked IM-based Promotion (MLP) is available since the mobile service provider is also a major fixed-line internet service provider. It offers a unique Windows-based IM client that links to a user's mobile device. When a customer is in front of the computer, a SMS sent to a customer's mobile device is displayed on the IM client. The service provider also displays additional SMS promotion through the IM client. The IM extends the company's mobile promotion business to access customers both through mobile devices and home computers. Its IM promotion works the same way as its mobile promotion. When a user starts the



instant message application on his computer, the service provider detects the user's presence and can deliver IM promotions through a web-based pop-up window. The message contents and designs across LMP, BMP, and MLP are exactly the same on any given day. For all three types of promotions, if a user decided to make a purchase, they use the same application with the same interface. The three types of promotions are managed independently of each other except that, to avoid over-marketing, the company controls the volume of SMS promotion messages. One customer would receive at most one SMS promotion message per day across the three channels.

The mobile company provided daily promotion and purchase data aggregated from over 3 million users during the period of August 1, 2009 and July 31, 2010. To protect customer privacy, the company only provides us with daily aggregated data on the volume of LMP, BMP, MLP, and total daily sales recorded by the mobile purchase application.

Given that the total daily sales data cover movie sales through all three promotions, we include all three types of mobile promotions in our analysis. The inclusion of all three types of mobile promotions also allows us to identify cross-promotion effects and interaction effects, which capture the extent to which mobile promotions complement or cannibalize each other in generating sales.

Table 2 provides the descriptive statistics of the number of mobile promotions delivered per day for each mobile promotion type. On average, the mobile service provider delivers 187,518 location-based promotions, 38,733 behavior-based promotions, and 925,312 mobile-device linked IM promotions per day. Given the size of the user base (3 million), these numbers suggest that on a given day, a mobile customer has a 6% chance of receiving an LMP, a 1.3% chance of receiving a BMP, and a 30% chance of receiving an MLP. Table 2 also indicates that, on average, the service provider sells about 2,432 movies tickets per day, which translates into a sell-through rate of 0.2%.

**Table 2. Descriptive Analysis of Mobile Promotions**

	Mean	STD	Min	Max
Sales	1,448	201	1,031	1,921
LMP	123,502	9,486	107,162	150,384
BMP	37,070	4,002	27,639	46,927
MLP	433,0148	86,762	277,992	570,418

Note: LMP = location-based Mobile Promotions, BMP = Behavior-based Mobile Promotion, and MLP = Mobile-linked IM-based Promotion

#### 4. Model and Estimation

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In this section, we extend existing time-series models to comprehensively capture the dynamic relationships between LMP and sales.

#### 4.1. Empirical Model

Vector auto regressive (VARX) models (Adomavicius, Bockstedt, and Gupta 2012; Chang and Gurbaxani 2012; Luo 2009) are commonly used to capture the time-series relationship with possible endogenous and dynamic effects. The standard VARX model can account for immediate and cumulative effects, but not contemporaneous effects (Dekimpe and Hanssens 1999). However, the real-time contemporaneous impact is important in our context because location-based mobile promotions are expected to generate a substantial amount of sales in real-time (outcomes of targeting the right customers at the right location in real time with location-based mobile technologies). Therefore, we extend VARX model with a dynamic structural equation model (DSEM), which accounts for the full interactions and dynamics among the endogenous variables (Cziraky 2004).

DSEM offers all modeling advantages of standard VARX and estimates dynamic impacts more comprehensively than VARX. First, DSEM decomposes dynamic effects into contemporaneous, short-term immediate, and cumulative effects, when quantifying the impact of LMP and other mobile promotions on movie sales (direct effects). These effects allow us to fully capture the dynamic nature of LMP and control for the influence of other ad channels on sales.<sup>3</sup>

Second, the model considers the feedback effects from sales to subsequent deliveries of LMP (indirect feedback effects) in a full dynamic loop, which accommodates the reality that managers often adjust future ad delivery decisions based on past sales performance.

Third, it models the autoregressive carryover effects of all variables (self-carryover effects). In particular, historical mobile movie sales could have carry-over effects on future mobile movie sales. Similarly, historical mobile promotions could influence the choice of future mobile promotions.

