Engagement, Search Goals and Conversion - The Different M-Commerce Path to Conversion

Research-in-Progress

Anat Goldstein
Coller School of Management,
Tel-Aviv University
anatgold@tauex.tau.ac.il

Orit Raphaeli
Department of Industrial Engineering
and Management
Ben-Gurion University of the Negev
oritrap@post.bgu.ac.il

Shachar Reichman
Coller School of Management,
Tel Aviv University and
Sloan School of Management,
Massachusetts Institute of Technology
shachar@mit.edu

Abstract

While the use of smartphones is increasing, conversion rates for mobile platforms are still significantly lower than those for traditional e-commerce channels, suggesting that these platforms are characterized by distinct consumption patterns. In this research, using detailed event log-files of an online jewelry retailer, we analyze user engagement and navigation behaviors on both platforms, model search goals and their effect on purchase decisions, and develop a conversion prediction model. Our initial results show that while user engagement is significantly higher in PC sessions compared to mobile sessions, in buying sessions, mobile sessions reflect a higher level of user engagement than PC sessions. These results indicate that m-commerce involves more than ensuring mobile-compatibility of websites, and that mobile consumers follow a distinct path to purchase involving distinct search and browsing behaviors. Therefore, analysis of the different types of consumption behaviors is necessary to understand the factors that lead to conversion on mobile e-commerce platforms.

Keywords: Mobile commerce, Browsing behavior, Online engagement, Navigation patterns, Conversion

Introduction

In 2015, mobile commerce (m-commerce) revenues in the United States totaled in 75 billion U.S. dollars, a 22% share of the total e-commerce revenues in the U.S., with a steady growth forecast for the next few years (Statista 2016). This trend underscores that mobile platforms have become a mainstream vehicle for online consumption. Nevertheless, while the use of mobile platforms is on the rise, conversion rates for mobile channels are significantly lower than those for PC platforms, 1.53% compared to 4.43% (Mometate 2016). These differences may imply that mobile consumption behaviors diverge from traditional PC patterns. Thus, there is a need to understand the consumption mechanism underlying m-commerce vs. well-studied e-commerce behaviors in order to enhance m-commerce effectiveness.

M-commerce features obviously differ from those of traditional e-commerce. First, due to the ever-present accessibility of the mobile Internet, m-commerce facilitates anytime, anywhere transactions

(Sumita and Yoshii 2010). In addition, mobile devices may be used while shopping in-store to perform searches and compare products and prices, creating new challenges for retailers (Piotrowicz and Cuthbertson 2014). Second, m-commerce might raise more privacy and security concerns among users than e-commerce, since not only can more information be collected on customers (e.g., time- and location-related information (Piotrowicz and Cuthbertson 2014), but data are also transferred wirelessly and interception is thus easier (Chong et al. 2012; Ipsos 2015). Third, small screens and low usability of mobile devices may hamper extended or complex use of m-commerce platforms (Ipsos 2015). These distinct inherent characteristics may affect web browsing behaviors in m-commerce compared to e-commerce[1].

Despite these differences and the growing significance of the m-commerce market, there is a scarcity of empirical research on m-commerce browsing behavior, mainly due to the unavailability of relevant data (Bang et al. 2013). The majority of empirical research is survey based, relies on self-reported use, and rarely uses system-captured metrics (Gerpott and Thomas 2014).

In this research we study the differences between mobile and PC consumption behavior, focusing on the browsing and searching behavior and their effect on conversion rate. While current understanding of users' search behavior is mostly on PCs, this paper extends the analysis of consumer behavior to mobile smart devices and compares channels. In particular, using detailed event log files of an online jewelry retailer, we analyze user engagement and navigation behaviors on both platforms, model and compare search goals and their effect on purchase decisions, and develop a purchase conversion prediction model.

Our initial analysis shows that in general, user engagement is significantly higher in PC sessions compared to mobile sessions, although consumers on mobile sessions demonstrate a higher level of engagement than PC sessions. These findings indicate that m-commerce involves more than merely adapting websites to mobile technologies, as mobile consumers follow a different path to purchase involving different search and browsing behaviors. Therefore, analysis of the different types of consumption behaviors should enhance our understanding of the factors that lead to conversion.

