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M-COMMERCE VS. E-COMMERCE: EXPLORING WEB SESSION BROWSING BEHAVIOR

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Research in Progress

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Abstract

With the growing popularity of mobile commerce (m-commerce), it becomes vital for both researchers and practitioners to understand m-commerce usage behavior. In this study, we investigate browsing behavior patterns based on the analysis of clickstream data that is recorded in server-side log files. We compare consumers' browsing behavior in the m-commerce channel against the traditional e-commerce channel. For the comparison, we offer an integrative web usage mining approach, combining visualization graphs, association rules and classification models to analyze the Web server log files of a large Internet retailer in Israel, who introduced m-commerce to its existing e-commerce offerings. The analysis is expected to reveal typical m-commerce and e-commerce browsing behavior, in terms of session timing and intensity of use and in terms of session navigation patterns. The obtained results will contribute to the emerging research area of m-commerce and can be also used to guide future development of mobile websites and increase their effectiveness. Our preliminary findings are promising. They reveal that browsing behaviors in m-commerce and e-commerce are different.

Keywords: M-commerce, E-commerce, Web Usage Mining, Log File Analysis.

1 Introduction

Advancements in wireless communication technologies and the new generation of mobile devices have increased the number of people using mobile devices, opening the door for rapid growth of m-commerce. M-commerce (MC) refers to ñany transaction, involving the transfer of ownership or rights to use goods and services, which is initiated and /or completed by using mobiles access to computer-mediated networks with the help of mobile devicesò (Tiwari and Buse, 2007). According to researchers, MC is now seen as the business model that has the potential to have a greater impact on business communities and industries than what e-commerce (EC) did in the early 2000s (Chong et al., 2011). It was estimated that the number of mobile phone subscribers is surpassing the number of Internet users in some countries (Xie et al., 2009). This growth has been related to the improved mobile broadband and mobile networks, the growing popularity of social networking, video services and voice over IP (VOIP) services, as well as significant advances in mobile handset technology (Church and Oliver, 2011). Realizing the potential of MC, many retailers are considering MC as a new venue for future growth and have invested significantly in the development of mobile-enabled sites for MC (Patel, 2011). According to current estimations, the US MC sales are predicted to reach $163 billion in sales by 2015, compared to $4.9 billion in 2011 (ABI, 2010). MC has different characteristics from traditional EC. First, due to the ever-present access of the mobile Internet, MC facilitates anytime, anywhere transactions. Therefore, while EC continues to be used for exploring the advantages of the Internet, mobile access appears to attract people because of its immediate accessibility (Sumita and Yoshii, 2010). In this context, it was also reported that a growing number of users are accessing the Web through mobile devices in non-mobile settings like at home or at work (Nylander et al., 2009). Second, personalization allows MC applications to be personalized in order to represent information or to provide services, which are appropriate to specific group of users. Unlike EC on computers, mobile devices such as mobile phones are usually owned by a single user. Third, with smartphones individual users are using their phones for various activities such as social networking, scheduling events, emailing, searching for maps and directions (Chong, 2013) Finally, small screens and low usability of mobile devices may hamper long and complex use of the MC channel. Relatively less time spent per visit and less complex navigation is expected on MC webpages (Bang et al., 2013). Despite the inherent different characteristics, little empirical research attention was given to investigate the manner in which these differences are realized in usage behavior. IS Studies which examined the post-adoption MC usage, provided evidence about usage intensity measures (e.g. visitôs duration and number of navigated pages) in MC, relying mainly on subjective methods (Gerpott and Thomas, 2014). However, these studies did not refer to the possible differences between MC and EC usage intensity measures. Moreover, usage intensity measures have limited contribution in understanding user behavior patterns. In the context of EC, Web usage mining was widely used to explore the hidden user browsing behavior patterns discovered from Web logs in order to understand and better serve the needs of Web-based applications (Liu and Keselj, 2007). However, as far as we know, Web usage mining was not used in the context of MC.

We argue that analysing usage behavior as reflected in Web pages accessed by a user may provide new insights regarding the differences between MC and EC usage behavior. In particular it is important to understand the navigation path at the session level, which provides an objective measure of usage behaviour (Chou et al., 2010). Therefore, we analyze Web-server log files, as they offer large samples of browsing information regarding Web pages accessed through various devices. We refer to the following research question: Is the device type (mobile Internet access versus stationary Internet access) associated with unique browsing behavior? To answer this question we perform an exploratory study through the application of a Web usage mining approach on Web-server log files of a large e-retailer in Israel, whose site can be accessed through mobile as well as stationary devices. This provides a unique opportunity to compare Web usage behavior on both MC and EC channels. The obtained results will contribute to the emerging research area of MC and can be also used to guide future development of mobile websites and increase their effectiveness.