Fourth, it allows for different types of promotions to jointly influence on sales (interaction effect) in both the short term and the long term. This feature allows us to assess the degree to which LMP complements or substitutes other promotional forms (non-location based mobile promotions or mobile-linked instant message-based promotions) in their impact on sales purchases. It also analyzes the cross-channel relationship (or cross-channel effect) between different forms of mobile promotions.

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<sup>3</sup> In strict sense, all VARX models are in reduced form, not structural models. Our application of DSEM rather than basic VARX here is to estimate the contemporaneous effects, in addition to the dynamic effects (Dekimpe and Hanssens 1999). See equation one for the right-hand-side matrix of contemporaneous effect specifications.

That is, we can test whether the inter-dependent relationship is positive, negative, or non-significant in a fully endogenous modeling system of equations.

Specifically, we construct the following DSEM for our analysis:

$$\begin{bmatrix} \Delta Sale_t \\ \Delta LMP_t \\ \Delta BMP_t \\ \Delta MLP_t \end{bmatrix} = \begin{bmatrix} \delta_{10} \\ \delta_{20} \\ \delta_{30} \\ \delta_{40} \end{bmatrix} + \begin{bmatrix} \delta_{11}t \\ \delta_{21}t \\ \delta_{31}t \\ \delta_{41}t \end{bmatrix} + \begin{bmatrix} 0 & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ 0 & 0 & \gamma_{23} & \gamma_{24} \\ 0 & \gamma_{32} & 0 & \gamma_{34} \\ 0 & \gamma_{42} & \gamma_{43} & 0 \end{bmatrix} \begin{bmatrix} \Delta Sale_t \\ \Delta LMP_t \\ \Delta BMP_t \\ \Delta MLP_t \end{bmatrix} + \sum_{j=1}^p \begin{bmatrix} \varphi_{11}^j & \varphi_{12}^j & \varphi_{13}^j & \varphi_{14}^j \\ \varphi_{21}^j & \varphi_{22}^j & \varphi_{23}^j & \varphi_{24}^j \\ \varphi_{31}^j & \varphi_{32}^j & \varphi_{33}^j & \varphi_{34}^j \\ \varphi_{41}^j & \varphi_{42}^j & \varphi_{43}^j & \varphi_{44}^j \end{bmatrix} \begin{bmatrix} \Delta Sale_{t-j} \\ \Delta LMP_{t-j} \\ \Delta BMP_{t-j} \\ \Delta MLP_{t-j} \end{bmatrix} + \sum_{j=1}^q \begin{bmatrix} \theta_{11}^j & \theta_{12}^j & \theta_{13}^j \\ \theta_{21}^j & \theta_{22}^j & \theta_{23}^j \\ \theta_{31}^j & \theta_{32}^j & \theta_{33}^j \\ \theta_{41}^j & \theta_{42}^j & \theta_{43}^j \end{bmatrix} \begin{bmatrix} Weekend_{t-j} \\ Holiday_{t-j} \\ Blockbuster_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} \quad (1)$$

In this model,  $\Delta Sales$  represents changes in movie tickets purchased via mobile phones,  $\Delta LMP$  represents changes in the number of location-based mobile promotions,  $\Delta BMP$  represents changes in the number of behavior-based mobile promotions, and  $\Delta MLP$  represents changes in the number of pop-up window IM promotions. All these variables are endogenous variables in the DSEM modeling system of equations. Moreover,  $p$  and  $q$  are the lag length, and  $\varepsilon$  is a random disturbance term.  $\delta_{10}$ ,  $\delta_{20}$ ,  $\delta_{30}$ , and  $\delta_{40}$  are intercepts;  $\delta_{11}$ ,  $\delta_{21}$ ,  $\delta_{31}$ , and  $\delta_{41}$  capture latent time-trend influences.