Literature Review

One of the most challenging tasks in retail is classifying prospective customers into "buyer" and "non-buyer" categories while they explore the (physical or virtual) store. Janiszewski (1998) distinguishes between two types of offline consumer search behavior: *exploratory* and *directed*. Moe (2003) extends this distinction to online shopping: directed search behavior is further divided into *directed buyers* – users who have a specific purchase product in mind, and *search/deliberation visitors* – users who exhibit goal-directed search behavior but have only a general product category in mind. Exploratory search is further divided by Moe into *hedonic browsing* – users who have no particular product or category in mind and may impulsively purchase based on their visit experience, and *knowledge-building visitors* – users who have no purchasing intention and are simply visiting the store to gather information about existing products.

Online engagement is another important aspect of consumer behavior that has been shown to affect conversion rates. Consumers' active online engagement plays an important role in improving website efficiency (O'Reilly 2007) and has been shown to increase online sales. User engagement measures how active users are on a website, using metrics such as bounce rate, number of pages, number of events per page, dwell time (session duration), average page duration, and return rate (Cevallos Rojas 2014; Clifton 2012; Lehmann 2015). Consequently, online retailers invest efforts to increase traffic and consumer engagement on their websites, in order to increase purchase probability (Agarwal and Venkatesh 2002; Brynjolfsson et al. 2013; Venkatesh and Agarwal 2006).

Understanding engagement differences of mobile and PC users may shed light on the differences in consumers' behavior and conversion rates of these two platforms. Ghose et al. (2012), for example, identify engagement differences in mobile and PC browsing behavior, resulting from higher search costs

[1] In this research, we only consider the use of smartphone activities as m-commerce and the use of PC as e-commerce. We exclude the use of tablets from both categories as the distinction between the PC and the mobile channel becomes blurred when considering tablet devices.

of mobile browsing. Their study shows that mobile users tend to click on items that appear higher on the page and therefore consume less effort, leading, at the same time, to lower engagement. In this research, we follow and extend their findings by investigating the differences between PC and mobile users' engagement and their effect on purchase decisions.

Three levels of engagement attributes have been used in the literature to predict e-commerce purchase conversion rates: 1. User-level attributes, describing user's demographic and geographic information and visit-history(Moe and Fader 2004; Van den Poel and Buckinx 2005); 2. Session-level attributes, describing various statistical and other features of each session (Montgomery et al. 2004; Van den Poel and Buckinx 2005); and 3. Page-level attributes, describing particular attributes of different pages in a session as well as page-to-page dynamics (Montgomery et al. 2004; Ting et al. 2009; Van den Poel and Buckinx 2005).

Using these attributes, several studies have linked users' goals to their browsing paths (Montgomery et al. 2004; Ting et al. 2009). For example, Montgomery et al. (2004) show that users' browsing paths may reflect users' goals and help predict whether the session will end with a purchase. Ting et al. (2009) represent clickstream data using footstep graphs, which allow identification of certain navigation patterns in a session (e.g., a "Mountain" pattern indicating of moving forward through a path of pages and then all the way back, a "Finger" pattern indicating a back-and–forward movement to different pages, and an "Upstairs" pattern indicating forward movement through not-yet visited pages), which are then associated with different search goals.

In this research, we propose a fourth level of engagement attributes – the page-event level, describing attributes of events occurring on a particular page (e.g., use of filters, clicks and other gestures within a page). Adding the forth level of attributes enables us to study the differences between mobile and PC users, in particular, differences in their engagement characteristics and navigation patterns, reflecting their search goals, and how these differences affect conversion rates. Furthermore, by identifying typical navigation paths of mobile and PC users, we can infer common search goals of mobile and PC users. An analysis of data on page events (the forth attribute level), may also shed light on users' goals.

This research stems from and contributes to the literature on e-commerce, m-commerce, and online consumer behavior. The empirical analysis of detailed online consumption activity should contribute to our understanding of the range of patterns of m-commerce behavior, and extend the current literature. The research also offers a practical contribution by proposing ways to optimize paths to conversion on mobile websites.

