https://doi.org/10.15813/kmr.2019.20.4.010

A Mobile App Strategy: An Empirical Study on the Effect of the Mobile Shopping App Usage[1]

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ABSTRACT

The growth of mobile commerce (m-commerce) has been accelerated around the world. Why do e-retailers have to put a great deal of effort for the distribution of their mobile apps? The literature has paid little attention to the influence of the introduction of an e-commerce app on shopping behaviors of consumers. By analyzing the dataset of 2,342 users in Korea, this study aims to broaden our understanding of mobile shopping app usage across competing e-retailers and different channels. We found that a user's prior usage of a specific e-commerce mobile app increases her subsequent usage of its website through a mobile web browser. Thus, mobile apps do not cannibalize the mobile web channel, and there could be a complementary relationship. We also found that a user's usage of competitors' apps is positively associated with her subsequent usage of a specific e-commerce app. Because many consumers search products and compare prices across multiple e-retailers, having a mobile app helps an e-retailer be exposed to more potential consumers. This study is among the first to study the role of mobile apps in e-commerce by showing the dynamics of cross-channel and cross-vendor usage by a user.

Keywords: *Mobile app, Mobile web, App usage, Knowledge management of m-commerce, Consumer behavior*

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1) This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2018S1A5A8030725).
논문접수일: 2018년 8월 31일; 1차 수정일: 2019년 11월 3일 게재확정일: 2019년 11월 11일
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1. Introduction

Smartphone has quickly penetrated into our society and daily lives. Based on its high user base, the growth of mobile commerce (m-commerce) has been accelerated around the world (Chung and Lee 2005). The worldwide m-commerce revenue is expected to reach about 47% of total e-commerce by 2018 (Siwicki 2014). In addition, the US retail mobile commerce sales will account for about 54% of total e-commerce in 2021. Looking further ahead, m-commerce is a new challenge and opportunity for the firms that seek a diversified channel by avoiding intensified competition and stagnant demand.

In analyzing m-commerce, it is difficult to apply the knowledge from an existing PC-based e-commerce environment because of the unique features of mobile platforms. For example, the services enabled by mobile are capable of providing ubiquitous shopping opportunities. The technologies related to location-based services enable firms to offer products and services to consumers at a suitable time and place. However, the inconvenient user interface of mobile devices because of a smaller screen size and limited text entry compared to a PC-based environment have increased search cost of users, which became a constraint for users in purchasing through a mobile device (Bang et al. 2013; Ghose et al. 2012; Verhoef et al. 2015). Another important feature that distinguishes a mobile platform from other traditional platforms is that the mobile provides a variety of applications. In particular, many e-commerce retailers have developed their own shopping applications, aggressively introducing to consumers together with promotional offers. Such retailers encourage their consumers to install and use their mobile apps, and purchase products via the apps. For example, when a customer installs their app, they offer a voucher or a gift. Besides, customers occasionally get a larger discount when they purchase products through mobile apps than other platforms.

Why do e-retailers have to put a great deal of effort for the distribution of their mobile apps? The average cost per click in the e-commerce industry for a sponsored link is over $1 on Google. Possibly, for retailers, it is better to let their customers access their stores through mobile apps and not to pay for advertisements. E-retailers expect their app to have a lock-in effect and lower competition because the users who run a certain e-commerce app have to put in extra effort to open a mobile web browser and visit a competitor's website for comparison of products. Nevertheless, the literature has paid little attention to the influence of the introduction of an e-commerce app on shopping behaviors of consumers. Thus, this study aims to broaden our understanding of mobile shopping app usage across competing e-retailers and different channels. Specifically, our main research questions are as follows:

(1) How does the usage of the mobile app of a specific e-retailer by a user affect her subsequent visit of the websites of the same e-retailer and its competitors through a mobile web browser?

(2) How do the prior visits of the website of a specific e-retailer by a user affect her subsequent usage of the mobile app of the same e-retailer and

its competitors?

Therefore, the two research questions ask whether the two channels, mobile app and mobile web, complement or substitute each other within the same retailer and across different e-retailers.

In this study, we analyzed the dataset of 2,342 users in Korea that consist of their visits of the mobile websites of three major e-commerce platforms—G-market, Auction, and 11st Street—and their usage of mobile apps provided by the three. Most importantly, our study is among the first to study the role of mobile apps in e-commerce and show the dynamics of cross-channel and cross-vendor usage by a user. Our study also offers important managerial implications that will guide e-retailers to refine their mobile app strategy.