The key parameters of interest in the DSEM are as follows:

- 1) **Direct dynamic effects of LMP on mobile movie sales.** There are three kinds of direct dynamic effects. First, the coefficients  $\gamma_{12}$ ,  $\gamma_{13}$ , and  $\gamma_{14}$  gauge the contemporaneous (same-day) effect of LMP and other mobile promotions on mobile sales. Second, the coefficients  $\varphi_{12}$ ,  $\varphi_{13}$ , and  $\varphi_{14}$  capture the immediate (next-day) effects of LMP and other mobile promotions on mobile sales. Third, the sum of these coefficients  $\varphi_{12}$ ,  $\varphi_{13}$ , and  $\varphi_{14}$  at future days ( $t+1$ ,  $t+2$ ,  $t+3$ , ..., and  $t+j$ ) measures the cumulative (future days) effects of LMP and other mobile promotion on mobile movie sales prior to equilibrium.
- 2) **Indirect feedback effects of historical sales on future LMP.** The coefficients  $\varphi_{21}$ ,  $\varphi_{31}$ , and  $\varphi_{41}$  capture feedback impacts of mobile sales on future volume of LMP and other mobile promotions. These indirect effects are important because the daily decisions of mobile

promotions are often based on prior mobile sales. If such feedback effects are ignored, the full endogenous circle is only modeled partially, and results could be biased.

- 3) **Self-carryover effects of LMP and other endogenous variables.** Coefficients  $\varphi_{11}$ ,  $\varphi_{22}$ ,  $\varphi_{33}$ , and  $\varphi_{44}$  measure the autoregressive carryover impact. That is, historical sales can affect future sales, and past promotion volumes can have carry-over effects on promotion volumes in the future. If not modeled, the error terms would be autoregressive, leading to potential biases.
- 4) **Cross-channel effects among LMP and other mobile promotion channels.** Coefficients  $\gamma_{23}$ ,  $\gamma_{24}$ ,  $\gamma_{32}$ ,  $\gamma_{34}$ ,  $\gamma_{42}$ ,  $\gamma_{43}$ ,  $\varphi_{23}$ ,  $\varphi_{24}$ ,  $\varphi_{32}$ ,  $\varphi_{34}$ ,  $\varphi_{42}$ , and  $\varphi_{43}$  capture the mutual influence between different mobile promotion channels. The volume of LMP in the current period may have positive or negative effects on the future volume of other promotion channels in both short and long terms, and vice versa. If the cross-channel coefficients are positive (negative), it suggests that the service provider believes there are synergistic (cannibalistic) effects between different promotion channels, and believes that different promotion channels may complement (compete) each other in their impact on movie sales over time.

In addition, we control for the impact of exogenous events such as weekend, holiday, time trends, and blockbuster movie effects. Also, the model has accounted for time trend and seasonality effects. Additional tests (results available upon request) with day of week as controls yield consistent results reported below. The description of these control variables is reported in Table 3. Weekend control variables included Saturday and Sunday as well as Friday because consumers usually watch movies on Friday nights. Blockbuster was measured by the number of movies with a box office performance of over 100 million RMB (blockbuster movie) in a given week.<sup>4</sup>  $\theta_{11, \dots}$  and  $\theta_{43}$  capture the effects of these exogenous factors.

**Table 3. Descriptive Analysis of Exogenous Control Variables**

	Mean	STD	Min	Max
<b>Weekend</b>	0.40822	0.49218	0	1
<b>Holiday</b>	0.06301	0.24332	0	1
<b>Blockbuster</b>	2.43562	1.05317	1	5

#### 4.2. Test of Stationarity and Model Selection

Similar to VARX, stationarity is an important precondition to implement DSEM and calculate dynamic sales responses. The most common stationarity testing method is the augmented

<sup>4</sup> We operationalize the blockbuster control as a count of total number of blockbuster movies in a given week because our mobile promotions provide discounts to all movies showing in the movie theatre in a given week.

Dickey-Fuller (ADF test). We implemented ADF tests and found that differences in all variables were stationary without unit roots ( $p < 0.01$ ). Thus, the null hypothesis that the differences in all endogenous variables are stationary cannot be rejected, as shown in Table 4. As such, these test results suggest that the differences do not cointegrate in equilibrium (Hamilton 1994). We thus estimate the DSEM model with differences in these endogenous variables (Luo 2009). Another advantage of using differences rather than levels is to control for non-time-variant factors such as observable demographics and unobservable attitudes and tastes, thus allowing us to more precisely model the sales impact of LMP. In other words, stationarity test results suggest that using changes (not levels) in the sales variable is appropriate.