2 Background and Related Work

In this section, we provide background on MC and discuss related empirical research on mobile usage, Web usage mining, and user browsing visualization.

2.1 Empirical research on m-commerce usage

Given that MC is still growing and many new applications are constantly being developed, there are various definitions of MC. Some researchers in the past have claimed that MC is an extension of EC (Ngai and Gunasekaran, 2007). They stated the MC is similar to EC, except the transactions in MC is conducted wirelessly using mobile device. On the other hand, other researchers argued that MC is much more than merely being an extension of EC (Feng, 2006). They claimed that since mobility relaxes the constraints of time and space and due to the unique features of mobile devices, such as ubiquity, flexibility, personalization, and dissemination, MC is different from EC conducted over the wired Internet (Siau et al., 2001). Moreover, according to Chong (2013), MC has different interactions with users, usage patterns and value chain, thus offering business models that are not available to EC.

Over the last decade, the adoption and utilization of MC has triggered a substantial body of research on MC use behavior of end-users. As indicated by Gerpott and Thomas (2014), research on MC usage (referred to as mobile Internet usage) can be grouped into work that looked at adoption intentions of

MC on the one hand and ongoing ñactualò MC use on the other. MC adoption has been often studied through the identification of the antecedents and consequences of MC use intentions, mainly based on theories such as the technology acceptance model (e.g., Feng, 2006). More recently, the post-adoption MC usage, has gained greater attention across research outlets of many disciplines such as information systems, electronic business, computer science, marketing and management. According to Gerpott and Thomas (2014), the majority of the empirical publications measured mobile Internet intensity in the post-adoption phase through subjective methods, relying on self-estimates of personal usage amounts, mainly collected through surveys. However, such methods are likely to be limited in accuracy and level of granularity (De Reuver et al., 2013). Other studies, using objective methods for assessing mobile Internet usage through ñsystem capturedò mobile Internet usage metrics, were less frequent (Gerpott and Thomas, 2014). Among the objective methods (such as handset monitoring, traffic measurement or log collection from server), log files of servers offer a valuable possibility for studying mobile Internet usage for specific MC applications and Web sites (Kivi, 2009). These logs generally provide large samples of the most complete and accurate usage data, although they do not record visits in cached pages, which are called from local storage of browsers or proxy servers. Analysis of user server-side logs (click-stream data) can aid in improving the understanding of MC user navigation behaviors by providing detailed information of how users navigate or browse through website hosted on that server. So far, to the best of our knowledge, browsing behavior in mobile devices has not been researched. In this study we use server-side logs, which record the (possibly concurrent) access to a Web site by multiple site visitors from both mobile and stationary devices. This enables us to compare browsing behavior of users in both platforms.

2.2 Web-Usage Mining

Web usage mining is the process of applying data mining techniques to Web server logs and discovering usage navigation patterns (Han and Kamber., 2001). A Web server log explicitly records usage data of Web pages accessed by multiple users containing such information as IP addresses, page references, and date and time of access (Srivastava et al., 2000). The raw Web log entries are used by the web usage mining algorithms to infer the browsing behavior or usage implication in an application domain. Studies utilizing web log records have focused on analyzing system performance (Iyengar et al., 2000), improving system design by Web caching, (Yang and Zhang, 2003), exploring page prefetching (Rangarajan et al., 2004) and personalization navigation (Eirinaki and Vazirgiannis, 2003), and improving website design and e-learning quality (Chou, et al., 2010). These examples demonstrate that processing the Web log data by Web usage mining algorithms reveals useful information like browsing behavior or patterns, and these are then applied in practice and provide knowledge in specific areas.