2. Theoretical Backgrounds

2.1 Online Experience and E-commerce.

Some prior studies on the Internet have focused on online experience and activities. For example, Emmanouilides and Hammond (2000) examined the predictors of Internet usage and heavy usage, and found that one's prior experience of using diverse applications is one of the important predictors. According to Ma et al. (2014), a user's past usage of online gambling application is a strong predictor of her future usage, which is reinforced by regular and extended diverse use of the application. Similarly, a user's future usage tends to be highly correlated with her prior usage (Kim et al. 2016; Ko and Dennis 2011). Therefore, we can infer that a consumer's visits to online shopping websites can be well explained by her prior experience of online shopping as well. Several studies have been conducted to identify the main drivers of online shopping behaviors. According to Forsythe and Shi (2003), an increase in online experience leads to a decrease in the perceived risk of online purchases. They found that the users who have used the Internet for a long period of time are more likely to purchase products online. Moreover, users also tend to buy online products more often when they have browsed non-shopping sites such as information and entertainment sites (Brengman et al. 2005). Thus, the literature suggests that a consumer's diverse experience of visiting e-commerce websites can be intertwined to form their future behaviors of visiting the e-commerce websites.

2.2 Mobile Applications

The mobile usage has grown exponentially in recent years. Since the advent of mobile phone, the scope of research on m-commerce has expanded beyond its basic features and tried to identify differences of consumer behaviors in PC and mobile-based environments. The main drivers of consumer's adoption of mobile device contain a wide variety. For example, users can use mobile devices for mobile banking (Chen 2013), payments (Zhou 2013), and shopping (Kang et al. 2015). In some cases, a mobile app may be simply a mobile version of online website, and retailers design and deploy apps that are similar to their online websites when they expand their business to a mobile platform (Cho et al. 2014). Prior studies on mobile platform reveal that there exist inherent differences between channels such as traditional PC-based channel, mobile web browsers and mobile apps because of their different features and characteristics (Chong 2013; Ghose et al. 2012). Mobile apps potentially allow users to have ubiquitous and easier access to shopping environments by a single touch (Kim et al. 2017). However, it is little known how the usage of mobile apps interacts with the usage of other channels including the mobile web that is accessible through a mobile web browser. Furthermore, it is unclear how the mobile app may affect user's usage of competing e-retailers' websites and mobile apps.

3. Hypotheses

Users with more digital experience are familiar with general online shopping environments because the interfaces and product displays in e-commerce websites are similar to each other. Therefore, digital experience in general can lower one's cognitive cost of using and learning about a particular e-commerce website, which in turn increases the frequency of visiting another e-commerce website. Prior digital experiences also relieve one's concerns about related activities, including the users' worry about security and privacy issues (Forsythe and Shi 2003), which is of a great concern among mobile users. Thus, we expect that a user's prior experience of visiting diverse websites through a mobile web browser will help her lower the cost of understanding a website of another e-retailer and visit the website to a greater extent. We hypothesize:

H1: A user's prior usage of diverse websites through a mobile web browser has a positive impact on her subsequent usage of a specific e-commerce website through a mobile web browser.