Research Objectives

In this research, we study the differences between m-commerce and e-commerce consumer behaviors and how purchase decisions on both platforms are affected by four levels of engagement. Specifically, we focus on the following hypotheses:

H1: Consumer's mobile engagement differs from their engagement in PC devices.

H2: Search behavior on mobile and PC devices represent distinct navigation patterns.

H3: The distribution of search goals (e.g., Moe and Fader 2004) on mobile is different from the distribution on PC. In particular:

a. PC users are more *search/deliberation visitors* than mobile users
b. Mobile users are more *directed buyers*
c. Mobile users are characterized by more hedonic browsing behaviors than are PC users, due to the ever-present accessibility of the mobile Internet.

A better understanding of these patterns should shed light on m-commerce processes and enhance our ability to model consumption behavior and improve conversion rate prediction. In this research-in-progress, we focus on *H1* and show how different aspects of engagement associate with different consumption features.

Summary of Data

This research is based on nine months (June 2015- March 2016) of data of an Australian jewlery brand website, captured in event log files that were created using Heap analytics. Heap analytics automatically tracks all events that occur on a website (e.g., page-view, click, form submission, touch, swipe, tap, and all other gesture events). Thus, our data encompasses the entire range of user behaviors in each session. Each session is identified by a unique session ID including a unique User ID[2], and a complete set of page-views and events occurring on each browsed page. This data collection method avoids two common problems of recording page requests on a Web server: The caching problem and IP-based identification of users, which is inaccurate since different users can be represented by the same IP. Session-level data are then aggregated into a user-level data structure, describing a user and her sessions.

Based on the page list of each session, we compute a corresponding footstep graph, from which we identify navigation patterns describing particular types of navigation path shapes, namely Mountain, Finger, Upstairs, and Downstairs (Chou et al. 2010; Ting et al. 2009). Thus, each session is associated with a sequence of navigation patterns, characterizing the navigation path through the website. Overall, the data include a total of 2,346,422 session events, which represent 42,837 sessions, 25,330 of which are PC sessions and 17,507 are mobile sessions[3]. We exclude data of tablet sessions since it is not clear if they should be classified as mobile or PC.

Sessions are described using a set 81 features, including technical information, time-related information, visit history, content, user engagement, and navigation patterns. Table 1 presents session features pertaining to users' engagement that are included in the current analysis

Table 1. Engagement-related session attributes

Attribute	**Description**
Duration	The total duration of the session
Number of Clicks	Number of clicks in the session
Number of Pages	Number of pages the user visited
Number of Searches	Number of general search activities during the session (such as most wanted view).
Number of Searched Product Types	Number of different product types searched during the session.
Number of Catalog Searches	Number of catalog searches during the session
Number of Filtered Products	Number of times the user filtered products during the session
Has Product Filter	1 - the session includes product filtering, 0 - otherwise
Has Catalog View	1 - the session includes a catalog search, 0 - otherwise
Has Most Wanted View	1 - the session includes a "Most wanted" view, 0 - otherwise
Has New Products Page View	1 - the session includes a "What's new" view, 0 - otherwise
Has Gift Search	1 - the session includes a gift search, 0 - otherwise
Has Blog View	1 - the session includes a blog view, 0 – otherwise

[2] "User ID" is a unique identifier of a user per device. A person is assigned a different "User ID" for each device that she or he uses.

[3] Data cleansing included removing sessions with no device classification, no duration or with duration that exceeded a reasonable session period (i.e. lasted more than an hour)

Methodology and Preliminary Results

As discussed in the previous section, previous literature has found that engagement levels on mobile devices significantly differ from those on PC. In this section, we focus on methods to allow more accurate specification of these differences with the aim of enhancing our ability to predict purchase and non-purchase activity on each platform.

Table 2 and Figure 1 summarize the distributions and conversion rates of mobile and PC sessions and demonstrate the difference in engagement behaviors (of purchasing and non-purchasing consumers across platforms) as well as the different behaviors of consumers on mobile vs. PC platforms.