2.3 Using Browsing Visualization: Footstep Graph

Despite the strengths of Web usage mining algorithms, the size and nature of click-stream logs can make pattern discovery and classification difficult and time consuming. Previous works suggested that one of the most basic ways to visualize the userôs clickstream data is to use the spanning tree technique to convert a log file into browsing maps using tools such as Web map (Dömel, 1994). Using such tools was found to be efficient in describing browsing paths of limited activities and users. However, they do not account for user browsing time and when the amount of click-stream data is too large or complex, such tools are not robust enough to construct a browsing map. Ting et al. (2005) introduce the *Footstep graph*, a visualization tool for identifying user navigation patterns, which facilitates transforming complex and unrecognized click-stream data into a more understandable form, suitable for interpretation. The footstep graph is based on a simple x-y plot, where the X-axis represents time (in seconds) and the distance between points indicates the time between two nodes (pages visited). The Y-axis represents the nodes along the userôs navigation route and the changes in the vertical axis indicate a transition from one node to another. An example of a footstep graph is shown in Figure 1. Based on the footstep graph description, Ting et al. (2005) further identify certain elements that illustrate user navigation behavior. These elements are named ñUpstairsò, ñDownstairsò, ñMountainò, and ñFingersò. The ñUpstairsò element is created when the user moves forward through previously unvisited pages in the website and the ñDownstairsò element is produced when the user moves back through pages already visited. The ñMountainò element (demonstrated in Figure 1 for time<70), where an Upstairs element is immediately followed by a Downstairs one, is found when the user moves through several pages and then returns from a specific page. The ñFingersò element (demonstrated in Figure 1 for time>70) is found when the user moves directly from one page within the site to another and then directly returns to the original page.

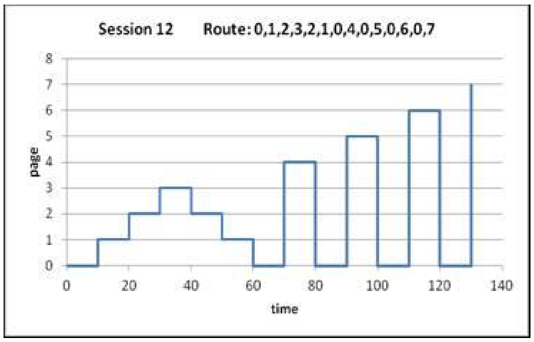

Figure 1: A sample footstep graph of a session.

Thus, a footstep graph can be represented as a sequence of these patterns. For example, the footstep graph in Figure 1 can be represented as a sequence of a ñMountainò followed by three ñFingersò. We use this approach for representing session navigation paths.

3 Data and Method

To answer our research question, a *Web usage mining* method (Srivastava et al., 2000) for the discovery of usage behavior is used. The usage data is gathered from web log files, which record requests for webpage content that are submitted to a Web server by multiple website visitors.

We analyzed Web server log files of a large Israeli e-retailer, which offers in its Web store a wide range of different product categories. The site supports both EC and MC, which makes it suitable for our purpose of comparing web-usage behavior of mobile and stationary users. In constructing the Web usage mining model, we follow three main phases, as presented in Srivastava et al. (2000): *data pre-processing*, *pattern discovery,* and *pattern analysis*. The details of these three phases are described in the following sub-sections. It should be noted that because this work is still in progress, further iterations of these three phases are planned, as explained in Section 4.

3.1 Data pre-processing

Web server log files record information on usersô requests made to the server. A typical log file entry includes parameters such as server IP address, HTTP request method, client IP address, request date and time, requested web resource (e.g. a URL), HTTP status code, user agent details (i.e., the hardware, browser and operating system from which the request was sent) and so forth. In order to identify access sessions, log file entries need to be pre-processed. A standard data pre-processing process has been developed in previous usage mining research (Cooley et al., 1999). In general, it includes data cleaning, user identification, session identification, and data formatting. Once session data is extracted from the log files, further pre-processing steps are conducted, in which additional variables describing each session are derived. In this study, variables that describe session access characteristics, e.g. usage intensity, timing and platform, and variables that capture its corresponding footstep graph (see Section 2.2), are derived.

3.1.1 Data cleaning

Not all log file entries are relevant for Web usage mining. Data cleaning aims at the elimination of irrelevant entries: requests made by automatic machines, e.g., Web robots or crawlers and not by humans; requests for image files that are associated with requests for actual Web pages; unsuccessful HTTP requests that contain error status; and entries with request method that is not ñGETò or ñPOSTò.

3.1.2 User identification

In order to analyze usage behaviors, we need to distinguish between different users in the log files. While usually in Web log files users are anonymous, we can approximately represent them in terms of their IP addresses (Liu and Keġelj, 2007). It should be noted, however, that a certain user may access the website from different devices and therefore be represented by different IPs. This is acceptable for our purpose, as the focus of our analysis is on Web access sessions, as described in the following section.

3.1.3 Session identification

Since in Web usage mining our goal is to identify usage characteristics and patterns, the focus of our analysis is on web access sessions. A session is a sequence of activities performed by a user (i.e., originating from a certain IP address) from the moment the user enters the website and until the moment he or she stops being active. Since a user may visit a Website more than once a day, the log file may contain more than one session per user per day. In order to identify all sessions of all users, we follow a *time-oriented sessionizing* heuristic that is used in the literature (Berendt et al., 2001; Liu and Keġelj, 2007), according to which the duration of a session does not exceed a threshold of 30 minutes, as determined to be optimal based on empirical findings. Applying this heuristic on the data results in a collection of session entries, each identified by a user IP and start time. In addition, each session is associated with a list of pages that were visited during the session, ordered by the page request time. This list of pages is the input to the *footstep-graph elements* identification process that is described in the next Section.

