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

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ABSTRACT,
With the possibilities smart mobile devices such as smartphones, tablets and desktop bear in a digital world, emerging questions concerning their influence on behavior and their relation in the customer journey came up. What is the effect, those devices have on purchase behavior in ecommerce and on the customer journey? To answer this question, an explorative field experiment on the website of a Dutch ecommerce company was conducted. In the study, web analytics was used to collect numerical, demographical as well as behavioral data such as heat/click/scroll maps. In the second step, a customer survey was used to validate the findings as well as discover underlying reasons for certain behavioral patterns. The new combination of methods opens a new way in observing and understanding website behavior of customers in real life. We found evidence that smartphone users are limited by their device type in the amount of information they can receive during a session compared to other device types. Next to that we saw no similarities between tablets and smartphones in terms of tapping behavior. Furthermore, we discovered that customers tend to use different devices for different activities at different times of the day in their journey. With our methodology we found a new and innovative way for getting insights in customer behavior on webpages. Therefore, for future research we suggest investigating the influence of cross device use on customer behavior during the customer journey and expand the possibilities we have discovered with the new use of methods.

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

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1. Introduction

1.1 Background

Online retail or ecommerce is the distribution of goods and services using the internet. In 2016 total sales volume was equal to 1.915 trillion dollars which will increase to 4.058 trillion dollars in 2020. Up then ecommerce is accountable for 14.6% of the entire retail volume (eMarketer, 2016a). For companies, ecommerce is no longer a channel to ignore. Traditional online retailers such as Amazon are opening physical locations while traditional retailers such as Walmart are buying online competitors (eMarketer, 2017). Regarding the shift to online sales, companies are struggling with the strategical implications of ecommerce as sales channel (eMarketer, 2016b). Next to the strategical implications of online environments, companies are struggling with the customers itself. A study found out one major problem in online environments concerning the fact that users are overloaded with information and keeping attention is one of the major obstacles (Horrigan, J. 2016). Related to this problem is the nowadays easy access to the internet. Mobile devices such as smartphones and tablets in combination with mobile internet make it possible to access the internet at any time from nearly every place. Traditionally ecommerce sales required a desktop PC or a laptop to purchase items on the internet. Recent development concerning mobile devices implicate a shift in the use of different mobile device types during customer purchase journey. Therefore, questions coming up how those mobile devices are influencing customer behavior.

Regarding different mobile device types, there is a trend in industry to the stronger use of smaller and smarter mobile devices. Until 2018 nearly half of all mobile phone users will possess a smartphone with mobile internet capabilities. In total over 4.3 billion people will then possess the capability to use the internet from nearly every place in the world (eMarketer, 2016c). As pointed out traditional desktop PC´s are becoming less important for accessing the internet. With the implications of mobile devices, customers nowadays can easily use their smart mobile devices to access the internet or buy items. Companies have already reacted to this trend in 2014 when desktop advertising budget reached its peak (McDermott, J. 2013). Another important trend concerns the number of tablet users, which will grow to 1.43 billion people until 2018 (eMarketer, 2015). Tablets have bigger screens than Smartphones but are heavier and less convenient to carry. On the other side, they are easier and more convenient to carry compared to laptops or even desktop PC´s (Fritsch, E. 2011). Tablets allow users to watch movies or browse for information on a bigger screen compared to smartphones. As those devices are closing the gap between small size devices and large screen devices, they have potentially influence on consumer behavior during ecommerce and a certain role in the customer journey. With the implications from tablets there were also questions regarding the use of this devices. As identified by Ghose, Goldfarb and Han (2013a) there is a gap in knowledge regarding the use of tablet devices compared to smaller mobile phones and bigger desktop PCs. The gap concerns influence of screen size on browsing behavior and if browsing behavior is more similar to desktop or smartphones. This gap needs to be closed to find out more about the implications of this new mobile device type. This gap was also identified by the Marketing Science Institute in its 2016 – 2018 research priorities. In their priorities, they asked the question how mobile devices are affecting purchase behavior and customer journey on different levels. One of the sub questions aimed directly on the influence of device type within ecommerce in different phases (Marketing Science Institute, 2016). Different devices seem to have different functions in the purchase process. With knowledge of the preferred device type for task, marketers, professionals and educators can better target their messages. Next to that with knowledge about touch points and device preference companies are able to tailor their offers better to the customer.

1.2 Research Goal

Concerning both domains there are emerging questions about customer behavior in ecommerce while taking the device type of customers in their purchase journey into account. Questions concerning how buying behavior between mobile devices is different. Next to that it is also interesting to see where there are similarities between devices and where users behave in the same way. Regarding the identified gap in knowledge, Ghose et. al have identified it is to ask what the implications of different mobile devices type on behavior is. Concerning the importance of ecommerce in the future years, there is a clear gap in research. According to Puccinelli et al. (2009) there are 4 stages in the purchasing process, need recognition, pre-purchase activities, purchase decision and post-purchase activities. The first two concerns informational behavior where users are looking for more information about a product. In these phases customers are likely to see a review or test page to gather more information about different products. Purchase/buying behavior is concerning the intention to buy a certain item. Customer in this phase are looking for the comparison of prices to find the best offer (Hanlon, A. 2013). In this research, the focus will be more on the later one. What are potential patterns in browsing behavior caused by device type and what is the influence of mobile devices on customer journey, especially with purchase intention. Next to that, it will be examined if device type has influence on the number of products customers typically browse through. It is to assume that people browsing on a category page are deeper in the funnel and already decided to buy a certain item. Therefore, purchase behavior will be characterized within this research as (intention of) out clicking from a product/category page to a shopping basket or to a page offering the product for a specific price. To guide the research and close the gap in knowledge the following main question with its three sub questions will be used.

What is the influence of device type (smart phone, tablet and desktop) on purchase behavior during ecommerce sessions in the customer journey?

- *What patterns in behavior are typical for each device type?*
- *How is device type influencing the number of products customers browse through?*
- *Is there a difference in out-clicking behavior regarding different devices?*

2. Literature Review

2.1 Theoretical Models

After defining the scope of the research, it is now to find literature. Cheung et al. (2003) have found out that principles influencing web behavior are not generally different from principles influencing real life behavior. This indicates that traditional models can also be applied in online environments. In this situation, the Technology Acceptance Model (TAM) is one of the most widely used models which use two key variables: perceived ease of use and perceived usefulness (Davis, Bagozzi & Warshaw, 1989). Some recent studies have extended the framework and added perception as third variable (Childers et. al, 2002). This indicates that the easier and more useful online purchases are for customers, the more they are used. The easiness of use related to certain device types could be a contributing factor in ecommerce too. Research by Jamil and Mat (2011) suggests that purchase intention may also positively influence purchase decision and is therefore also to count as influencing variable. According to Kim and Hong (2010) website owners should understand customers behavior in order to build and maintain a good relationship with them. Research has shown that the more experience a user has with ecommerce in particular, the more likely they are satisfied (Pappas et al. 2014). In the buying process itself, Kumar and Dange (2012) have identified different contributing factors and grouped them together in the FFF model. In this model, there are there are three stages. First internal and external factors affect consumer buying motivation. Then various filter elements apply to make a selection of a store to buy from and finally purchase motives are revised and an item is bought. In their model is a strong focus on privacy, security and trust, which heavily influence customer behavior and readiness to buy so customer rather tend to leave a shop they did not trust.