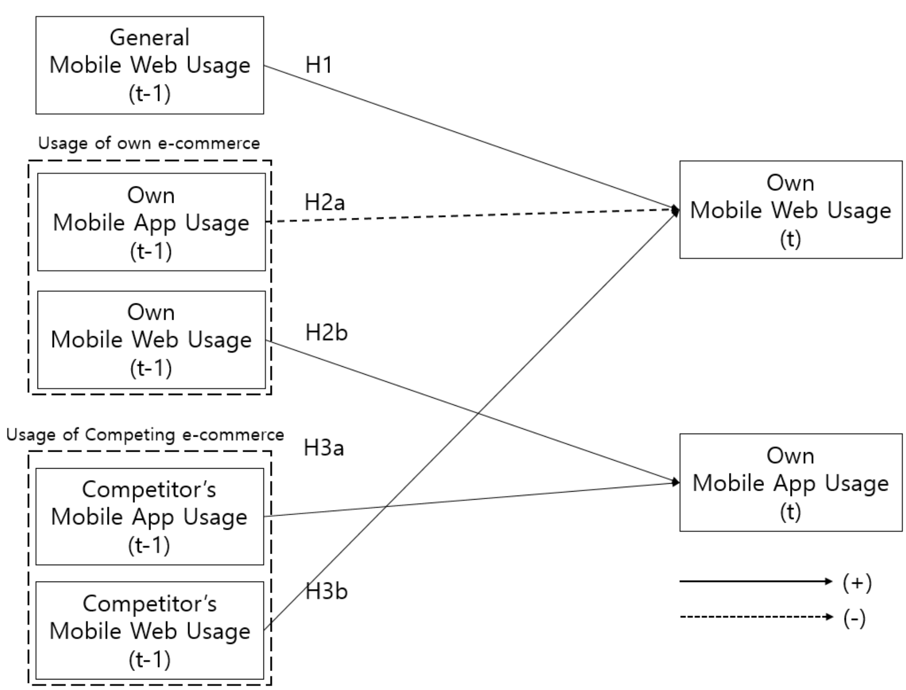
Many e-retailers expect various potential benefits by driving their customers to install and use their mobile apps. For instance, an e-retailer does not have to pay for the advertising cost per click that is incurred when their customers visit its website through sponsored advertisements. It can also expect a lock-in effect by which customers become more loyal to the e-retailer and visit its store more frequently with easier access by a single tap. Therefore, many e-retailers offer their customers a number of incentives to install their mobile apps. In addition, whenever a customer accesses a website via the mobile web, she is often encouraged to install the app through a pop-up window. Many e-retailers design and distribute their apps that are usually similar to their existing websites so that customers can adopt to the new environment easily while overcoming the limited mobile resources characterized by the cost of data usage and small screen size (Ghose and Park 2013; Gupta 2013; Nylander et al. 2009). Therefore, we expect that a user's prior usage of a mobile website of a certain e-retailer is positively associated with her future usage of a mobile app from the same e-retailer.

However, once a user starts using an e-commerce app, she is likely to access an e-retailer's store through the app while reducing her visits to the website of the same e-retailer through a mobile web browser. This is because users have limited time for shopping while the mobile app provides users an easier way to access a virtual store. In addition, the services and features provided by the mobile app is likely to be equivalent to those from the website. Users can more easily access a mobile app than Web-based content as well (Morrison et al. 2014). Therefore, we expect that a mobile app of an e-retailer will become a substitute for its mobile website. Taken together, we hypothesize,

H2a: A user's prior usage of a specific e-commerce mobile app will have a negative impact on her subsequent usage of its website through a mobile web browser.

H2b: A user's usage of a specific e-commerce website will have a positive impact on her subsequent usage of its own app.

The literature on learning curve suggests that prior experience can reduce the cost of performing similar activities in the future (Argote and Epple 1990). Similarly, prior studies have shown that previous website visits lower the cost on additional website visits (Emmanouilides and Hammond 2000). In addition, consumers visit several e-commerce websites to compare prices and search for special deals when they purchase products. With the lowered cost of visiting another website and an incentive for price comparison and special deals, the usage of e-commerce mobile websites is likely to lead to the usage of additional e-commerce website. Similarly, a user's usage of multiple shopping apps would increase her chance of using another e-commerce app if she has already installed it. Therefore, we propose the



<Figure 1> Research Model

following hypotheses:

H3a: A user’s usage of competitors’ apps will have a positive impact on her subsequent usage of a specific e-commerce app.

H3b: A user’s usage of competitors’ websites will have a positive impact on her subsequent usage of a specific e-commerce website. <Figure 1> summarizes our research model.

4. Methods

4.1 Data

We collected our dataset from Nielsen Koreanlclick, a global market research company. The dataset includes the usage of mobile apps and mobile web browser by its customer panel who are using an Android-based smartphone. Our panel dataset covers the period between December 2013 and June 2014. For our analysis, we selected three e-commerce companies—G-market, 11th Street and Auction—that are the top three in terms of market share in the Korean e-commerce industry during the data collection period. The three e-commerce companies had the market share of 35% (G-market), 30% (11th Street), and 28% (Auction). These companies provide large e-commerce marketplace that links between vendors and individual consumers as in Amazon.com (See <Figure 2>). For mobile users to access their stores, they can visit its website via a web browser or use a mobile app provided by e-commerce companies. Our dataset contained the weekly usage log of 2,342 users who visited the websites of these three e-commerce companies and/or used the mobile apps.