Table 2. Device type distribution and conversion rates

	Total	With purchase	Conversion rate
PC	25330	367	1.45%
Mobile	17507	110	0.63%
Total	42837	477	1.11%

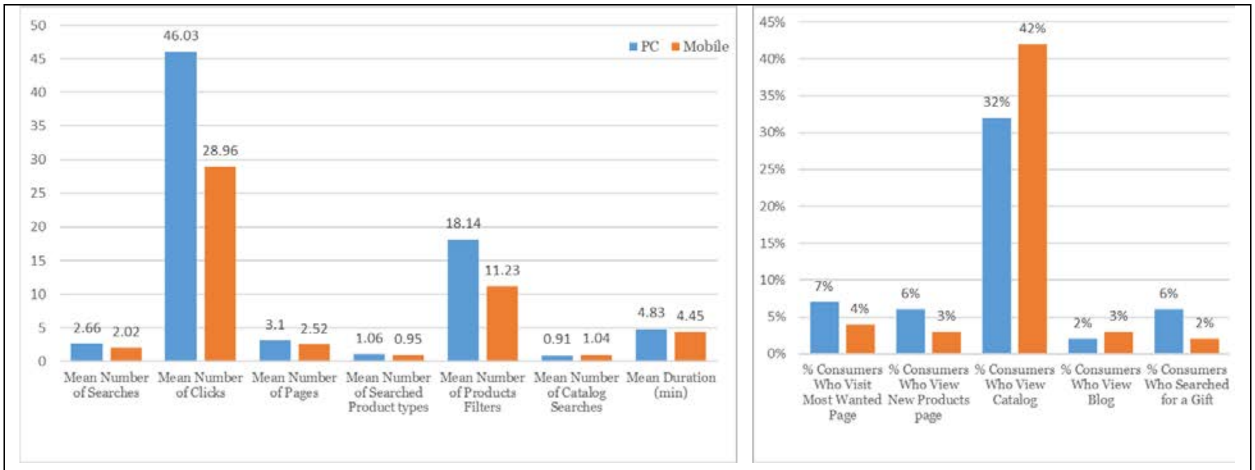

Figure 1. Session statistics per device type

Comparing engagement attributes

To test H1, which predicts that consumers' mobile engagement differs from engagement on PC devices, we performed t-test analysis comparing the means of the engagement related attributes (Figure 1). Table 3 presents the means, standard errors and t test results for each of the engagement attributes. Results show that means of all 12 engagement attributes are significantly different in mobile and PC devices. For most attributes (with the exception of "Number of Catalog Searches") the means of PC devices is higher compared to mobile. In addition, events such as most wanted view, new products page view, and gift search are more likely to occur in PC rather than mobile sessions, while catalog and blog views tend to be more frequently used in mobile sessions. In general, the results indicate that consumer engagement on PC devices is higher compared to their engagement on mobile devices, thus supporting our first hypothesis (H1).

Table 3: Engagement attributes in PC and mobile sessions								
	Mean (SE)		t-test for Equality of Means					
	PC	Mobile	t	df	Sig. (2-tailed)	Mean Difference	95% CI	
							Lower	Upper
Duration	4.83 (0.04)	4.45 (0.05)	6.07	39272.6	<0.01*	0.38	0.26	0.50
Number of Clicks	46.03 (0.41)	28.96 (0.32)	32.69	42704.4	<0.01*	17.06	16.04	18.09
Number of Pages	3.1 (0.02)	2.52 (0.01)	26.31	42746.7	<0.01*	0.57	0.52	0.61
Number of Searches	2.66 (0.04)	2.02 (0.03)	11.26	42702.2	<0.01*	0.64	0.53	0.75
Number of Searched Product Types	1.06 (0.01)	0.95 (0.01)	13.46	40663.6	<0.01*	0.11	0.09	0.12
Number of Catalog Searches	0.91 (0.02)	1.04 (0.02)	-4.35	42835.0	<0.01*	-0.13	-0.19	-0.07
Number of Products Filters	18.14 (0.18)	11.23 (0.14)	29.27	42789.3	<0.01*	6.91	6.45	7.37
Has Most Wanted View	0.07 (0.001)	0.04 (0.001)	14.36	42388.0	<0.01*	.0321	.027	.036
Has New Products Page View	0.06 (0.001)	0.03 (0.001)	13.54	42555.0	<0.01*	.027	.023	.031
Has Catalog View	0.32 (0.003)	0.42 (0.004)	-21.78	36245.8	<0.01*	-.103	-.112	-.094
Has Blog View	0.016 (0.001)	0.023 (0.001)	-4.28	33937.2	<0.01*	-.005	-.008	-.003
Has Gift Search	0.06 (0.001)	0.02 (0.0012)	17.85	42796.6	<0.01*	.034	.030	.038