2.2 Factors in web environments

For online environments, extensive research was done to identify different contributing factors for purchase intention and decision. The first important factor concerns trust. As mentioned, trust and privacy issues are of high importance in web environments. Research by Tsai et al. (2011) has shown that perceived privacy invasion results in a negative attitude towards a brand or a shop. This negative attitude can negatively affect customer willingness to buy. According to Kim, Ferrin and Rao (2008), the negative effects can cause customers to look for different web shops or postpone their purchase decision. Therefore, marketers should aim to generate trust and use trust building factors in order to do so (Hsu et. Al, 2014). This effect also applies for remarketing efforts when certain ads appear too often. In this case users feel vulnerable and avoid clicking on the website or the add (Aguirre et al. 2015). The perceived risk of transactions and privacy plays an important role in the process of building consumer trust. Businesses need to develop appropriate strategies and tools to ensure security for customers in order to facilitate further growth of online channels and ecommerce (Akther, S. 2014).

Next to trust related factors, also other factors contribute to the purchase decision. Constantinides and Geurts (2005) have identified that one of the most important factor for purchase behavior is the usability of the website. If the loading time of the page or the usability and find ability of products is difficult, then users tend to leave the page. Next to that, research has shown evidence that product type is influencing buying decision in online advertising. Bart, Stephen and Savary (2014) found out that high involvement and utilitarian products are more likely to sell in online advertising. A study by Grewal and Levy (2016) found out that customers frequently use apps to search for information, e.g. to find the best restaurant in the area around them. The same applies for mobile searches as well where customers are able to view information instantly at any place and any time they want. Research has shown that those location based services and their impact for ads is influenced by external factors such as time of day or local crowding (Andrews et al. 2015 and Baker, Fang and Luo 2014). This means that external factors can also contribute to user behavior in a way which can facilitate or cease marketing efforts. Data has shown that customers are most likely to react on email with shopping intent around 8am to 1pm and from 5pm to 6 pm (Presman, J. 2015). For research in online environments, these external effects could bias data collection or even be responsible for certain findings. Research by Molitor, Reichhard and Spann (2014) supports this claim as they identified that response rate for SMS coupons and consumer choice is highly depending on time, weather, place and mobility of customer. Taking this information into account, it is to assume that those factors can also have influence on purchase behavior. Therefore, external factors are of importance when evaluating consumer behavior regarding device type. These external factors can also bias the results of our research so there needs to be an eye on it.

2.3 Device Type

Another important factor is the device type itself. Mobile screen size varies between different device types from 3.5 inch for the smallest Smartphone available to 12.9 inch for an iPad Pro, a Tablet device. The size of the screen is substantially influencing browsing behavior as shown by Ghose, Goldfarb and Han (2013a), which identified that search costs for users are higher on smaller screen as they require more time spending. This time effect could have also influence on general user behavior in buying situations as mobile devices require a higher amount of time spent to reach a certain goal. Screen size can also have influence on reaction time for users in the context of surveys, Liebe et al. (2015) discovered that users on mobile spend more time on filling out a survey that compared to tablet or desktop devices. Next to that survey, quality is not affected by the use of mobile devices. As most mobile devices are equipped with touch screens, they also have implications for user behavior. Brasel and Gips (2014) have identified that touch screens can lead to endowment effects in advertising which enhances its effect. This leads to higher response rates of users. In general, it is to state that device type and screen size substantially influence the user in his behavior. Lee at al. (2017) found out that Smartphones and Tablets are complementing each other which indicates a relation in the customer journey. Moreover, traditional desktop PC´s are less important compared to the implications of tablets. Burford and Park (2014) have identified that tablet devices limit the amount of information user's access by the stronger focus on apps. Implications are coming from past research, where Smartphone users typically spend less time on websites than desktop users (Chaffey, D. 2017). Taking different variables of influence for the usage of different devices into account, it is to mention that age of the participants has an influence on how they use a certain device type (Kang and Yoon, 2008). Regarding cross device use it is to state that Smartphone's as well as Tablets are wide spread among the population, which means people use a variety of device types for accessing the internet (eMarketer, 2016d). On top users are strongly focused on mobile devices while desktop only shrinks to less than 10% in the population (eMarketer, 2016e). Switch from device types could mean on the on hand that users only use one device type or the usage of device types is more fractioned which could also influence the research and should be monitored in the process.

2.4 Website Research

Ghose, Goldfarb and Park (2013b) have identified that experimental research has a lot of unused potential. This approach involves different experiments and observations directly on a web page to draw inferences about consumer behavior as well as information about the influence of certain marketing techniques. For our type of research, different analytical tools can be utilized. Web analytics can be divided in several sub domains; one is for example the field of click analytics. According to Kaur and Singh (2015), the click behavior of users is analyzed in order to draw inferences which parts of the website they click on. Clicks can be interpreted as points of interests, so with the use of click maps it is possible to draw conclusions why people are clicking on certain parts of the website. In usability testing of websites different heat maps, tapping maps and block maps are applied to measure behavior. According to Choros (2011), it is possible to use scroll maps do determine how much of a webpage a user has seen. With tap and click maps one can see which parts of a webpage are of interest for customers and which parts are not regarded interesting. Next to this relatively new research method, classical web analytics allows to collect data such as time on website, bounce rate or previous/next page visited (DeMers, J. 2014). The time on webpage allows to draw inferences how interested users are while bounce rate allows to draw inferences about the percentage of users which is instantly not interested (Pakkala et al. 2012). Next to that, with Google Analytics it is possible to draw a lot of other demographic data about customers such as age, gender, landing channel or device type. Those data is used a lot in classical web marketing and by site owners. According to Patel (n.a) data from web analytics can have tremendous effect on web performance and allow marketers to tailor messages more effectively to the customer. The obstacle with this kind of data mining is that each tool has advantages and disadvantages that need to be in balance when it comes to scientific research.

2.5 Hypothesis

H1: Customer on smartphones will browse through fewer shop articles than people on tablets or desktops

This hypothesis bears from the fact that search costs are higher for users on Smartphones compared to Tablets and Desktops (Ghose, Goldfarb and Han, 2013a) because of screen size. Customers using Smartphones typically have to spend more time on the page to see and equally big part of the page content than other users. Interpreting the results from Chaffey D. (2017), where users on Smartphones spent less time on the page, it is to expect that there is a connection. The smaller screen size compared with lower time spending on the web page will limit the amount of articles Smartphone users can browse through.

H2: Tablet and Desktop users will apply more filter options in the shop to group items

As taking the time on a webpage into account, it is to expect that users on Desktop and Tablet spent more time on the webpage (Chaffey D. 2017). Therefore and corresponding to H1 it is to expect that users will use the time to alter the webpage according to their needs. Next to that typical Apps limit the amount of information for users. In web environments, this fact does not apply (Burford and Park, 2014). Hence, we conclude that Tablet and Desktop users will typically use more of the available filter options.

H3: Tapping behavior on Smartphone and Tablets is similar

As identified by Brasel and Gips (2014), touch screen lead to endowment effects for users. In web surveys, this effect leads to higher response rates. Next to that, in the research of Liebe et al. (2015) it was discovered that there are no differences in Smartphone and tablet behavior when filling out a survey. Because both device types are equipped with touch screen and size of screen is not significantly different, rather it is to expect that user behavior on these devices is rather similar.