4.2 Variable Definition

We measured one’s general mobile web usage by the duration of the total mobile web, which did not include the visit time of the three focal e-commerce companies. In the same vein, one’s usage of a specific e-commerce mobile website and its mobile app was measured by the duration of website visit and mobile app usage, respectively.

We further included other control variables such as Number of Apps used by a user and Search App Duration to account for a user’s activities

<E-commerce website> <E-commerce app> <Encouraging message>

<Figure 2> Example of e-commerce website, app and encouraging message for app installation

by using a mobile phone. Further, we added the usage of bus app, navigation app, and map app as control variables. Given the ubiquity of mobile platforms, we expect these variables to control for a user's shopping behaviors induced by external stimuli while traveling. That is, the usage of these apps can affect her later usage of e-commerce app because a user can be stimulated to buy certain products while traveling or waiting for a bus or driving. <Table 1> summarizes the definitions of all the variables used in our econometric analysis later. <Table 2> presents summary statistics. <Table 3> shows correlations among these variables.

4.3 Model Specification

To examine the effect of mobile web usage and the usage of the three e-retailers' app on

<Table 1> Variable Definition

Variable	Definition
Independent and Dependent Variables	
Mobile Web Duration it	User i's usage of Web on mobile in week t excluding the duration of G-market, 11st street and Auction websites (in seconds)
G-market Web Duration it	User i's usage of G-market website on mobile in week t (in seconds)
11st street Web Duration it	User i's usage of 11st street website on mobile in week t (in seconds)
Auction Web Duration it	User i's usage of Auction website on mobile in week t (in seconds)
G-market App Duration it	User i's usage of G-market app on mobile in week t (in seconds)
11st street App Duration it	User i's usage of 11st street app on mobile in week t (in seconds)
Auction App Duration it	User i's usage of Auction app on mobile in week t (in seconds)
Control Variables	
Search App Duration it	User i's usage of search-related apps in week t (in seconds)
Number of Apps it	Number of mobile apps used by user i in week t
Navigation App Duration it	User i's usage of Navigation app in week t (in seconds)
Map App Duration it	User i's usage of Map app in week t (in seconds)
Bus App Duration it	User i's usage of Bus app in week t (in seconds)

<Table 2> Descriptive Statistics

Variable	N	Mean	Std. Deviation	Min	Max
Mobile Web Duration	67,918	7,814	15,474	0	312,063
G-market Web Duration	67,918	41	299	0	13,622
11st street Web Duration	67,918	39	390	0	24,041
Auction Web Duration	67,918	48	567	0	44,235
G-market App Duration	67,918	192	1,291	0	61,327
11st street App Duration	67,918	168	1,118	0	60,151
Auction App Duration	67,918	267	1,952	0	110,793
Search App Duration	67,918	84	713	0	31,314
Number of Apps	67,918	34	15	0	135
Navigation App Duration	67,918	105	1,429	0	107,666
Map App Duration	67,918	148	638	0	24,114
Bus App Duration	67,918	30	209	0	11,337

<Table 3> Correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Mobile Web Duration											
(2) G-market Web Duration	0.182										
(3) 11st street Web Duration	0.2034	0.1844									
(4) Auction Web Duration	0.1647	0.237	0.2427								
(5) G-market App Duration	0.0406	0.0596	0.0427	0.0141							
(6) 11st street App Duration	0.0283	0.0574	0.1445	0.032	0.1117						
(7) Auction App Duration	0.0081	0.0366	0.055	0.0303	0.1167	0.0819					
(8) Search App Duration	-0.0004	0.0002	-0.0005	0.0014	-0.0001	0.0087	0.0026				
(9) Number of Apps	0.1382	0.0604	0.0713	0.0312	0.0812	0.1129	0.0651	0.0127			
(10) Navigation App Duration	-0.0078	-0.005	-0.0034	-0.0034	-0.006	-0.0032	-0.005	-0.0016	0.0302		
(11) Map App Duration	0.0314	-0.0025	0.0042	-0.001	0.0032	0.026	-0.0025	0.0119	0.1325	0.0137	
(12) Bus App Duration	0.0177	0.0127	-0.0035	0.0072	-0.003	0.002	0.0066	-0.005	0.0549	-0.001	0.0558