Cluster analysis

In this phase, we identify meaningful clusters of sessions and analyze the distribution of mobile and PC session across the identified clusters. We evaluate clusters with respect to engagement and navigation patterns. We used k-means algorithm with k = 2 on the model variables. K=2 was chosen to represent *exploratory* and *directed* shopping search behaviors, the two types proposed by Janiszewski (1998).

The resulting two clusters are presented in Figure 2 and Figure 3. It is easy to see that cluster-2 (36.3% of the sessions) represents sessions with higher engagement than cluster-1, as almost all of the engagement-related variables have higher values or are more frequent in sessions in cluster-2. Parameters in Figures 2 and 3 are ordered according to their importance in distinguishing between sessions. The purchase decisions distribute across the two clusters as follows: among the non-buying sessions 63.8% belong to cluster-1 and 36.2% belong to cluster-2. The buying sessions are more evenly distributed: 54.5% belong to cluster-1 and 45.5% belong to cluster-2.

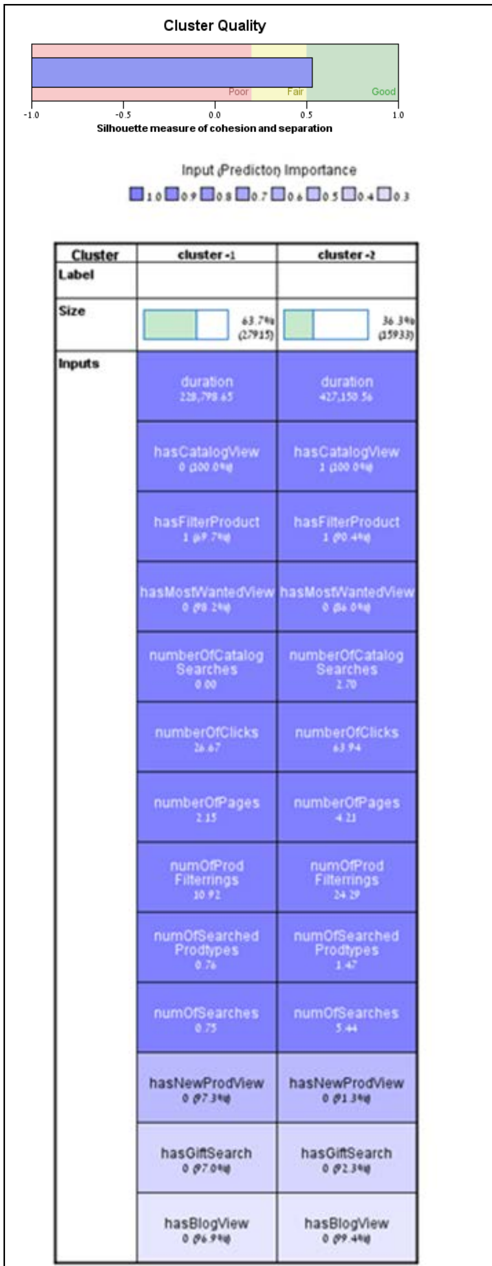

Figure 2. Clusters' characteristics

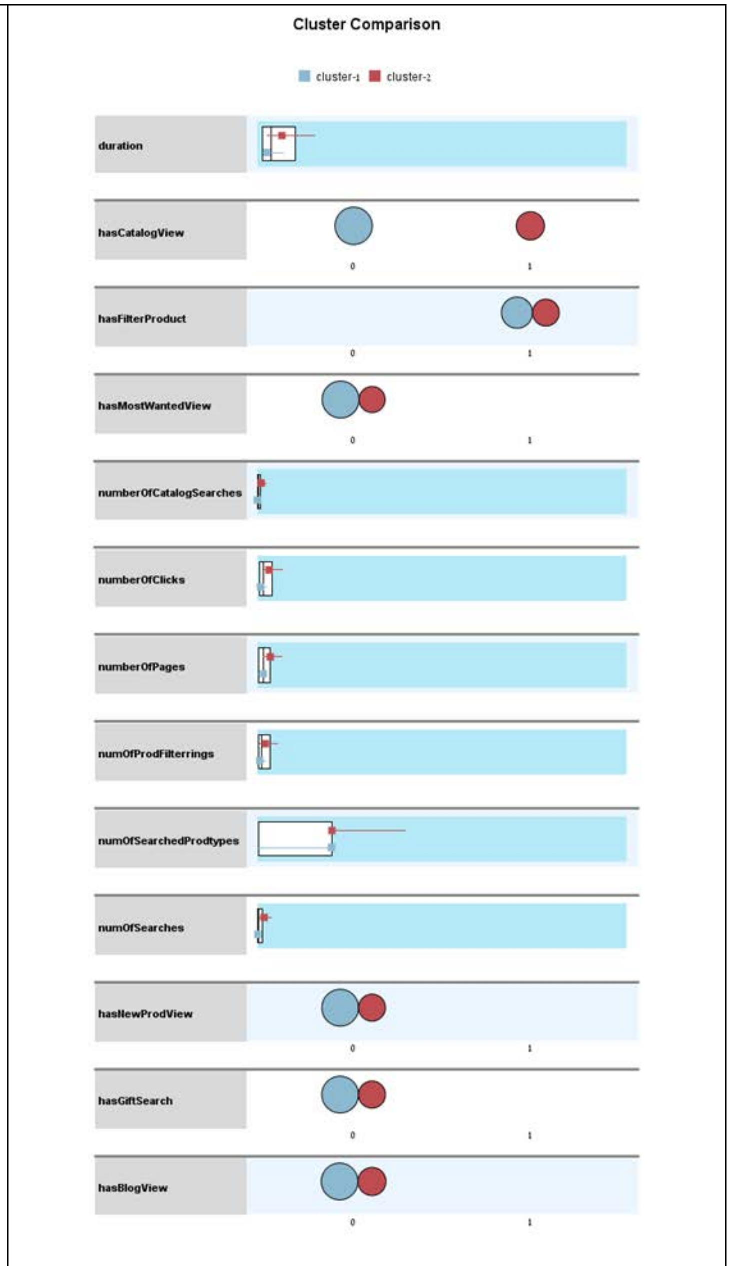

Figure 3. Graphical comparison of clusters' characteristics