3. Methodology

3.1 Overview

To answer the research question, a real live experimental setting is employed. As pointed out in Fig. 1, we will use a three-step research framework. Because traditional survey research does not provide insights in actual customer behavior, we will use a new combination of already existing methods will be used where survey research is the last step. First, web analytics will be used to draw inferences about customer behavior on page. Classical tools such as Google Analytics will be used to collect general demographic data as well as information which can be used to identify general patterns in behavior. Together with the KPI´s and data from click maps in Hotjar, this can be used to answer the first sub question. The number of products customers browse through will be answered using scroll maps in Hotjar as well as information from Google Analytics. In the last step and to answer the last sub question a survey will be sent out which aims at discovering the motivation of customers for using certain device type during ecommerce. A drawback of the survey is that it cannot be sent to the same people who were observed in the first place but to the same population of people. It can therefore be assumed that this fact will not harm the validity and reliability of this research element. For ensuring validity of the previous collected data, the data in the survey will also be compared to the demographic data from Analytics and device data from Hotjar. To be able to collect

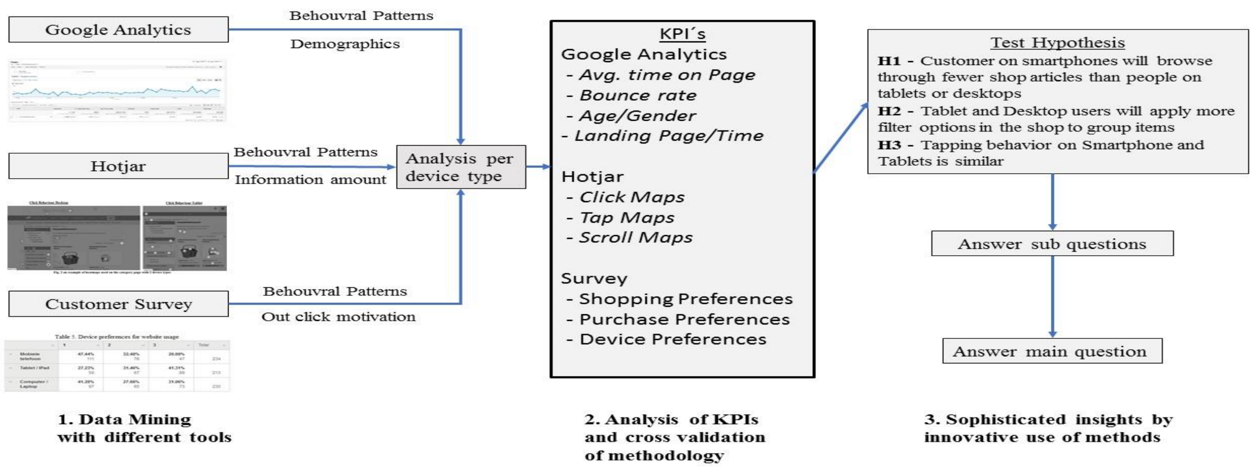

Fig. 1 Research Model/Conceptual Framework

data from customers, the research will be conducted together with a Dutch ecommerce company which provides access to their customer behavior data. The combined use of data mining techniques in combination with different sub questions aimed at different aspects of the construct allows for new insights into customer behavior. The reliability of the different methods will be measured by different indicator as well as compared between methods. If the variance between the different methods is increasing, one can expect that the reliability as well as validity goes down. For the analysis, different variables and KPIs will be measured. Device type itself will be the independent and nominal variable. In the research, we do not have influence which device type customers chose for. This metrics will also be used as one of the tests to determine the reliability and validity of the research. As one can see in the model, each data mining part has its own KPI´s which will be combined to first test the hypothesis and then answer the research question.

3.2 Website description

The website is from a large Dutch online retailer/comparison company. On the website are different sections such as a comparison part for products, blog articles and e books. The e books provide information about the market niche and are the first step in acquiring new customers. Next to that, blog articles are published on a regular base to generate organic traffic for the webpage. On the shopping part customers can compare different products from different online retailers. They can employ certain filter functions as well as search for unique characteristics of the product they want. Information such as pictures, prices, shop descriptions, characteristics and product details are available for the customer. If the customer decides to purchase a certain item, he will be forwarded to the web shop offering the product. On the website are over 50.000 unique products available for comparison with an average of more than 2.000 visitors a day for the entire website as of January 2017. Regarding page load time it is to mention that the page itself loads very quickly so customer behavior will not be biased by this factor,

3.3 Design

In the research, the regular traffic of the website will be observed over a timeframe of six weeks. The timeframe is considered long enough to rule out any kind of selection bias caused by special events or seasonal effects. Next to that, due to the timeframe, any effects regarding day time and landing channel are not biasing the results which improves the validity of the study. For the research one category page will be equipped with mentioned web analytical tools and used for observation. In the total time of observation around 20.000 unique page views were counted for the entire shopping part. On the mentioned category page 805 unique page views were observed. This counts of 3.87% of all shopping sessions and provides a reliable base to draw implications about user behavior. The classical web analytics tool collects information about every page visit while the advanced tool uses a sample of the users. For this sample 530 sessions were counted on Hotjar which accounts for 65,84% of website visits. On the category page the user can find utility products for the market niche (N=38). It can be considered that the product type does not have influence on user behavior in this research. It is because customers on a product page are considered to browse with purchase intent. Next to that, the products are not luxury items which involve high engagement of the customer.

For the second level, a survey will be send out to the customers with questions regarding their motivation behaving in a certain way. The survey is also used to validate the findings drawn in phase one by web analytics. For privacy reasons sending out the questionnaire to the same people who were observed is not possible. To solve the issues and get a reliable sample, the emailing list and social account of the participating company will be used to send the survey out. In this list over 4000 emails of customers are collected and over 10.000 customers like the page on Facebook. Due to size of the sample collected, it is to assume that the population observed and the population from the questionnaire is behaving in the same way. To ensure this expectation is met, different control questions will be ask to be able to compare the demographic data of customers to the previous collected data on page. The survey will be sent out and declared as help in optimizing the webpage. Due to the unobtrusive character of the survey, response bias can be ruled out which improves validity. For a higher response rate, a price will be given away among the participants. The price is a special item worth around 80€ which was used to increase response rate.

3.4 Web analytics

For the observation two different tools for web analytics will be used. For ethical as well as legal reasons customers browsing on a webpage need to declare consent that cookies are placed to track information about web site visit. In the case of this research the same fact applies which rules out ethical as well as legal problems. In Google Analytics, one can see a large set of different variables. Among those variables are information such as device category, time spent on webpage, landing channel, out clicks, gender, age, region or visiting time. This kind of tool allows to collect a large set of demographics as well as personal information. The most important KPI´s are mentioned in Fig. 1. Time on page and bounce rate were chosen as they also tend to provide information about trust of the customer as well as the level of interest. High bounce rates are associated with problems on the webpage. Age and gender are used together with the survey for cross validation of the findings. The limitation of this method is that it only provides numbers and no information how customers behave. To close this gap, Hotjar will be used. It allows to create different maps to grasp information about how customer interact with the webpage and with different information on it. We will create heat maps, where clicks, tapping and scrolling behavior can be measured. In combination with classical web analytics this kind of information will bring new insights into the field of consumer behavior research. To be sure to analyze the same sample, the counts for different device types will be analyzed which increases validity of the study. As pointed out, Hotjar uses a sample of web sites visitors which is typically above 50% of all web site visitors. The sample is randomly collected and evenly over the day to rule out any form of bias.