**Table 4. Stationarity Tests after First Differencing**

	Tau	p-value
$\Delta$ Sales	-12.68	<0.001
$\Delta$ LMP	-13.38	<0.001
$\Delta$ BMP	-12.23	<0.001
$\Delta$ MLP	-14.10	<0.001

Note: all stationarity tests are of zero mean type. All variables differences are stationary without unit roots.

## 5. Results

### 5.1. Results on the Dynamic Impact of Location-based Mobile Promotions

Table 5 shows the contemporaneous (same day), immediate (next day), and cumulative (future days until equilibrium) effects of location-based mobile promotions on movie sales. Our key research interest is on the immediate and cumulative impact of location-based mobile promotions (in bold-face), after accounting for the sales effects of other channels. The analysis results show that location-based mobile promotions have significant contemporaneous, immediate, and cumulative effects on mobile movie sales for non-movie-fan-club users (all  $p < .01$ ).<sup>5</sup>

Specifically, for non-movie-fan-club mobile users, on average, each location-based mobile promotion increases the same-day movie sales by 0.005 (translated into 1,500 movie sales purchases via the mobile app), and next-day movie sales by 0.003 (or 900 movie sales purchases via the mobile app). The sales effect lasts for nine days after receiving the promotions with a cumulative sales

<sup>5</sup> Consistent with the VARX literature, we report the results on the basis of impulse function estimations (Dekimpe and Hanssens 1999; Luo 2009). This is because impulse function results precisely track the sales responses due to one unit ‘shock’ in LMP after accounting for the endogenous biases (cross-channel, auto-regression, and feedback effects).

increase of 0.007 (or 2,100 movie sales purchases via the mobile). Also, the contemporaneous effect accounts for 34% of the total effects for location-based mobile promotion, while the dynamic effect (immediate and cumulative) accounts for 66% (= 19% + 47%) of the total effects for location-based mobile promotion. Thus, without explicitly quantifying the dynamic effects, managers would only capture one-third of the total effects and significantly under-estimate the power of location-based mobile promotions among non-movie fan users.

**Table 5. Dynamic Impact of Location-based Mobile Promotions on Movie Sales**

Promotion Channels	Contemporaneous Sales Effects	Immediate Sales Effects	Cumulative Sales Effects	Total Sales Effects	Decay Time (Days)
Location-based Mobile Promotions (LMP)	0.00475*** (0.00195) 34%	0.00265*** (0.00115) 19%	0.00651** (0.00328) 47%	0.01391	9
Behavioral-based Mobile Promotions (BMP)	0.01023*** (0.00363) 28%	0.00856*** (0.00250) 23%	0.01831** (0.01046) 49%	0.03710	3
Mobile-linked IM-based Promotions (MLP)	0.00017*** (0.00007) 35%	0.00014** (0.00007) 35%	0.00014** (0.00007) 29%	0.00048	1

Note: \*\*\*represents  $p < 0.001$ , \*\* represents  $p < 0.05$ , \* represents  $p < 0.1$ . Contemporaneous effects represent the impact at  $t$  period, immediate effects represent the impact at  $t+1$  period, and cumulative effects represent the impact from  $t+1$  period to  $t+j$  period. Total Effects = contemporaneous + immediate + cumulative effects.

## 5.2. Additional Bayesian Results for the Dynamic Impact of LMP on Sales

To more rigorously quantify the dynamic sales impact of location-based mobile promotions, we also employed the Bayesian Vector Auto Regression (BVAR) methods (Chakravarty and Grewal 2011; Pfaff 2008; Cowpertwait and Metcalfe 2009). BVAR offers three advantages in terms of accounting for measurement error, the omitted variable bias, and inaccurate standard errors for small samples, thus providing a more robust technique to gauge the dynamic sales impact of location-based mobile promotions. As such, we adopted this Bayesian approach and employed the Markov Chain Monte Carlo (MCMC) methods with a Gibbs sampling algorithm and 5,000 draws for burn-in.

As reported in Table 6, the Bayesian results are consistent with those reported in Table 5. Again, we support that location-based mobile promotions have significant contemporaneous, immediate, and cumulative effects on mobile movie sales among non-movie-fan-club users.

