The Effect of Device Type on Buying Behavior in Ecommerce: An Exploratory Study

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ABSTRACT
In this research, the effect different devices (smartphone, tablet, desktop) have on purchase behavior in ecommerce was explored. With an innovative combination of web analytics (Google Analytics/Hotjar) and a customer survey, a field experiment was conducted on the website of a Dutch retailer. It was found that smartphone devices limit the customer in ecommerce, while in the customer purchase journey several devices are used for different tasks at different times. The innovative approach used allows identification of different variables and their implications and effects on consumer behavior in web environments.

Keywords

Online consumer behavior, buying behavior, device type, smartphone, tablet, desktop

INTRODUCTION

Online shopping or ecommerce is the distribution of goods and services using the internet. It will be responsible for 14.6% of the entire retail volume by 2020 (eMarketer, 2016a). Already by 2018 there will be 5.7 billion people in possession of at least one internet capable device such as a smartphone or a tablet, not accounting for classic desktop users (eMarketer 2016b/2015). With the evolving use of mobile internet on different device types, questions concerning their implications on customer behavior are emerging (Marketing Science Institute, 2016). *What is the influence of device type (smartphone, tablet, desktop) on purchase behavior during ecommerce sessions in the customer journey*?

LITERATURE REVIEW

Decision making in online environments

Cheung et al. (2003) found that factors influencing online behavior are not significantly different from factors influencing real life behavior. This indicates that classic behavioral models can also be applied to web research. One of the most widely used models is the Technology Acceptance Model with two key variables: perceived ease of use and perceived usefulness (Davis, Bagozzi & Warshaw, 1989). Recently, the framework was extended by a third variable: perception (Childers et. al, 2002). The implications for online research could be that the easier customers perceive the shopping experience to be, the more likely it is that they place an order. We could assume that website design as well as device type are key drivers of consumer behavior.

Factors in web environments

Research has shown that perceived privacy invasion results in a negative attitude of customers towards a brand or a web shop (Tsai et al. 2011). This results in customers looking out for a different web shop or postponing their purchase decision (Kim, Ferrin and Rao, 2008). A similar negative effect occurs when remarketing is used and certain ads are shown too often to the same customer. Customers then feel vulnerable and avoid clicking on the ad (Aguirre et al. 2015). Another important factor is the usability of the page itself. In ecommerce customers tend to leave the page if loading time is perceived to take too long (Constantinides and Geurts, 2005). On product level, high involvement as well as utilitarian products tend to sell best in online retail (Grewal and Levy 2016). Another external factor to consider is time. Research has shown that customers most likely react to emails with shopping intent in the morning and late afternoon (Presman, J. 2015). Hence, external factors at different levels have the potential to influence consumer behavior.

Implications of device type

Screen size is an important variable in browsing behavior as small screen sizes are more time consuming and are therefore associated with higher search costs (Ghose, Goldfarb and Han, 2013a). Therefore, smartphones also require more time spending compared to other devices when filling out surveys as discovered by Liebe et al. (2015), but survey quality is not affected by device type. Tablets on the other hand limit the amount of information customers receive because of their strong focus on apps (Burford and Park, 2004). In the customer purchase journey, different stages such as need recognition or information search are associated with different types of behavior (Puccinelli et al. 2009). Research by Lee et al. (2017) discovered that smartphones and tablets are complementing each other in the customer journey. It is important to mention that in the journey, smartphone users typically spend less time on a page compared to desktop users (Chaffey, D. 2017). The variable age can also influence how customers use certain device types (Kang and Yoon, 2008). Overall, it can be said that differences in device types and their usage are likely to be drivers for consumer behavior in ecommerce sessions.

Website research

In website research, there is a lot of unused potential in the field of experimental research as identified by Ghose, Goldfarb and Park (2013a). Besides classic methods such as surveys, (field)-experiments allow for another angle when examining behavior. In web environments, different types of data collection methods can be employed. Google analytics can be used to draw inferences about customer demographics or time on page as well as other important metrics such as age, gender, device type and much more (DeMers, J. 2014). Another key metric is the bounce rate, which determines the percentage number of users that are not interested in the page (Pakkala et al. 2012). Aside from Google Analytics, Kaur and Singh (2015) analyzed click behavior to identify different points of interest on a web