3.5 Participants

Participants are observed as regular users of the mentioned category page. For the first part of the research the following statistics apply. The sample comprises of 1129 page views from which 805 are unique page views within one session. Participant’s age collected from 570 page views ranged from 18 to older than 65 grouped in 6 categories, including 235 persons where no information about age could be collected. In case of gender information for 579 customers is available while for 226 customers was no classification possible.

The email with the questionnaire was opened by 1121 customers while 350 clicked on the corresponding link to the questionnaire. On Facebook, the post was liked 34 times. In total, after one week, the questionnaire was answered by 395 people. For ensuring validity and reliability we only used fully completed surveys and took only people in the final sample who have ever visited before the webpage. Hence the final sample comprises of 286 customers.

3.6 Variables

The variables taken into consideration in this research are taken from different data sources as one can see in Fig. 1. From Google Analytics data such as device category, age, gender, time spent on webpage, next page visited will be considered to answer the first sub question. Next to that some other information such as region, visiting time and traffic type will be checked to rule out potential bias in the data and ensure validity and reliability of the findings. Also bounce rate will play a role as it is an how satisfied customer are with the webpage. From Hotjar click maps, scrolling maps, tapping and mouse movement maps per device category will be analyzed in the research to answer the second question. Both data sources allow us to grasp a full picture about how people behaving on the webpage. Based on these variables and on the findings a survey will be sent out to validate the findings.

The survey is indented to deal with two main elements. First the validation of findings from phase one as well as discovering reasons for certain behavior. In the first questions customer are asked general questions to themselves (age and gender) as well as they have ever visited the webpage to only have significant answers. Next questions to their preferences for certain device types in certain situations are asked. Then questions are asked which deal with discovered patterns in web analytic and finally situations are given in which customers can chose or a certain device type in purchase situations (Exh. 1).

3.7 Procedure

The research started with the simultaneous set up of the two mentioned analytical tools on the webpage. In the upcoming four weeks, data was automatically collected and already pre-observed. This pre-observation was necessary to set up the survey. In week five the survey was sent out by email as because it was not wanted from the partner company to directly ask customers. To be able to get information from the same population for the survey the collected email list of the partner company was used. We assume that both samples are from the same population so validity and reliability is ensured. By comparing demographic and device data we will test this hypothesis before the final analysis. Hence, it is to conclude that the two separate ways of data collection are useful to answer the different sub questions and provide better insights into customer behavior on web pages. We expect that the combined use of methods allows researcher to more easily collect information for future research. Because the methods are looking at the same population (shop visitors) we believe that the two studies are not independent from each other but complementary.

3.8 Limitations

Due to the nature of the research, there are some limitations. Because the study is only conducted on one web page, it cannot be concluded that the findings are generalizable for the entire population of ecommerce visitors. For the heat maps there is no distinction possible between new and returning visitors. This problem cannot be solved with the current use of technology as this program at the moment is not able to fulfill the task. Regarding device types, it is to say that it is with the technology at hand not possible to draw a perfect line between new and returning customers when it comes to different devices, therefore cross device influence on behavior cannot be measured. The last obstacle comes from the nature of the research because different methods are combined. There is not much research done about combining those methods together. There is the possibility that the outcome of the research is affected by the methodology. Overall, we will test at different stages if the characteristics of the population are the same to ensure validity but there is still the possibility that some variance is caused by the method of research.

4. Data Analysis

4.1 Google Analytics Statistics

4.1.1 Device type

The first and most important metrics to look at is how visitors are split among the different device types. Then other important metrics will be used to grasp their level of influence on device type. As 805 being the total number unique page views, 311 are using mobile devices such as smart phones to access the webpage (38.63%). On the other side 270 customers using desktops to access the page which equals 33.54% of total sample. The last device type is the tablet with 224 users in the observed timeframe which equals 27.83%. Regarding just the use of the device types it is to mention that smart phones are used the most but on the other side there are also high numbers and percentage values for the other devices. Concerning average time on webpage smart phone users spent around 0.53 minutes on the page, desktop users 1.04 minutes and tablet users 1.06 minutes. Taking bounce rate into account the highest one is visible for smart phones with 46.98% while desktops (35.04%) and tablets (37.10%) are very close together. Taking the numbers of average time on page into account at this point it is to state that desktop and tablet devices are more similar than tablet and smart phones. Regarding validity and reliability, there are no problems as data is directly taken from customers device which is nearly impossible to manipulate.

Table 1. Device types

	Unique Page Views	Avg. Time on Page
Smartphone	425 (37.64%)	0.53 min
Tablet	314 (27.81%)	1.06 min
Desktop	390 (34.54%)	1.04 min

4.1.2 Age of web site visitors

The first variable which could influence the behavior is age which is grouped in 6 categories. As one can see from the graphic the different age groups are divided relatively equal among the customers. Low percentage values are only observed for customers between 18-24 and +65. This equal distribution indicates that the data will not be biased by a certain age group. Interesting in the data is that the average time on page for people younger than 25 is significantly different from the rest of the customers while bounce rate is highest for customer between 25-34 years.

Table 2. Age groups

Age	Unique Page Views (N=570)	Unique Page Views in%	Avg. Time on Page in seconds (Total 0.58s)	Bounce Rate in % (Total 40.67)
18-24	44	7.72%	0.27s	37,21%
25-34	102	17.89%	1.09s	53,41%
35-44	94	16.49%	0.55s	47,78%
45-54	162	28.42%	0.57s	34,42%
55-64	129	22.63%	1.03s	35,25%
65+	39	6.84%	1.02s	41,03%

Concerning age over device type (App. 1), one can see that for younger customer (18-34) no comparison is possible as the in both categories one device type was not used at all. In the category of 35-44 we found a significant difference in the time spent between devices. Smart phones are accounting for the highest time spending with around one minute time spending while desktop and tablet values are roughly half. In category of 45-64 devices are equally distributed while the time spending on tablets is significantly (around 45 seconds) higher than for desktop and smart phone. Regarding bounce rate there are no big differences between certain groups. Drawing conclusion tablet devices are more comparable to desktop than to smart phones when regarding the influence of age on device type. As age is estimated by Google Analytics, the validity of this metrics cannot be fully guaranteed but will later be compared with the survey.

4.1.3 Gender of web site visitors

Next to the age the gender is of interest as it allows drawing inferences about the target population. As stated previously data was available for 579 customers in total which is due to the algorithm of Analytics. During the observation, it turned out that 476 customers, which accounts for 82.21% of the sample, are female. On the other side 103 customers were male which accounts only for 17.79% of the sample male. There is no significant difference in bounce rate between male and female. These numbers do fit to the general population of the product which means that the high number of women is no other than expected. It will be assumed that gender does not have significant influence on purchasing behavior in this research.

4.1.4 Traffic Type

In case of traffic type, 77.27% of the traffic is organic which means 622 entered the page by a search engine. Compared 97 customers came in by a link which accounts for 12.05% of the sample. The other 85 customers entered the URL directly in their browser and one customer found the page by a link in an email. Traffic type can have an influence on behavior as it shows how people came to the webpage. Concerning time on page for organic visitors the average time is 0.58 minutes while customers who entered the webpage directly spent on average 1.21 minutes on the page. The difference is not quite big and potentially because people who enter the page directly most probably are returning visitors. Concerning bounce rate there are no differences between the groups.

Regarding traffic type over device type (App. 2) we found that for organic traffic the average time on page is with 1.08 minutes the highest for tablets while smart phone (0.52 min.) and desktop users (0.55 min.) comparably spent less time on the page. Taking bounce rate into account which is highest for smart phones with 46.05 percentage points while tablets (38.58%) and desktop (34.92%) values are slightly lower. The same applies for referral traffic; also here tablets and desktop values are more similar than Smartphone values.