3.1.4 Computing session access variables

Other than IP address and Date/Time that identify the session, each session is characterized by a collection of attributes. First, we derive the *Device type* from which the session is initiated. Device type can be either handheld mobile devices (e.g., smartphones) or stationary devices (e.g., desktop or laptop PC). We derive this attribute from the *UserAgent* string that is recorded for each requested page in the log file. Second, session browsing behavior variables are derived. Session browsing behavior is characterized by the sequence of pages through which the user navigates during his/her visit in the website. Page navigation sequences are often visualized using ófootstep graphsô, as described in Figure 1. In order to identify the navigation behavior of a session, we follow the approach presented in Ting et al., (2007), which extracts underlying footstep-graph elements from clickstream data. Clickstream data of each session goes through a number of transformations that turn it from a sequence of numbered web pages (e.g., [0, 2, 0, 3, 0, 4, 4]) into a sequence of footstep- graph elements (e.g., [FINGER, FINGER, UPSTAIRS]). Based on this logic, we computed the *footstep string* variable that describes the resulting sequence of footstep-graph elements in a session. In addition, four *footstep element frequency* variables were computed, representing the percentage of each footstep-graph element in the footstep string for each session. Third, *Session outcome* is included to indicate whether the session ended with a purchase (i.e., ended in a ñthank you for shoppingò page). Session outcome serve as a moderating variable. It is used to study differences in browsing behavior of sessions that end with a purchase in MC and EC. Additional variables describing timing, intensity and other aspects of the session are also included. While these variables are not directly used to answer our research question, they will be used in future iterations of the research method. Including them will improve our understanding of the relations between the device type and usage behavior in MC and in EC. Timing variables include *Date*, *Day of Week* (the day of the week in which the session started), and *Daytime*: morning (06:00-12:00), afternoon (12:00-18:00), evening (18:00-00:00), or night (00:00-06:00). Intensity variables include *Number of Pages*, session *Duration*, and *Median of page* stay duration (in minutes). Both timing and intensity variables are derived from the date/time data that is recorded in each log file entry, representing the time each page was accessed. Table 1 summarizes the list of both session usage and footstep-graph variables that are used in this study at this stage.

Variable	**Description**
Device type	Was the session initiated from a mobile device (1) or from a stationary device (0)
Footstep-graph string	A string of footstep graph elements describing the session (e.g. {MOUNTIAN, FINGER,FINGER, MOUNTAIN})
Footstep-graph element(i) frequency	The percentage of footstep graph element (UPSTAIRS, DOWNSTAIRS, MOUNTIAN, FINGER) in the footstep string
Session outcome	Did the session lead to a sale (1) or not (0)
Day of week	The day of week in which the session occurred (e.g. Monday (1), Tuesday (2) é)
Daytime	The time of day in which the session occurred (e.g. morning, evening)
Duration	Session duration
Avg. page duration	Average duration the client stayed on a page during the session
Median page duration	The median of page-stay durations
Number of pages	The number of navigation steps the client performed

Table 1: Model variables

3.2 Pattern Discovery

The pattern discovery phase starts with a descriptive statistical analysis of session access variables, in order to examine whether these variables can distinguish between mobile and stationary sessions. We used SPSS to compute central tendency measures and graphical representation of frequency distributions and the Pearson chi-square for testing whether differences between distributions are statistically significant. Following this, we applied the sequential association rules (AR) technique to the *Footstep string* variable. The Sequence algorithm detects frequent sequences, that is, sequences of navigation patterns that tend to occur in a predictable order (Han and Kamber., 2001). Since the Footstep string of a session includes a sequence of *Footstep elements*, sequential AR may be useful in discovering frequent sequences of Footstep elements characterizing sub-groups of mobile and stationary sessions. For example, the output of the algorithm can be the sequence MOUNTAIN → FINGER, meaning that it is often that a MOUNTAIN pattern is followed by a FINGER pattern. For each identified sequence, the algorithm also provides additional parameters such as the support of the rule and its confidence. The Sequence association rule mining was conducted using PASW MODELER 14.

3.3 Pattern Analysis

In this step, the discovered patterns (i.e., the output of the previous phase) are analyzed. Uninteresting rules found in the pattern discovery phase are filtered out and interesting relations discovered between the model variables are interpreted. Based on the analysis, usage characteristics of MC sessions are distinguished from usage characteristics of EC sessions and the research question is addressed.