the subsequent usage of mobile websites, we adopt an econometric approach. We specified the fixed-effects model. Given the relatively large standard deviation of each variable, we took log transformation to alleviate the effect of extreme observations. We lagged all the control variables because of the concern about the possible reverse

$$\ln(Gmarket\ Web\ Duration)_{it} = \alpha_i + \beta_1 \ln(Mobile\ Web\ Duration_{it-1}) + \beta_2 \ln(Gmarket\ App\ Duration_{it-1}) + \beta_3 \ln(Search\ App\ Duration_{it-1}) + \beta_4 \ln(Number\ of\ Apps_{it-1}) + \beta_5 \ln(Navigation\ App\ Duration_{it-1}) + \beta_6 \ln(Map\ App\ Duration_{it-1}) + \beta_7 \ln(Bus\ App\ Duration_{it-1}) + \varepsilon_{it} \quad (1)$$

α_i is a constant term that captures time-invariant user i specific effects; $Week_t$ is the week- fixed effects; εit is the idiosyncratic component of the error term. We used robust standard errors clustered within each user. β_1 measures the effect of mobile web duration (i.e., general mobile web usage) on *G-market Web Duration*. We expect $\beta_1>0$ if a user's prior usage of other websites in general through a mobile web browser has a positive impact on her subsequent usage of G-market website through a mobile web browser. (H1). β_2 captures the substitutive effect of the usage of e-retailers' app on the subsequent use of its own website. H2a could be supported if $\beta_2<0$. Then, the dependent variable was replaced by *11st street Web Duration* and *Auction Web Duration*. In this case, the independent variable corresponding to β_2 should be also replaced by the mobile app usage of a corresponding e-retailer.

To test for H2b, the dependent variable in Equation (1), *G-market Web Duration*, was replaced by *G-market App Duration*.

Similar to Equation (1), the dependent variable was replaced by *11st street App Duration* and *Auction App Duration*, respectively.

Next, to investigate the effect of using competitors' channels on the usage of a focal e-commerce app, we estimate the following

$$\ln(Gmarket\ App\ Duration)_{it} = \alpha_i + \beta_1 \ln(Mobile\ Web\ Duration_{it-1}) + \beta_2 \ln(Gmarket\ Web\ Duration_{it-1}) + \beta_3 \ln(Search\ App\ Duration_{it-1}) + \beta_4 \ln(Number\ of\ Apps_{it-1}) + \beta_5 \ln(Navigation\ App\ Duration_{it-1}) + \beta_6 \ln(Map\ App\ Duration_{it-1}) + \beta_7 \ln(Bus\ App\ Duration_{it-1}) + \varepsilon_{it} \quad (2)$$

β_2 and β_3 refer to the effect of using competitors' app. We expect that β_2 and β_3 are positive. (H3a). The dependent variable for app duration will be replaced by web duration variables to test for H3b. For example, if *Gmarket App Duration* is replaced by *Gmarket Web Duration*, we expect β_4 and β_5 to be positive.

5. Results

<Table 4> presents the main estimation results for Equation (1). All the models have high R^2. For example, R^2 with fixed effects for Column (1) is 91.36 percent. Columns (1), (2) and (3) show a significant effect of general mobile web experience on the subsequent usage of a particular

<Table 4> Estimation Results of Equation (1)

	(1)	(2)	(3)
Variable	log(G-market Web Duration)	log(11st street Web Duration)	log(Auction Web Duration)
log(Mobile Web Duration)it-1	0.0563*** (0.00457)	0.0353*** (0.00293)	0.0398*** (0.00347)
log(G-market App Duration) it-1	0.0126 (0.00973)		
log(11st street App Duration) it-1		0.0270*** (0.00802)	
log(Auction App Duration) it-1			0.0230** (0.0117)
log(Number of Apps) it-1	0.00919 (0.0149)	0.0370*** (0.0109)	0.00463 (0.0111)
log(Search App Duration) it-1	-0.00264 (0.00367)	-0.000265 (0.00341)	0.000284 (0.00298)
log(Navigation App Duration) it-1	0.00904 (0.00638)	0.00412 (0.00628)	-0.00190 (0.00655)
log(Map App Duration) it-1	6.09e-05 (0.00311)	-0.00208 (0.00316)	-0.00136 (0.00291)
log(Bus App Duration) it-1	0.00623 (0.00571)	0.0112* (0.00592)	0.00729 (0.00548)
Constant	0.138** (0.0560)	0.0210 (0.0452)	0.187*** (0.0450)
Observations	67,918	67,918	67,918
Within R-squared	0.012	0.010	0.009
Number of panels	2,342	2,342	2,342