4.1.5 New over returning visitors

When taking new and returning visitors into account, we observed 641 sessions which are classified as new visitors and 164 sessions which are classified as returning visitors. For reasons such as clearing browser history, using different access devices on different times the true numbers could vary from the ones collected which has influence on the validity of this section. Taking time into account the average time on page for new users is 0.54 minutes while returning users spent on average 1.28 minutes on the page. Bounce rate for new visitors is lower (37.92%) than for returning visitors (52.34%). In general, we would expect from returning visitors a significantly lower bounce rate as a longer average time spent on web page should indicate.

Concerning new and returning visitors over device type (App. 3) one can see that for smart phones new users typically spent 0.54 minutes on the page compared to 0.50 minutes for returning users. Also bounce rate is higher for returning users (69.64%) compared to new visitors (41.74%). For desktop devices time on page for new visitors is with 0.51 minutes significantly lower than for returning visitors with 1.45 minutes. Concerning bounce rate new visitors have a value of 32.54% compared to 51.52%. Looking at tablets new visitors spent on average 0.57 minutes compared to returning visitors with 1.41 minutes. Concerning bounce rate new visitors have a value of 39.01% compared to returning visitors with 28.21%. Drawing conclusion we can see that from the numbers the values for tablets and desktops are more similar.

4.1.6 Day and time

When looking at the days when most visitors come to the site one can see from the table that in the beginning until the mid of the week most visitors enter the page (App. 4). In the weekends, the numbers are a little bit lower. Regarding time spent on page there is not much difference between the days. When looking at the exact hours of a day, one can see that in the mornings and evenings where most people commute visiting time goes down and bounce rate goes up. In general, as day go forward the number of visitors increases. So, we found that daytime has an influence on the number of visitors.

Regarding device type we see a clear pattern. Within the day desktop and tablet users are mostly more present than mobile devices. With the end of the working days desktop declines and smart phones are dominantly used while tablets are the second largest group. Same applies for time spent on page where numbers for tablets are constantly higher than for mobile and mostly comparable to desktop. We can conclude that daytime plays an important role for device choice and therefore has influence on the behavior of the customers. This information also gets interesting when it comes to cross device use over the day. (App. 5).

4.2 Hotjar data collection

4.2.1 General Statistics

In the observation time 530 samples in Hotjar were collected. As the program, itself randomly takes a sample of the website visits, the samples are drawn from the total number of unique page visits which is equal to 805. Therefore, Hotjar took a sample of 65.84% of all page visits in the time, ignoring new and returning visitors. The sample is as already pointed out randomly taken across all page views of a day and evenly over the day collected. Therefore, the sampling algorithm of Hotjar rules out potential sampling bias automatically. The problem which arises is that the sample size could potentially be too small. In this case because 65% of the Google Analytics sample are represented in Hotjar we would expect this threat as to be relatively small. Therefore, the validity of the data is relatively high, problems could arise with the reliability. Because Hotjar automatically takes information from the customers the following numbers are completely valid as they directly come from the visitors themselves and it is potentially very hard to manipulate the data. To ensure the results are valid and reliable, the following numbers will then be compared with the previously collected data. For smartphone, the sample is 233 which accounts for 43.96%. Tablets account for 145 page views which are equal to 27.36%. The number for desktop is quite the same with 28.68% or 152 page views in total. Comparing the numbers to analytics data from the previous section one can see that the number for Tablet is quite the same with approximately 1% variance. The percentage value for Desktop is roughly 8% higher and the value for Smartphone roughly 7% lower. The difference could be explained by the algorithm behind Hotjar. Drawing conclusion we can say that the variance is not very big between the two different data sets which strengthens our conclusions. This methods conclusion also gets valuable when comparing different data sources on a webpage in the future.

4.2.2 Scroll maps

The scroll maps measure how much of a web page a user has seen and how deep he has gone on the webpage. Because of mobile and desktop optimized websites it is necessary to find a way where it is possible to compare each device type. Therefore, in this analysis and based on the webpage the number of products a user has seen will be base for the analysis. On the left side of the table one can see the number of products while in the middle there is the percentage amount of people who have seen this number of products.

We found that for tablet and desktop devices the numbers are nearly equal. Only slight differences apply which can possibly be based upon the different site structure on each device type. For smartphones, the numbers are on average 20% lower which indicates that smart phones small screen could limit the amount of information users can receive. One reason for the lower numbers is possibly the site structure where smart phone users get to see a longer introduction text. Another reason is the mobile site structure which shows less products in the same moment compared to other devices, on average 2-4 products less on screen. In combination with the lower average time on page for smart phones we can conclude that this device type limits the amount of information. One concluding remark would be that tablet and desktop devices are better suitable for online shopping as they allow to see more products in less time. When taking **H1** into account we can prove with the data that smart phone users indeed see fewer articles compared to tablet and desktop users. To see the same number of articles smart phone users have to scroll deeper and spent more time on the page. As mentioned with average time on page we can say that the opposite effect is true. Therefore, smart phones limit the amount of articles people can see which has influence on online shopping.

Table 3. 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%

4.2.3 Click maps

From the click maps one can see where the users clicked and showed interest on the webpage. To draw inferences about user's behavior two different ways of analyzing the results will be applied. First, we will look where points of interest are in general and how they are distributed among the page and between device types. Then based on the results, clicks will be counted for different areas and be compared for certain devices. By observing the tap and click maps of the different devices we found a strong focus of clicks on several key areas. The clicks were mostly spread among key functions of the webpage such as sort function and filter function (Fig. 2) Those areas can be used to order the products according to their prices as well as searching for different products based on several characteristics. Next to that, clicks and taps were spread among the product image, the short description of product as well as the yellow "*Call to Action*" button. Based on these findings we decided to count the different clicks and spread them among device type.

As one can see in the table we found that the sort function was used rarely. For Smartphone users only 2 clicked and changed the sorting function. Tablet users did not used the sort function as no clicks were counted and only 5 desktop clicks were counted in this area. The next area of interest is the filter function which influences how the product list is presented. For the filter functions no smart phone customer used this function at all. For tablet devices 15 clicks were counted and 27 desktop clicks were counted. According to the data we can prove **H2** that Smartphone users apply less filter options than users from other devices. As they spent less time on the page, smart phone users typically take the page as it is. We conclude therefore that smart phone devices do not only limit the amount of information people receive on a page as stated in **H1**. This device type also limits how people interact with the page itself as people get used to accept a webpage as it is which could be exploited by companies.