Table 4 summarizes the distribution of PC buying (B) and non-buying (NB) and mobile buying and non-buying across the two clusters. Interestingly, while most of the PC buying sessions (59.1%) have relatively low engagement (i.e., they belong to cluster-1), most of the mobile buying sessions (51.8%) have relatively high engagement (i.e., they belong to cluster-2).

Table 4. Device type and purchase decision distribution across clusters

		PC		Mobile	
		cluster-1	cluster-2	cluster-1	cluster-2
B	Count	217	150	53	57
	Row %	59.128	40.872	48.182	51.818
	Column %	0.797	0.961	0.195	0.365
	Total %	0.507	0.35	0.124	0.133
NB	Count	16951	8012	10000	7397
	Row %	67.904	32.096	57.481	42.519
	Column %	62.272	51.306	36.736	47.368
	Total %	39.571	18.703	23.344	17.268

Search goal modeling and analysis

The next step in our research will model the four search goals defined in the introduction section, using a series of engagement, history and consumer attributes.

To test our models, we will conduct an experiment, in which Amazon Mechanical Turk workers will be assigned specific search tasks representing different search goals. Their recorded sessions will then be identified and analyzed, and correspondence with the defined search models will be evaluated. Based on the experimental findings, we plan to attribute different clusters to each search goal. The final step of this part of the research will focus on defining the unique patterns and features of each search goal type on each platform.