*** p<0.01, ** p<0.05, * p<0.1. Clustered robust standard errors were shown in parentheses[3]

3) Our log-transformed regressions are analyzed with Stata's "xtreg" command with panel data. It automatically provides standard errors and within R2 clustered at panel level. The R2 with fixed effect is 0.4275, which the variation of our dependent variables can be explained about 43% by the selected independent and control variables.

<Table 5> Estimation Results of Equation (2)

	(1)	(2)	(3)
Variable	log(G-market App Duration)	log(11st street App Duration)	log(Auction App Duration)
log(Mobile Web Duration)it-1	-0.00427 (0.00292)	0.00796** (0.00370)	0.00689** (0.00332)
log(G-market Web Duration) it-1	0.0200*** (0.00754)		
log(11st street Web Duration) it-1		0.0595*** (0.00898)	
log(Auction Web Duration) it-1			0.0323*** (0.00993)

*** p<0.01, ** p<0.05, * p<0.1. Clustered robust standard errors were shown in parentheses. We do not report the coefficients for control variables for brevity.

e-commerce website. For example, one percent increase in *Mobile Web Duration* is associated with 0.0563 percent increases in *G-market Web Duration*. The results for two other e-retailers, 11st street and Auction, are consistent. Therefore, H1 is well supported.

Interestingly, the results of the effect of using a specific e-commerce app turned out to be contrary to our initial expectation (β_2 for G-market=0.0126, $p<0.01$; β_2 for 11st street=0.0270, $p<0.01$; β_2 for Auction=0.0230, $p<0.01$). We expected that e-commerce apps could substitute their usage of mobile web through mobile web browser because they provide similar functions. However, the usage of e-commerce apps complements the usage of the e-retailers' website through a mobile web browser. Thus, H2a is not supported. These results can be explained by the fact that customers may use an e-commerce app first and then visit the website in which it is easy to perform such tasks as price comparisons.

<Table 5> shows our estimation results on the effect of the usage of a specific e-commerce mobile website on the usage of its own app. Column (1) represents that G-market Web Duration has a positive relationship with G-market App Duration. That is, a one-percent increase in G-market Web Duration leads to an increase in G-market App Duration by 0.02 percent. The results are consistent across other e-commerce companies. The coefficients for 11st street and Auction are 0.0595 and 0.0323, respectively. Thus, Hypothesis 2b is supported.

<Table 6>, Column (1) presents the estimation results for Equation (3) in case of G-market. The results show that the usage of competitors' app increases the usage of a focal e-retailer's app (β_2 for 11st Street=0.0322, $p<0.01$; β_3 for Auction=0.0590, $p<0.01$). In Column (2), the usage of competitors' web significantly increased the usage of a focal e-retailer website as well. In details, one percent increase in 11st street Web Duration is associated with 0.0386 percent increases in G-market Web Duration (β_5 for Auction Web Duration = 0.151, $p<0.01$). The results remain consistent when the dependent variables

<Table 6> Estimation Results of Equation (3)

	(1)	(2)
Variable	log(G-market App Duration)	log(G-market Web Duration)
log(Mobile Web Duration)it-1	-0.00316 (0.00293)	0.0453*** (0.00405)
log(11st street App Duration) it-1	0.0322*** (0.00829)	0.0149** (0.00648)
log(Auction App Duration) it-1	0.0590*** (0.0121)	0.0110 (0.0101)
log(11st street Web Duration) it-1	0.00309 (0.00545)	0.0386*** (0.00732)
log(Auction Web Duration) it-1	-0.00628 (0.00759)	0.151*** (0.0124)
log(Number of Apps) it-1	0.101*** (0.0162)	0.00214 (0.0135)
log(Search App Duration) it-1	0.00427 (0.00374)	-0.00307 (0.00357)
log(Navigation App Duration) it-1	-0.0114** (0.00564)	0.00718 (0.00618)
log(Map App Duration) it-1	0.000902 (0.00353)	0.000189 (0.00298)
log(Bus App Duration) it-1	-0.00286 (0.00652)	0.00460 (0.00553)
Constant	0.198*** (0.0600)	0.137*** (0.0513)
Observations	67,918	67,918
Within R-squared	0.014	0.033
Number of panels	2,342	2,342