Table 4. click distribution per device type

	Smartphone	Tablet	Desktop
Sort Function	2 (100%)	0 (0.00%)	5 (15.15%)
Filter Function	0 (0,00%)	15 (100%)	27 (81.82%)
Total Sort & Filter	2 (1.42%)	15 (15.15%)	33 (24.44%)
Image	53 (38.13%)	43 (51.19%)	53 (51.46%)
Description	18 (12.95%)	6 (7.14%)	19 (18.45%)
Call to Action Button	68 (48.92%)	35 (41.67%)	31 (30.10%)
Total Product clicks	139 (98.58%)	84 (84.85%)	103 (76.30%)
Total Clicks	141	99	135

The actual buying behavior is measured by clicking on the product. Here it was decided to split the product in three different areas of interest, the product picture, the short description and the CTA button. For product picture, we found that 38.13% of all smart phone clicks were placed on the product picture. Compared to tablet users where 51.19% of all clicks were placed on picture and desktop with 51.46%. The variance between tablet and desktop is rather small while there is big difference compared to smart phones. The description text was clicked by 12.95% of all smart phone users compared to tablets with 7.14%. Again, desktop users have the highest value with 18.45%. For the CTA button, we found that nearly 50% of all smart phone clicks were directly

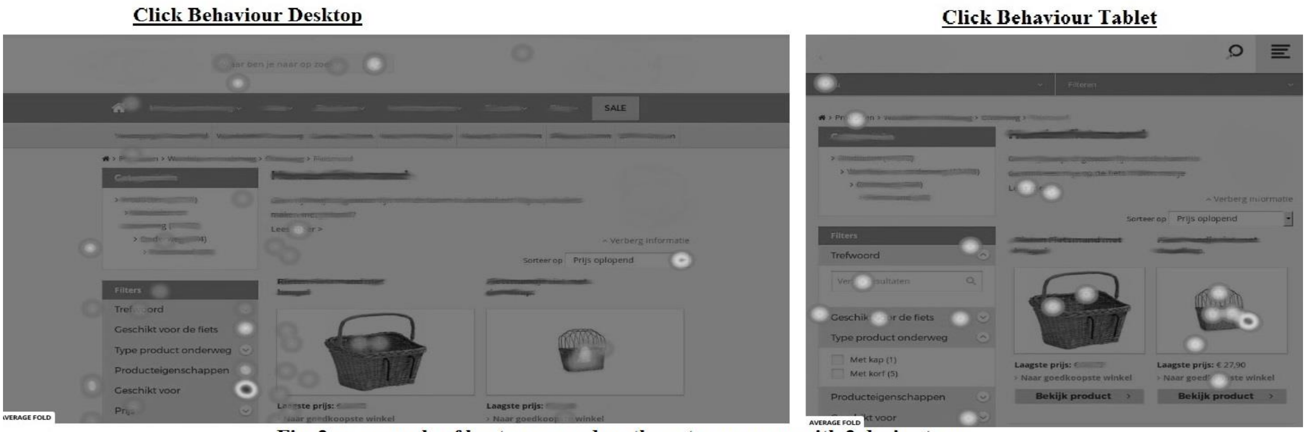

Fig. 2 an example of heatmaps used on the category page with 2 device types

placed on the picture. The numbers for tablet devices are with 41.67% closer to smart phone than to desktop with 30.10%. In general, the clicks among desktop devices are more focused on product images. Tablets are equally divided among Image and CTA button and smart phone users have a strong preference for the CTA button. One can conclude that the smaller screen size emphasizes clicking behavior which is aimed at points of interest on the webpage which are directly visible like a differently colored CTA button.

Regarding **H3** that tapping behavior on touch screen devices is similar we need to reject the hypothesis. Concerning images, we can clearly see that smart phone behavior is not as similar as tablet behavior because people are clicking less on the product pictures, around 13% less clicks. Comparing the behavior between both devices by clicking behavior on descriptions there is also a difference of 5%. The last difference we can see is that clicking behavior on CTA buttons varies with around 7%. Regarding those numbers we have to reject our hypothesis. Possible reason for the difference in clicking behavior could be that tablet devices are not just an extension of smart phones but an independent device type in the customer journey. For possible reasons, the following questionnaire could provide insights in customer behavior and reasons for choice of certain device types.

4.3 Survey data collection

4.3.1 General Statistics

The survey has three main functions. First it is aimed to answer the third sub question and find motivation why certain device types are used and which device type is most likely used in ecommerce and for different functions in customer journey. Second it aims at discovering motivation and extra information for the other research questions. Lastly, the survey aims at validating and cross checking the data collected in the previous section. Regarding reliability and validity, it is to say that the survey was sent out to the same population. To ensure validity and reliability three questions were added to be sure the same population is addressed. The first question was if people have ever visited the website of the Dutch retailer before. Because we only included positive and full answers of the 395 responses a sample 286 respondents will be used for analysis. After that question, we asked for the age of the respondents. These values are similar compared to the data collection from Google Analytics. The variance in percentage is between one to three percentage points which can be regarded as not significant to influence the results. Therefore, at this point we conclude that from the age of the participants both samples do match which also increases validity of the findings. Next metrics to consider is gender of the participants. Here we found that from the 286 respondents 27 (9.51%) were male while 257 (90.49%) were female. Comparing the results to the findings in analytics we see a variance of eight percentage points between male and female. We see that the category for women is bigger in the survey sample than compared to the analytics sample. The variance could be explained by the fact that Google Analytics takes data of the users into account to estimate gender. Therefore, a certain failure rate seems to be normal. In general, we can conclude that in this regard validity of the data is ensured. Hence, we conclude that both sample belong to the same population and that the characteristics between both samples are the same. These findings strengthen the conclusion that for future research the combination of different methods will be of interest.

4.3.2 Preferences use of device

First question in the survey was to rank with which device types the users prefer to visit the webpage. The ranking contained the three mentioned device types and a ranking element from 1 (preferably used) to 3 (not preferred device). As one can see from the crosstab there is a strong preference for smart phones as 47.44% of the visitors prefer to use this device type to access the page. Compared to desktops which rank second with 41.28% of the users. On the other side tablet device are smaller with 27.23% of the users preferring to use it. The second preferences are divided as follows. Again, on the first place are smart phones with 32.48% preference. On the second place, we found tablets with 31.46% and desktop on third place with 27.66%. On second place, we found desktops with 31.06% and on first place smart phones with 20.09%. Comparing the data to the previous collecting methods, we see that for tablets the values are nearly equal. For the other two devices, we see that mobile phones are the most preferred device with 10% variance to the Analytics data. The variance for desktops is a little bit lower with around 7%. For Hotjar there is no comparison needed as the variance between Hotjar and Analytics was very low. The reason for the variance in device types could possibly be found by the two observed variables time and new and returning visitors as well as the third variable cross device usage. From the time variable, we saw that during the day desktop devices were used more frequent while in the evening smart phones was the preferred device. Next to that, in the new over returning data (App. 3), we saw that the values for both devices are closer together than in the regular data. The third variable, which we cannot measure, could therefore have influence on the user preferences as it is likely that users during the day use more than one device type.

Table 5. Device preferences for website usage

	1	2	3	Total
Mobiele telefoon	47.44% 111	32.48% 76	20.09% 47	234
Tablet / IPad	27.23% 58	31.46% 67	41.31% 88	213
Computer / Laptop	41.28% 97	27.66% 65	31.06% 73	235

4.3.3 Preferences for device in ecommerce

To emphasize the differences in device type and the differences in behavior we decided to ask the customers which device they prefer in online shopping. The pre-condition was that they do shop articles in the internet. From the 286 customers 275 responded positively and where presented the question. In this case we saw from the data that 56.85% of the customers prefer to use their desktop in online shopping. Smartphone was used second with 31.58% and last place was Tablet with 24.06%. Here we see a strong preference for desktop devices while tablets are not used that frequently. When we looked at the opposite, which device was least preferred, we discovered that users had a strong standing against using tablets in online shopping. In this question 42.45% of the customer reported that they most likely will not use their tablet for online shopping. As concluding remark, we can say that the data from observation does not support these values. Here we saw that smartphone are the preferred devices. For increasing content validity, we decided to ask the question slightly different again.