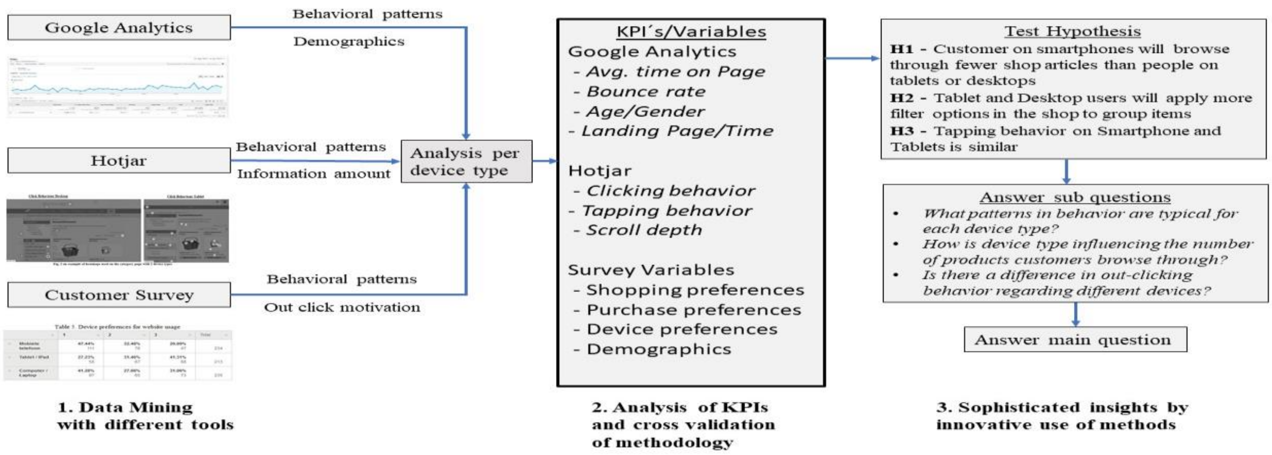

Fig. 1 Research Model/Conceptual Framework

page. Different heat, tap and scroll maps can be applied to draw inferences about customer behavior and website usability on page, for e.g. using Hotjar (Choros, 2011). So, this method allows for observation of the customer directly on the web page. According to Patel (n.a), web analytics can be utilized to improve a page and better tailor marketing messages for the audience. Each of the mentioned tools has specific advantages and disadvantages which need to be considered when working with them, especially when used by scholars with regards to validity and reliability.

METHODOLOGY

Overview

Due to the nature of the research and fast evolving technology, a new combination of methods is needed. Therefore, together with a Dutch ecommerce company, a real live experimental setting with a three-step research framework (Fig. 1) was employed. As survey research alone does not provide insights into actual user behavior, a new combination of different web analytic tools as well as customer survey to close the gap between observation and customer feedback was employed. With Google Analytics, demographic as well as other numerical data about customers on page was collected. In accordance with the chosen KPIs this data will be analyzed to draw first inferences about customer behavior. Besides analytics, as it allows only to see what is happening on the webpage, but not how visitors interact with the web site, the tool Hotjar will be used to create different heatmaps to analyze clicking and tapping behavior as well as scroll depth of customers. This combination allows to draw inferences about on page consumer behavior at different levels. To discover underlying reasons for certain patterns, a survey will be used. The collected data will also be analyzed according to certain KPI´s taken from the literature. Hypothesis taken from literature study as well as sub questions to break down the main question were used (Fig. 1) to guide the research and analysis more clearly. As final step, new insights into the field of consumer behavior will be presented.

Design

As mentioned, the research is carried out together with an ecommerce company. They provide access to the tooling as well as to their customer data base. In the first step, a category page (different products of the same subtype) is chosen where the tooling is installed. Then over a timeframe of 6 weeks the page is observed. Due to different technical reasons, it is not possible to ask questions to the same people who were observed at the category page. To close this gap, the emailing list of the company will be used to distribute the survey. It is assumed that both samples belong to the same population and therefore the data of the survey and the web analytics can be used in combination to draw inferences about the customers. The survey itself is sent out in week 5 of the observation, due to the observational character of the research. The aim is to validate the findings and discover the motivation of customers for several behavioral patterns. To not bias the respondents, it is declared as an intent to improve web design. To ensure validity and reliability of the findings and data, the different data sources will be compared among each other using different observed variables such as device type, gender and age.

The final sample size of Google Analytics consists of 805 customers in the 6 weeks which rules out sampling bias. For the Hotjar part, as the program automatically draws a sample of the visitors, 530 visitors were observed, equal to 65% of the Google sample. In the survey, a total number of 395 responses was collected. As only complete answers and only people who visited the website before were counted, the final survey sample consists of 286 respondents.

ANALYSIS

Finding one – smartphone limits users in ecommerce

The data analysis reveals that smartphone users on average spent 0.53 min on page compared to desktop users with 1.06 min and tablet users with 1.04 min. This indicates that on average customers on smartphone are ~12s less on the page compared to bigger screen devices. Next to that, Hotjar was used to create a scroll map to measure how much of the page users saw when they browsed through. To make the results comparable over different devices, only the number of products was counted (see Table 1). It was found that tablet and desktop users typically scrolled 20% deeper into the page. This indicates that they saw more products than smartphone users which proves H1. Next to that, smartphone users did not apply any filter or sorting functions on the page as proven by click map analysis. This proves H2 which suggests that smartphone users are limited by their device. In conclusion, it is possible to say

Table 1. Scroll depth per device type

	Smartphone	Tablet	Desktop
6 Products	67,10%	91,00%	91,40%
12 Prodicts	58,80%	78,60%	75,70%
18 Products	46,10%	68,30%	65,80%
24 Products	34,20%	54,50%	53,30%
30 Products	28,90%	48,30%	44,10%
36 Products	19,70%	37,20%	38,80%

that customers on smartphones are limited by their device type on various levels during the shopping process compared to bigger screen devices.