*** p<0.01, ** p<0.05, * p<0.1. Clustered robust standard errors were shown in parentheses.

are replaced by 11th street and Auction. Thus Hypothesis 3a and 3b are supported. Interestingly, the usage of competitors' mobile web does not affect the usage of a focal retailer's mobile app in Column (1). In addition, the usage of competitors' apps does not necessarily affect the usage of a focal retailer's mobile website. Therefore, the cross-channel spillover effect is weaker across e-retailers.

6. Discussion and Conclusion

Many online retailers develop and distribute standalone apps as well as websites for mobile phone users. All these efforts have been made because these apps are expected to help e-retailers catch up with the industry trends and remain competitive. Notwithstanding the potential economic value of a mobile app strategy, the literature has paid little attention to the dynamics of e-commerce app usage and mobile web page visits.

In this paper, we first found that a user's prior usage of many websites through a mobile web browser is positively associated with her subsequent usage of a specific e-commerce website through a mobile web browser. Thus, prior digital experience in general lowers the cost of using other similar services and related concerns about privacy and security.

Second, a user's prior usage of a specific e-commerce mobile app increases her subsequent usage of its website through a mobile web browser, which was opposite to our expectation. Further, a user's usage of a specific e-commerce website is related to the subsequent usage of its own app. That is, the mobile app usage and the mobile web usage complement each other, which provide a justification for launching a mobile app because they do not cannibalize the other channel.

Lastly, we found that a user's usage of competitors' apps (mobile websites) is positively associated with her subsequent usage of a specific e-commerce app (mobile website). Therefore, these results show the potential benefits of launching a mobile app in case competitors already have mobile apps. Because many consumers search products and compare prices across multiple e-retailers, having a mobile app helps an e-retailer be exposed to more potential users.

Our findings are expected to contribute to the literature in several ways. First, we are among the first to study the role of mobile apps in e-commerce by showing the dynamics of cross-channel and cross-vendor usage by a user. Second, our study shows the complementary relationship between channels because a mobile app is not a substitute for a mobile web channel. The usage of apps is perceived to undermine the website visits, but our results suggest that both channels can successfully co-exist. Third, there are no lock-in effects against competitors' apps. The switching cost is very low in the age of e-commerce, and our results show that a mobile app does not make customers more loyal to a single e-retailer.

Our study also has important managerial implications. First, it is beneficial for e-retailers to induce their customers to install and use their apps. Mobile apps do not cannibalize the mobile web channel, and there could be a complementary relationship. Furthermore, mobile apps help e-retailers be exposed to more customers when other competitors already have mobile apps. Second, despite the benefit, a mobile app per se may not offer competitive advantage but is a competitive necessity because of no evidence of lock-in effect. It may also encourage users to engage in more price comparison behaviors across e-retailers.

Our study is not without limitations. First, our analysis is limited to the three major e-retailers. Although they account for a large market share in Korea, future research can be directed to include more e-retailers. Second, our dataset covers a single country, and thus our results may not be generalizable to other countries with different culture. Lastly, we were not able to test the causal relationship because of the nature of research design and dataset. Despite such limitations, we believe that our study can shed a new light on the value of the mobile app strategy.

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저 자 소 개

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현재 연세대학교 경영대학 정보시스템 박사과정에 재학 중이다. 주요 관심분야는 모바일 플랫폼, deep learning, 인공지능(AI) 등이다. 지금까지 Information Systems Review 등에 논문을 발표하였다.

김 승 현 (Seung Hyun Kim)

현재 연세대학교 경영대학에 부교수로 재직 중이며 National University of Singapore 정보시스템학과에서 조교수로 근무한 바 있다. 연세대학교 경영학과를 졸업하고 Carnegie Mellon University에서 박사학위를 취득하였다. 주요 연구분야로는 디지털 마케팅, 정보보안, 의료정보시스템 등이 있다. 관련 연구들은 MIS Quarterly, Information Systems Research, Decision Support Systems, Communications of the ACM 등에 논문이 게재되었다.