Table 6. Preference of device type in ecommerce from 1 to 3

	1	2	3	Total
Mijn mobiele telefoon	31.58% 72	42.11% 96	26.32% 60	228
Mijn tablet / IPad	24.06% 51	33.49% 71	42.45% 90	212
Mijn computer / laptop	56.85% 137	17.84% 43	25.31% 61	241

In the second question, we asked the customers to imagine they found an article they want to purchase and they have the choice for a certain device type for the buying process. In this ranking, we discovered nearly the same values as in the first question. Here 55.33% of the customers responded that they prefer to use their desktop PC. On second preference, we found smartphone with 32.62% and on third place tablet devices with 25.12%. The reverse values are nearly the same as in the first question. A possible explanation with regards to previous collected data is that customers prefer to use certain devices in the buying process. This explanation is also true with regards to the data when we look at the hour of the day. During office hours, we see that customers more frequently use their desktop than other devices. Therefore, with regards to the data we believe that people do use a mix of device types during the customer journey with different touch points each with different implications on behavior.

Table 7. Case question for preferred device in buying situation

	1	2	3	Total
Mijn mobiele telefoon	32.62% 76	37.34% 87	30.04% 70	233
Mijn tablet / iPad	25.12% 53	33.65% 71	41.23% 87	211
Mijn computer / laptop	55.33% 135	20.90% 51	23.77% 58	244

With regards to our third sub question we can say that device that has influence on buying behavior. We can expect that customers who browse an ecommerce web shop on the wrong device type are less likely to purchase an item in the same session. In combination with the findings that certain device types limit the amount of information, a customer can receive it supports our claim that device type has influence on the buying behavior of customers. Regarding the theoretical models such as TAM, the perceived ease of use could be the explaining factor for this finding.

4.3.4 Influence factors on the page

To rule out potential influence factors on the page we decided to ask two questions to find out more about these factors which could bias our results. The first question was aimed to find potential disturbing factors. As basis for the question we used commonly reported problems for web shops. Here we found that the biggest problem for customers in ecommerce is slow web page. For this question 181 customers used this answer option, which is equal to 67.15%. Second biggest influence factor are the product pictures were 169 customers (61.68% reported that small pictures are a problem in ecommerce. The third big influence factors concern the product description. In this question 137 (50%) of our sample answered that short product descriptions are a problem. The last problem we discovered concerns the presorting of products. For this question 81 respondents stated that this is disturbing in ecommerce. As we see from the data in Analytics and the observation we found that loading time for the web page is no problem in our research, also product pictures are not a problem as a sufficiently high number of people clicked on the product pictures. Confusing with regards to the click maps is that people in the survey reported that the presorting is a problem but only a small percent of the users used the function to regroup the products and only if they had used a device type with bigger screen (App. 6). The second question we asked with regards to the finding in Hotjar for the product picture. We asked our respondents to group the importance of pictures in ecommerce on a likert scale with five choices. We found that nearly two third of our sample thought that a good product picture is very important and one third of the sample thought that it is important to have a good product picture (App. 7). The collected clicks support the claim that product picture. Next to that, the CTA button could possibly enhance clicking behavior in ecommerce which could be exploited by web designers and shops.

4.3.5 Device type

The last questions we asked where about the device type and the preferences of the users. Here we wanted to know how the screen size is influencing the browsing behavior and if a bigger screen is more convenient than a smaller screen. We found that nearly two third of our customers rated a bigger screen important or very important with regards to convenience in browsing (App. 8). This finding is very interesting with regards to the strong use of mobile devices. We found that even though most people in the survey prefer bigger screen devices, small screen devices are widely used and among the biggest fraction of web site users according to the collected data. With regards to the previous finding, there could be a correlation between screen size and willingness to buy as discovered in the previous section. It also strengthens our new hypothesis that there are multiple touch points in customer journey that are reached with different devices.

The second information we wanted to know was for which activities people use a certain device type. Here we found that smart phones are mostly used for easy activities which do not require large time effort. We found that a big fraction of smart phone users for example search for information but a much smaller fraction uses it for ecommerce or comparing products. Compared to that, desktops are mostly used for these activities which require a larger time effort and more extensive activity on screen such as buying and comparing products and services. On the other side, tablet devices are stuck in the middle as there we did not found an area where they were dominantly used. Also, a big fraction reported that none of points is true which suggests that either way the people don't possess a Tablet or they don't use it frequently for those activities. When we match this information to the previous findings of the survey as well as the findings from web analytics, we do see that different devices are used for different functions. In the customer journey, different touch points are done with different devices. We can therefore conclude that different device have influence on buying behavior and each device type has its specific role in the customer journey.

5. Discussion and conclusion

5.1 Contribution to theory

In this study about the influence of device type on buying behavior in ecommerce we observed behavior on different layers in real life setting. First, we found out that customers on smart phones browse through fewer articles compared to tablet and desktop users. This effect gets even stronger when we consider that smartphone users in general and over different influencing variables spent less time on page than customer with other devices. We believe that this finding will contribute to the understanding about the influence of screen size on consumer behavior and especially on buying behavior. Small screen devices limit the customer in the way he is experiencing the shop. We believe that this finding could also be true for other areas in which people use their smartphones. Next to that we found out that smart phone users in our research did not use the filter and sorting functions. This finding also contributes to our opinion that smartphones do limit the amount of information customers can process. Here we believe that if this finding would be generalizable to the entire population, it can drastically change how scholars see the influence of device types on behavior. To previous research about influencing factors we have done now the first step to add device type as influencing factor in customer experience too.

We have also found evidence that different devices are used for different tasks which contributes to the knowledge about touch points in customer journey. Different devices influence the way how customers interact with a web page. Next to the actual buying behavior we found evidence that in the customer journey, different device types are used at different times and for different tasks which indicates that customer journey can no longer be seen as linear process. We think that the customer journey consists of multiple steps in which different devices have specific advantages and disadvantages for the customers. Due to the limited technical capabilities of our study we were not able to go more in detail with cross device tracking which could have provided even more findings in relation to customer journey. What we have seen is that both from behavior and customer response there are clear differences between the device types. We needed to reject our hypothesis that smartphones and tablet usage is similar. We would therefore point out a new hypothesis aiming at the discoveries of the study. Different device types are used in the customer journey for different tasks such as information search, price comparison and buying. Customers of today get in touch with a brand on different ways, different times and different devices. We therefore believe that our study sheds light on the influence of different device types on buying behavior and how customers perceive their use.

Another important contribution to theory is the innovative use of different data mining techniques in this research. Despite the explorative character of the study which lowers the generalizability of the findings. We strongly believe that through cross validation of different variables during the study we decreased bias and increased validity and reliability as far as possible. In future research, we believe that the cross use of different data mining techniques bears huge potential as it opens the scholars the possibility to observe customers in real life setting at different touch points. With even more sophisticated techniques there is the possibility to further increase validity and reliability in this kind of study. We believe also that our methodology could be applied in other areas which work with device type as factor or online environments.