**Table 6. Bayesian Results for the Dynamic Impact of LBA on Mobile Sales**

Promotion Channels	Contemporaneous Sales Effects	Immediate Sales Effects	Cumulative Sales Effects	Total Sales Effects	Decay Time (Days)
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Location-based	0.00493***	0.00271***	0.00639**	0.01403	9
Mobile Promotions	(0.00226)	(0.00128)	(0.00322)		
	35%	19%	46%		

Note: \*\*\*represents  $p < 0.001$ , \*\* represents  $p < 0.05$ , \* represents  $p < 0.1$ . Results are the average coefficients estimated on the basis of MCMC methods with a Gibbs sampling algorithm and 5,000 draws for burn-in.

### 5.3. Results on Cross-Channel Effects between Location-based Mobile Promotions and Other

#### Mobile Promotions

It is also useful to examine whether different mobile promotions influence each other (cross-channel effects in DSEM). Table 7 shows no significant cross-channel relationship between Mobile-linked MLP and mobile-based channels of LMP and BMP ( $p > 0.10$ ). This suggests that the mobile service provider tends to use mobile and PC channels independently, i.e. the high or low usage of mobile channel promotions does not affect the usage of IM-based promotions targeting home computers. This result indicates that mobile promotion and mobile-linked IM-based promotion are viewed by the management as different platform technologies, perhaps due to the inherent differences between mobile- and computer-based user behaviors as reported in Ghose, Goldfarb, and Han (2013).

However, the two mobile-based promotional channels had a significant negative effect on each other. For non-movie-fan-club customers, the contemporaneous effect coefficients for the influence of *location*-based mobile promotions (LMP) on behavioral-based mobile promotions (BMP) and for the influence of *BMP* on LMP were both negative (-0.058 and -0.167, respectively,  $p < 0.001$ ), and the cumulative effect coefficients were also both negative (-0.0234 and -0.136, respectively,  $p < 0.001$ ). Also, the magnitude of the influence of BMP on LMP is more than three times larger than the reversed direction, suggesting an asymmetry in influence. Thus, these negative relationships suggest some *within-mobile* channel effects. That is, the mobile service provider tends to use the two mobile-based channels alternatively. If more location-based mobile promotions are sent to users, the service provider tends to use less behavioral-based mobile promotions, and vice versa.

**Table 7. Cross-Channel Effects among Location-based Mobile Promotion, Behavioral-based Mobile Promotion, and Mobile-linked IM-based Promotion**

Cross-Channel Effects	Contemporaneous Effects	Dynamic Effects	Total Effects
Mobile-linked IM-based Promotion → Behavioral-based Mobile Promotion	0.0017 (0.0014)	0.0001 (0.0009)	Not Significant
Behavioral-based Mobile Promotion → Mobile-linked IM-based Promotion	-3.3337 (2.6934)	-2.6299 (1.5856)	Not Significant

Mobile-linked IM-based Promotion →	-0.0116	-0.0101	Not Significant
Location-based Mobile Promotion	(0.0093)	(0.00769)	
Location-based Mobile Promotion →	-0.3228	-0.4185	Not Significant
Mobile-linked IM-based Promotion	(0.3573)	(0.2841)	
<b>Location-based Mobile Promotion→</b>	<b>-0.0583***</b>	<b>-0.0234***</b>	<b>-0.0813</b>
<b>Behavioral-based Mobile Promotion</b>	<b>(0.0197)</b>	<b>(0.0110)</b>	
<b>Behavioral-based Mobile Promotion →</b>	<b>-0.1672***</b>	<b>-0.1363***</b>	<b>-0.2981</b>
<b>Location-based Mobile Promotion</b>	<b>(0.0556)</b>	<b>(0.0285)</b>	

Note: \*\*\*represents  $p < 0.001$ , \*\* represents  $p < 0.05$ , \* represents  $p < 0.1$ .

The analysis above shows how managers handle different types of mobile promotions jointly. To inform managers whether these decisions are optimal, it is necessary to quantify the *interactive* effects of different promotional channels on sales purchases. Specifically, we test whether location-based and behavior-based as well as mobile-linked IM-based mobile promotions have substitute or complementary relationships in their influence on movie sales.