4 Current State and Outlook

Thus far, we completed a first iteration of the methodological phases described in Section 3. In this first iteration, our goal was to discover common navigation patterns of mobile and stationary sessions and to analyze the differences between them. The output of this iteration is intended to serve as input for future iterations, in which classification techniques (e.g., Logit modeling) will be used to identify the variables that best distinguish between MC and EC browsing behavior. At this point, we limited the investigated dataset to a period of two months, from October 31, 2013 to December 25, 2013, due to technical limitations related to the amount of data to be analyzed. The time frame selected does not include holidays or other special occasions and is thus representative. In future iterations, we intend to use advanced tools suitable for big data analysis. This will allow us to extend the investigated dataset to a period of a year. Table 2 summarizes the characteristics of the log file data in the investigated period of time.

	Total	**Mobile**	**Stationary**
Number of sessions	2,439,597	557,135	1,882,462
Average number of visits per day	43,564	9,949	33,615
Number of sessions with more than 3 pages	482,712	135,932	346,780
Original log files volume	58.8GB		
Clean data volume (after pre-processing)	438MB		

Table 2 Characteristics of the collected data

Our preliminary results are promising. First, they show that mobile sessions have different timing characteristics (e.g., the frequency of mobile sessions is equally distributed throughout the days of the week as opposed to stationary sessions which are less frequent over the weekend) and different intensity characteristics (e.g., stationary sessions have longer durations but contain less navigated pages on average). Second and more importantly, mobile sessions are characterized by different navigation patterns than stationary sessions, indicating different browsing behaviors. For example, we found that sequences of MOUNTAIN elements (such as MOUNTAIN → MOUNTAIN or MOUNTAIN → FINGER) show higher frequencies in mobile sessions (44% and 42%) than in stationary sessions (25% and 17% respectively). This finding indicates that usersô behavior in mobile sessions is more ñsearch orientedò than in stationary sessions (Chou et al., 2010). Furthermore, we found that sequences of consecutive FINGER elements (e.g., FINGER → FINGER), which describe scenarios of users unable to find the information they need, have higher frequencies in mobile sessions (around 30%) compared to stationary sessions (close to 0). Additional results are not detailed due to space limitations.

5 Summary

This study is an exploratory investigation of the behavioral characteristics of EC and MC, conducted through the application of a web usage mining method on usage data gathered from web log files of a large Israeli e-retailer. Our goal is to support the discovery of browsing behavior characteristics in mobile and stationary sessions. Descriptive statistical techniques were used to discover general characteristics of both mobile and stationary sessions. Footstep graph elements were identified in order to represent the basic navigation patterns of the session. These navigation patterns were later analyzed using sequential rule mining that extracts frequent sequences of navigation patterns. Preliminary results revealed interesting characteristics of search and purchase behavior on EC and MC channels, based on actual behavior. Key findings suggest that mobile sessions are more ñsearchò oriented compared to stationary sessions. In addition, mobile sessions are more likely to fit situations in which users cannot find the information they need. Moreover, we found that in buying sessions, stationary sessions were characterized by a more efficient browsing behavior, while mobile sessions were more likely to consist of search browsing elements.

The contribution of this study to the state-of-the-art is threefold. First, the study offers an integrative research method of web usage mining, combining footstep graph and sequence association rules mining to analyze click-stream data. Such a method can be used in various contexts to compare mobile-based usage behavior against traditional usage. Second, this method is applied in the context of MC, enabling us to investigate the differences between MC and EC usage patterns, an area that is currently under-researched. Finally, we employ predictive analytic techniques, which according to (Shmueli and Koppius, 2011)advance IS research by creating practically-useful models, that can also help alongside explanatory modeling in theory building and theory testing.

Our research has the following limitations: First, separate sessions, either initiated from a single device or from different devices, may be interdependent. Therefore, it might be that the browsing behavior of one session affects the browsing behavior of a second session. Since a user is identified by an IP address, such situations cannot be identified and are therefore ignored in this study. Even if some sessions are interdependent, our finding that mobile sessions tend to be more ñsearch-orientedò than stationary sessions is still important and may even explain such session interdependency. In the future, we intend to extend our research and use dedicated log files of the e-retailer that also record the actual user identifier. This would allow us to track user behavior across different sessions. Second, session data recorded in server log files do not include cashed pages and ignore AJAX calls. While this means that some of the navigation activity is not recorded, the effect of this limitation on mobile sessions and stationary sessions is similar. Moreover we plan to expand this research to Web-log files obtained from additional e-retailers.

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