Conversion rate prediction

The final step of the research will explore consumers' path to conversion on mobile and PC platforms. We will model and test H3 and investigate the effect of adding device type as a feature. We plan to develop a purchase conversion prediction model using cluster dimensions and the experiment findings.

Summary

Our initial analysis of the data shows that hypothesis 1 (H1) can be accepted. Table 1 shows that every engagement-related variable is significantly higher or more common in PC sessions than in mobile sessions. For example, the average number of pages and events in PC sessions is significantly higher than in mobile sessions (3.07 pages and 45.54 events in PC compared to 2.5 pages and 28.35 events in mobile), PC sessions are longer on average (4.77 min. compared to 4.3 min.), and on average PC sessions include significantly more search and filtering activities, although the average duration per page is similar on both platforms.

The cluster analysis resulted in two clusters distinguishing high and low levels of engagement. Analyzing these clusters revealed that while for non-buying sessions the majority of both mobile and PC sessions belong to the low-engagement cluster, for buying sessions there is a difference between mobile and PC: the majority of mobile-buying sessions belong to the high-engagement cluster and the majority of PC-buying sessions belong to the low-buying cluster. This suggests that there is a difference between mobile and PC sessions beyond level of engagement. The fact that mobile buying sessions reflect higher engagement may indicate that mobile users are more search/deliberation visitors compared to PC users and that PC users are more directed buyers (performing less filtering and search activities), as suggested in Hypothesis H2. However, such claims require further research, as we propose in our research program.

A potential alternative explanation is that the heterogeneity in customers causes the conversion rate differences found in our analysis. Excluding the effect of heterogeneity on the conversion rate requires careful econometric identification using individual level data, which is an important component of our future research program.

Concluding Remarks and Future Directions

The increasing rate of smartphone usage is reflected in steady growth of m-commerce in the online retail market. While firms invest significant efforts on building mobile sites or mobile-compatible websites, conversion rates of the mobile channel are still significantly lower than those of traditional e-commerce. The discrepancy between growing use and low conversion rates highlights our lack of understanding of m-commerce consumption behavior and of how it differs from e-commerce over PC. This research aims to bridge this knowledge gap and provide insights on mobile consumption processes by analyzing online retailer event log data.

Our initial results show that mobile behavior is significantly different from PC behavior. Specifically, engagement indicators are higher on PC comparing to mobile, implying more exploratory behavior. At the same time, in buying sessions, mobile users demonstrated higher engagement levels than PC users, suggesting that mobile buying consumption may be more strongly associated with exploratory characteristics compared to PC. These findings demonstrate that current e-commerce practices cannot be applied directly to m-commerce and that identification of the factors that drive direct mobile consumers and lead to a purchase decision is necessary. A better understanding of m-commerce processes will enhance our ability to accurately model consumption behavior and improve conversion rate predictions, which have both academic and practical implications.

We plan to extend the research to include an online field experiment to study consumers search goals and navigation behavior. The experiment will focus on identifying the cause of the differences between mobile and PC conversion rates, test different attributes that may affect purchase decisions, and also account for consumer heterogeneity in each group (e-commerce and m-commerce consumers). The research will also include a predictive model of individual consumers' purchase decisions based on consumer's location, visit history, session navigation behavior, and engagement.

The combination of the different parts of the research offers a novel approach that will contribute to the fields of information systems, economics, and marketing by providing new perceptions on m-commerce and the path to purchase on this platform.

References

Agarwal, R., and Venkatesh, V. 2002. "Assessing a Firm's Web Presence: A Heuristic Evaluation Procedure for the Measurement of Usability," *Information Systems Research* (13:2), pp. 168-186.

Bang, Y., Han, K., Animesh, A., and Hwang, M. 2013. "From Online to Mobile: Linking Consumers' Online Purchase Behaviors with Mobile Commerce Adoption," *PACIS 2013 Proceedings*, p. 128.

Brynjolfsson, E., Hu, Y. J., and Rahman, M. S. 2013. "Competing in the Age of Omnichannel Retailing," *MIT Sloan Management Review* (54:4), p. 23.