A unique aspect of our data is that the mobile service provider self-imposes a constraint that at most one movie promotion message will be sent to each mobile user on a given day. As such, users do not receive multiple mobile promotions simultaneously. Our analysis at the daily level shows no interaction effect between different types of mobile promotions, which confirms the company policy. However, while consumers do not receive different types of mobile promotions on a given day, they may receive different types of mobile promotions on subsequent days. This insight allows us to measure the interaction effects between multiple types of mobile promotions by aggregating data over a short time window. Based on the optimal statistics results of Bayesian Information Criterion (BIC), we choose 3 days as our time window. Following Luo et al. (2013), we build the following extended-VAR models.

$$\begin{matrix} \circ \end{matrix} \begin{bmatrix} \Delta Sale_t \\ \Delta LBP_t \\ \Delta BBP_t \\ \Delta PWP_t \\ \Delta LBP_t \times \Delta BBP_t \\ \Delta LBP_t \times \Delta PWP_t \\ \Delta BBP_t \times \Delta PWP_t \end{bmatrix} = \begin{bmatrix} \delta_{10} \\ \delta_{20} \\ \delta_{30} \\ \delta_{40} \\ \delta_{50} \\ \delta_{60} \\ \delta_{70} \end{bmatrix} + \begin{bmatrix} \delta_{11} \\ \delta_{21} \\ \delta_{31} \\ \delta_{41} \\ \delta_{51} \\ \delta_{61} \\ \delta_{71} \end{bmatrix} + \begin{bmatrix} 0 & \gamma_{12} & \gamma_{13} & \gamma_{14} & \gamma_{15} & \gamma_{16} & \gamma_{17} \\ 0 & 0 & \gamma_{23} & \gamma_{24} & 0 & 0 & \gamma_{27} \\ 0 & \gamma_{32} & 0 & \gamma_{34} & 0 & \gamma_{36} & 0 \\ 0 & \gamma_{42} & \gamma_{43} & 0 & \gamma_{45} & 0 & 0 \\ 0 & 0 & 0 & \gamma_{54} & 0 & 0 & 0 \\ 0 & 0 & \gamma_{63} & 0 & 0 & 0 & 0 \\ 0 & \gamma_{72} & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta Sale_t \\ \Delta LBP_t \\ \Delta BBP_t \\ \Delta PWP_t \\ \Delta LBP_t \times \Delta BBP_t \\ \Delta LBP_t \times \Delta PWP_t \\ \Delta BBP_t \times \Delta PWP_t \end{bmatrix} + \sum_{j=1}^p \begin{bmatrix} \varphi_{11}^j & \varphi_{12}^j & \varphi_{13}^j & \varphi_{14}^j & \varphi_{15}^j & \varphi_{16}^j & \varphi_{17}^j \\ \varphi_{21}^j & \varphi_{22}^j & \varphi_{23}^j & \varphi_{24}^j & \varphi_{25}^j & \varphi_{26}^j & \varphi_{27}^j \\ \varphi_{31}^j & \varphi_{32}^j & \varphi_{33}^j & \varphi_{34}^j & \varphi_{35}^j & \varphi_{36}^j & \varphi_{37}^j \\ \varphi_{41}^j & \varphi_{42}^j & \varphi_{43}^j & \varphi_{44}^j & \varphi_{45}^j & \varphi_{46}^j & \varphi_{47}^j \\ \varphi_{51}^j & \varphi_{52}^j & \varphi_{53}^j & \varphi_{54}^j & \varphi_{55}^j & \varphi_{56}^j & \varphi_{57}^j \\ \varphi_{61}^j & \varphi_{62}^j & \varphi_{63}^j & \varphi_{64}^j & \varphi_{65}^j & \varphi_{66}^j & \varphi_{67}^j \\ \varphi_{71}^j & \varphi_{72}^j & \varphi_{73}^j & \varphi_{74}^j & \varphi_{75}^j & \varphi_{76}^j & \varphi_{77}^j \end{bmatrix} \begin{bmatrix} \Delta Sale_{t-j} \\ \Delta LBP_{t-j} \\ \Delta BBP_{t-j} \\ \Delta PWP_{t-j} \\ \Delta LBP_{t-j} \times \Delta BBP_{t-j} \\ \Delta LBP_{t-j} \times \Delta PWP_{t-j} \\ \Delta BBP_{t-j} \times \Delta PWP_{t-j} \end{bmatrix} + \sum_{j=1}^q \begin{bmatrix} \theta_{11}^j & \theta_{12}^j & \theta_{13}^j \\ \theta_{21}^j & \theta_{22}^j & \theta_{23}^j \\ \theta_{31}^j & \theta_{32}^j & \theta_{33}^j \\ \theta_{41}^j & \theta_{42}^j & \theta_{43}^j \\ \theta_{51}^j & \theta_{52}^j & \theta_{53}^j \\ \theta_{61}^j & \theta_{62}^j & \theta_{63}^j \\ \theta_{71}^j & \theta_{72}^j & \theta_{73}^j \end{bmatrix} \begin{bmatrix} Weekend_{t-j} \\ Holiday_{t-j} \\ Blockbuster_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix}$$