Finding two – smartphone and tablet tapping and usage behavior is not similar

Through the use of click maps, it was measured where users clicked on the page. It turned out that there was a big variance in different areas of the page (description, product picture, CTA button) between tablet and smartphone users. On average, the variance was between 5-13%, not counting clicks with tablet devices on sorting and filtering functions. Next to that, in the general Google Analytics analysis it turned out that there are no similarities between tablet and smartphone in usage. This finding proves H3, indicating that tablets and smartphones are not similar devices.

Finding three - different devices are used for different tasks in customers journey

With the implication that behavior regarding clicks and other numerical data is not similar, data from Analytics was analyzed too. In the analysis, it was found that during working hours, tablet and desktop usage is higher compared to the evenings where primarily smartphones are used. Customers indicated strong preferences (50%) to complete a purchase on the internet with their desktop PC rather than their tablet or smartphone, even though in the observation the entire value of desktop device visitors was only 37.64%. For the question which device is most likely to be used for information search, it turned out that smartphone values are equally high as desktops. On the other hand, product comparison was more likely done with a desktop while tablets for all tasks are in the middle. The conclusion one can draw from the data is that customers use different devices in the purchase journey for different tasks. It is likely that time is influencing device usage too, as customers most likely have different touch points with a brand or a shop.

Finding four – reliable and valid insights into how customers are affected by device type

To cross check the validity of the data, different metrics were considered. Google Analytics (GA) was particularly useful to rule out influence of third variables which could otherwise bias the findings. Between GA and Hotjar (HJ) the variance of device types was minus 1 percentage point for tablets, plus eight percentage points for desktops and minus seven percentage points for smartphone. Between GA and the survey, the variance in age of both samples was plus eight percentage points more female respondents in the survey while the age between both samples only varied by one to three percentage points. Regarding the devices, the variance between GA and the survey was nearly equal to the variance between GA and HJ with around seven percentage points. This implies that both samples belong to the same population which further strengthens the validity of the data. Hence, these findings facilitate future research in examining and observing how customers are affected by device type.

PRACTIAL IMPLICATIONS

The outcomes of this study are useful for a variety of audiences. First, companies and web shop owners can make use of the implications about smartphone users in two ways. First the design of user-friendly webpages which decrease the limiting factor of this device type could be one field. Secondly, companies can change the sorting of their category and product pages to influence customers to buy certain items or services. The societal relevance of these findings can be found in litigation cases about search engine results pages, where those practices and their possible malicious implications on behavior, in this case by Google Shopping, are already under question (European Commission, 2017). Furthermore, the study reveals implications about the general influence of device type on behavior, which is an important field with regards to digitalization of the society. Particularly useful is the knowledge gained about the correlation between willingness to buy and certain device types. With this information companies can further strengthen their remarketing efforts and better tailor the right messages to the right customers at the right time (Presman, J. 2015). Without knowledge in this area it is more likely that companies send out the wrong messages that harm marketing efforts and are perceived as invading by customers (Aguirre et al. 2015). With evolving tracking capabilities, it becomes possible to track customers across devices which provides further insights in the customer journey and customers behavior at different stages.

FUTURE RESEARCH

This study only covers a small fraction of influencing variables in ecommerce. There are many more factors which contribute to the customer decision to buy. The factors that were not examined include for example trust which can have a large influence on customer behavior (Tsai et al. 2011). Another example is the influence of cross device usage. It is likely that many customers own more than one device and use different devices for different tasks. Further research should use even more sophisticated tooling to track customers across devices and better model the customer journey at different touch points. Another limitation of the study is the small scale which does not make it possible to generalize the findings to the greater population of web site visitors. This would be especially useful to further validate the power of used methodology. Findings in this area will further shed light on the influence of device type on purchase behavior and general interaction of consumers in web environments. As mentioned, this was an exploratory study, testing a new methodology and its fit for scientific research. Therefore, potential sources of bias influencing validity and reliability could not be ruled out entirely. Despite this, it turned out that through cross validation the observed variance between different variables was rather small. Hence, it is to conclude that there is great future potential in this type of research, especially concerning questions dealing with how consumers behave in web environments. With more sophisticated tooling, heat maps and analytics data can be utilized to further draw inferences from customers as done in previous studies (Pakkala et al. 2012/ Choros, 2011). Another interesting field to research and validate the methodology could be to check the correlation between this technique and eye tracking studies which also provide insights into how customers interact with a page/device.

ROLE OF THE STUDENT

Nicolai Fabian was an undergraduate student under the supervision of Dr. E. Constantinides, Dr. S. de Vries and Prof. P.C. de Weerd-Nederhof. During the time of the study he was working at the corresponding company as junior online marketer. The topic idea came from the MSI ´16-´18 research priorities and was then discussed for feasibility with the company and the supervisors. The detailed question was then worked out by the student. The company implemented the tooling on page while survey design, processing of results as well as analysis and conclusion were done by the student.

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