Cevallos Rojas, R. A. 2014. "Optimising User Engagement in the Public Sector: A Web and Social Media Analytics for the Lambeth Council," in: *Business Information Systems*. University of Westminster.

Chong, A. Y. L., Chan, F. T. S., and Ooi, K. B. 2012. "Predicting Consumer Decisions to Adopt Mobile Commerce: Cross Country Empirical Examination between China and Malaysia," *Decision Support Systems* (53:1), pp. 34-43.

Chou, P. H., Li, P. H., Chen, K. K., and Wu, M. J. 2010. "Integrating Web Mining and Neural Network for Personalized E-Commerce Automatic Service," *Expert Systems with Applications* (37:4), pp. 2898-2910.

Clifton, B. 2012. *Advanced Web Metrics with Google Analytics*. John Wiley & Sons.

Gerpott, T. J., and Thomas, S. 2014. "Empirical Research on Mobile Internet Usage: A Meta-Analysis of the Literature," *Telecommunications Policy* (38:3), pp. 291-310.

Ghose, A., Goldfarb, A., and Han, S. P. 2012. "How Is the Mobile Internet Different? Search Costs and Local Activities," *Information Systems Research* (24:3), pp. 613-631.

Ipsos. 2015. "Ipsos Study for Paypal Reveals Drivers and Barriers of Mobile Shopping around the World." from https://www.ipsos-mori.com/researchpublications/researcharchive/3532/Ipsos-study-for-PayPal-reveals-drivers-and-barriers-of-mobile-shopping-around-the-world.aspx

Janiszewski, C. 1998. "The Influence of Display Characteristics on Visual Exploratory Search Behavior," *Journal of Consumer Research* (25:3), pp. 290-301.

Lehmann, J. 2015. "From Site to Inter-Site User Engagement: Fundamentals and Applications," in: *Departament de Tecnologies de la Informació i les Comunicacions*. Universitat Pompeu Fabra.

Moe, W. W. 2003. "Buying, Searching, or Browsing: Differentiating between Online Shoppers Using in-Store Navigational Clickstream," *Journal of consumer psychology* (13:1), pp. 29-39.

Moe, W. W., and Fader, P. S. 2004. "Dynamic Conversion Behavior at E-Commerce Sites," *Management Science* (50:3), pp. 326-335.

Mometate. 2016. "Monetate Ecommerce Quarterly Report, Q4 2015 ".

Montgomery, A. L., Li, S., Srinivasan, K., and Liechty, J. C. 2004. "Modeling Online Browsing and Path Analysis Using Clickstream Data," *Marketing Science* (23:4), pp. 579-595.

O'reilly, T. 2007. "What Is Web 2.0: Design Patterns and Business Models for the Next Generation of Software," *Communications & strategies*:1), p. 17.

Piotrowicz, W., and Cuthbertson, R. 2014. "Introduction to the Special Issue Information Technology in Retail: Toward Omnichannel Retailing," *International Journal of Electronic Commerce* (18:4), pp. 5-16.

Statista. 2016. "Mobile Retail E-Commerce Sales in the United States from 2013 to 2019 (in Billion U.S. Dollars)." from http://www.statista.com/statistics/249855/mobile-retail-commerce-revenue-in-the-united-states/

Sumita, U., and Yoshii, J. 2010. "Enhancement of E-Commerce Via Mobile Accesses to the Internet," *Electronic commerce research and applications* (9:3), pp. 217-227.

Ting, I.-H., Clark, L., and Kimble, C. 2009. "Identifying Web Navigation Behaviour and Patterns Automatically from Clickstream Data," *International Journal of Web Engineering and Technology* (5:4), pp. 398-426.

Van den Poel, D., and Buckinx, W. 2005. "Predicting Online-Purchasing Behaviour," *European Journal of Operational Research* (166:2), pp. 557-575.

Venkatesh, V., and Agarwal, R. 2006. "Turning Visitors into Customers: A Usability-Centric Perspective on Purchase Behavior in Electronic Channels," *Management Science* (52:3), pp. 367-382.