The results are reported in Table 8. The results suggest that the two mobile-based promotion channels (LMP and BMP) have significant and negative effects in both contemporaneous and dynamic sales effects ( $p < 0.05$ ). These results suggest the two mobile promotions are substitutes for each other, supporting the managers' decisions to use them alternatively as highlighted in Table 7.

The analysis also shows that there are only marginally significant negative interaction effects



between location-based mobile promotion and mobile-linked IM-based promotion in terms of the contemporaneous sales effect ( $p < 0.10$ ). The dynamic sales effect of this interaction, however, is significant and negative ( $p < 0.01$ ). This finding of substitute relationship suggests that the managers should be aware of the dynamic nature of substitute or complementary relationship between different types of mobile promotions. The lack of substitute relationship in the contemporary term does not necessarily indicate a lack of substitute relationship in the immediate or dynamic terms and in such cases, the two promotion channels shall not be considered as independent of one another (Shankar et al. 2010).

**Table 8. Interactive Effects of Location-based Mobile Promotion, Behavioral-based Mobile Promotion, and Mobile-linked IM-based Promotion on Movie Sales**

Promotion Channels	Contemporaneous Sales Effects	Immediate Sales Effects	Cumulative Sales Effects	Total Sales Effects	Decay Time (Days)
Location-based Mobile Promotion	<b>0.00459***</b> (0.00193)	<b>0.00267***</b> (0.00113)	<b>0.00649**</b> (0.00323)	0.01375	9
Behavioral-based Mobile Promotion	<b>0.01020***</b> (0.00361)	<b>0.00856***</b> (0.00190)	<b>0.01845**</b> (0.00912)	0.03721	2
Mobile-linked IM-based Promotion	<b>0.00016***</b> (0.00006)	<b>0.00015**</b> (0.00007)	<b>0.00015**</b> (0.00006)	0.00046	1
Location-based Mobile x Mobile-linked IM-based Promotion	-0.00177* (0.00098)	<b>-0.00135**</b> (0.000635)	<b>-0.00318**</b> (0.00154)	-0.00631	1
Location-based Mobile Promotion x Behavioral-based Mobile Promotion	<b>-0.00305***</b> (0.00056)	<b>-0.00225**</b> (0.000586)	<b>-0.00818**</b> (0.00352)	-0.01348	3
Behavior-based Mobile Promotion x Mobile-linked IM-based Promotion	0.00005 (0.00006)	0.00082 (0.00741)	0.00021 (0.00056)	Not Significant	0
Location-based Mobile Promotion x Mobile-linked IM-based Promotion x Behavioral-based Mobile Promotion	0.00000 (0.00001)	0.00005 (0.00130)	0.00006 (0.00025)	Not Significant	0

Note: \*\*\*represents  $p < 0.001$ , \*\* represents  $p < 0.05$ , \* represents  $p < 0.1$ . Contemporaneous effects represent the impact at t period, immediate effects represent the impact at t+1 period, and cumulative effects represent the impact from t+1 period to t+j period. Total Effects = contemporaneous + immediate + cumulative effects.

## 6. Discussion and Implications

### 6.1 Discussion and Limitations

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The ubiquity and location-sensitivity of mobile technologies offer a superlative platform for real-time promotions. However, many businesses equate real-time marketing solely with impulsive purchases, and such perceptions could distort the potent of mobile promotions.

In this research, we conduct rigorous analyses of the sales impact of LMP. Our analyses with over 3 million real-world mobile users reveal two key findings. First, the impact of LMP on consumer purchase decisions is dynamic. LBA not only influences product sales in the contemporaneous period (Butcher 2011; Ververidis and Polyzos 2002), but also induces future sales in the immediate and longer terms. To the best of our knowledge, this research is the first in IS and marketing to quantify the dynamic effects of LMP with a rare, large sample of actual mobile users.

Second, we found different forms of mobile promotion have different dynamic effects. Surprisingly, location-based mobile promotion has the longest effect on product sales (9 days), compared with behavior-based mobile promotion and mobile-linked IM-based promotion. These findings highlight the importance of understanding the dynamic effect of each mobile promotion form in assessing their true effect on product sales. They suggest the need of accounting for the delayed, cumulative sales effects of LMP and other mobile promotion efforts. Practitioners and researchers could reach the wrong conclusion on the value of mobile promotion if they only calculate the spontaneous effect with impulsive buying and neglect the delayed cumulative effects.

Third, we found that different forms of mobile promotions have different substitute and complementary relationships with each other and that managers' use of different forms of mobile promotions is not fully consistent with their true relationships. In some cases, we found that managers' decisions are consistent with the true relationship between different types of mobile promotions. For example, managers treat located-based mobile promotions and behavior-based mobile promotions as substitutes in their decision process, consistent with the finding of a substitute relationship between the two types of promotions. In other cases, managers' decisions are inconsistent with the underlying relationship. For example, our analysis reveals that a substitute relationship between location-based mobile promotion and mobile-linked IM-based promotion, but managers treat them as independent of each other.

Methodologically speaking, we add to the emerging systematic time-series models in IS research (Adomavicius, Bockstedt, and Gupta 2012; Chang and Gurbaxani 2012). We employ time series models to track the persistence and decay patterns in the dynamic sales impact of LMP. The developed

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DSEM is an endogenous modeling system capturing most complete interactions and dynamic sales responses. It can (1) gauge the spontaneous, short-term, and long-term direct effects of LMP on sales, (2) estimate the indirect feedback effects of past sales on future LMP decisions, and (3) account for possible endogenous complementary or cannibalistic effects among different mobile promotion delivery technologies.

The results of this study shall be interpreted with its limitations. In particular, users reached through the LMP technologies were dynamically changing. While the DSEM models control for time-invariant observable or unobservable characteristics of the user population, they are not able to control for the effects of changing samples. Further, our findings on the dynamic effect of LMP are established in the context of movie ticket purchases. Movie ticket purchases have a number of unique characteristics. In particular, movie going is a social event (or a family event), which requires time-consuming coordination. At the same time, movie tickets are relatively inexpensive and are thus more likely to be subject to impulsive purchase, peer-pressure (Zhang, Hui, and Hou 2011), and word-of-mouth influence (Clemons, Gao, and Hitt 2010). Also, our study is limited because we do not have data on the geographic location where customers live (Forman, Ghose, and Goldfarb 2009) although all of our users are living in large metropolitan areas. Additional location variables may affect their movie-going decisions. Given these unique characteristics, it would be worthwhile to generalize our analysis to other product categories.

Also, due to privacy concerns, we do not have user-level data or transaction-level data (such as those used in Ghose, Ipeiritis, and Li 2012 and Molitor, Reichhart, and Spann 2012), which limit our ability to identify the relationship between individual characteristics and the sales effect of LMP. It is important for future research to uncover the individual level processes and track the complete path from receiving an LMP to actually buying via the mobile app.

## **6.2. Conclusion**

In conclusion, this study exemplifies an initial step in quantifying the dynamic sales impact of LMP on the basis of three million real-world mobile users. The developed time-series models reveal that the impact of LMP on consumer purchases is dynamic and different mobile promotions have different levels of substitute relationships. We call for more studies in IS and marketing to further probe this important research area with respect to the dynamic sales impact of location-based mobile promotion and how location-based mobile promotion interacts with other forms of mobile promotion.

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