5.2 Contribution to practice

Practical implications come from the nature of our research as it helps to define and understand the influence of different variables on behavior. With the mentioned findings, we have proven that device type indeed has an influence on buying behavior and that there is the possibility that people would postpone a buying decision if they are online with the wrong device type. Companies can use this knowledge to discover in which phase of the customer journey the use of a certain device type is most likely. Based upon companies can improve their cross-device tracking capabilities. On the market are already possibilities to track customers over different devices. We strongly believe with our findings that the importance of such tracking technology will increase soon. Another useful contribution for practice is the use of re-marketing efforts which comes from the finding. With the knowledge of device tracking and times when certain device types are used companies can improve their re-marketing efforts to tailor their messages better to the customer. Studies have proven that wrong re marketing efforts can harm customer relations. We believe that with the right use of this technology and the knowledge about the influence of different variables on behavior, one can enhance the company's capabilities to send out useful and valuable marketing efforts.

Secondly, we believe that in the future companies can use sophisticated findings about the influence of different devices to further improve their web sites and provide a site structure which does not limit the customer. Another and probably dark use of our findings would be that companies exploit how smartphones limit the amount of information and slightly change the presorting of items and/or information to sell some items better. Especially for comparison pages these findings can be of importance as they allow to rank items higher than others. The knowledge about search rankings and device usage could therefore also be used to trick customers.

6. Directions for future research

With the findings of our research we would suggest some key areas to further prove our findings to greater population. First one drawback of our study was the implication and tracking on only one website and only one category page. Limitations can be found here in the strong percentage of female over male customers. We would therefore suggest implementing a similar study on different ecommerce websites across the internet to further investigate on our findings. Next to that, we suggest investigating the cross device use as our findings indicate that customers use different devices in their purchasing journey. By investigating cross device use of customer we believe that a big gap in knowledge can be closed. At first, we suggest on page research to further investigate in which purchase steps different device types are most dominantly used. Based on those findings classical surveys and interviews should be used to further determine the underlying reasons behind. Next to that, we believe that as there is a lot of unused potential in the area of scientific web research. Studies such as Choros (2011) and Pakkala et al. (2012) have already employed single parts of our employed methods. Regarding the reliability of the data we believe that web analytical tools are a good fit for scientific use. With the control variable of device type we have seen that there is little variance between the different techniques. Other tools which work similar to Hotjar also collect entire website data and or cross device use and allow distinction between new and returning visitors which further strengthens validity and reliability.

With regards to the validity and reliability of our methodology we have proven with the cross validation of different factors that the population values are very similar with the used methodology. We therefore suggest to further test the methodology to explore its fits for scientific research on greater scale. We did a first step to reduce bias and increase validity and reliability and believe that with further efforts there is great potential for the methodology. Not only in ecommerce but also in the area of general browsing and web site behavior. With regards to the validity and reliability of those techniques, an interesting approach for the future could be to check if our methods correlate with the findings of eye tracking studies so if clicking and tapping behavior is similar across this type of study. A positive correlation would allow researcher to have an easy to use and cheap technique to draw inferences about customer behavior on web pages without the necessity of laboratory experiments.

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Appendix

Appendix 1. – Age over Device Type

Page	Age	Unique Page Views	Avg. Time on Page	Bounce Rate
All Users		570	00:00:58 Avg for View: 00:01:24 (-30.37%)	40.67% Avg for View: 71.22% (-42.89%)
Tablet Traffic		145	00:01:11	37.76%
Mobile Traffic		260	00:00:50	47.22%
Desktop Traffic		148	00:00:59	31.45%
1.	45-54			
All Users		162 (28.42%)	00:00:58	34.42%
Tablet Traffic		49 (33.79%)	00:01:15	31.25%
Mobile Traffic		70 (26.92%)	00:00:49	39.71%
Desktop Traffic		43 (29.05%)	00:00:51	28.95%
2.	55-64			
All Users		129 (22.63%)	00:01:03	35.25%
Tablet Traffic		52 (35.86%)	00:01:31	39.22%
Mobile Traffic		38 (14.62%)	00:00:46	36.11%
Desktop Traffic		39 (26.35%)	00:00:46	28.57%
3.	25-34			
All Users		102 (17.89%)	00:01:09	53.41%
Tablet Traffic		0 (0.00%)	00:00:00	0.00%
Mobile Traffic		59 (22.69%)	00:00:44	63.79%
Desktop Traffic		34 (22.97%)	00:01:26	28.57%
4.	35-44			
All Users		94 (16.49%)	00:00:55	47.78%
Tablet Traffic		18 (12.41%)	00:00:33	55.56%
Mobile Traffic		58 (22.31%)	00:01:05	48.21%
Desktop Traffic		18 (12.16%)	00:00:37	37.50%
5.	18-24			
All Users		44 (7.72%)	00:00:27	37.21%
Tablet Traffic		11 (7.59%)	00:00:27	9.09%
Mobile Traffic		25 (9.62%)	00:00:27	54.17%
Desktop Traffic		0 (0.00%)	00:00:00	0.00%
6.	65+			
All Users		39 (6.84%)	00:01:02	41.03%
Tablet Traffic		15 (10.34%)	00:01:17	53.33%
Mobile Traffic		10 (3.85%)	00:01:05	20.00%
Desktop Traffic		14 (9.46%)	00:00:45	42.86%

Appendix 2. – Traffic Type over Device Type

Page	Traffic Type	Unique Page Views	Avg. Time on Page	Bounce Rate
All Users		805	00:01:01	40.37%
Tablet Traffic		224	00:01:06	37.10%
Mobile Traffic		311	00:00:53	46.98%
Desktop Traffic		270	00:01:04	35.04%
1.	organic			
All Users		622 (77.27%)	00:00:58	40.20%
Tablet Traffic		188 (83.93%)	00:01:08	38.38%
Mobile Traffic		229 (73.63%)	00:00:52	46.05%
Desktop Traffic		205 (75.93%)	00:00:55	34.92%
2.	referral			
All Users		97 (12.05%)	00:01:01	40.58%
Tablet Traffic		16 (7.14%)	00:00:57	31.25%
Mobile Traffic		29 (9.32%)	00:00:43	55.56%
Desktop Traffic		52 (19.26%)	00:01:15	37.14%
3.	direct			
All Users		85 (10.56%)	00:01:21	41.46%
Tablet Traffic		20 (8.93%)	00:00:56	30.00%
Mobile Traffic		52 (16.72%)	00:01:06	48.08%
Desktop Traffic		13 (4.81%)	00:03:26	30.00%

Appendix 3. – New and Returning over Device Type

Page	Device Category	Unique Page Views	Avg. Time on Page	Bounce Rate
All Users		805	00:01:01	40.37%
New Users		641	00:00:54	37.92%
Returning Users		164	00:01:28	52.34%
1.	mobile			
All Users		311 (38.63%)	00:00:53	46.98%
New Users		246 (38.38%)	00:00:54	41.74%
Returning Users		65 (39.63%)	00:00:50	69.64%
2.	desktop			
All Users		270 (33.54%)	00:01:04	35.04%
New Users		212 (33.07%)	00:00:51	32.34%
Returning Users		58 (35.37%)	00:01:45	51.52%
3.	tablet			
All Users		224 (27.83%)	00:01:06	37.10%
New Users		183 (28.55%)	00:00:57	39.01%
Returning Users		41 (25.00%)	00:01:41	28.21%

Appendix 4. – Day of the week

Page		Day of Week	Unique Page Views	Avg. Time on Page	Bounce Rate
		Days of the week, 0-6 (0=Sunday)	805	00:01:01	40.37%
1.		3	128 (15.90%)	00:00:51	37.07%
2.		0	135 (16.77%)	00:00:58	37.50%
3.		2	126 (15.65%)	00:01:32	41.88%
4.		1	117 (14.53%)	00:00:42	40.54%
5.		5	100 (12.42%)	00:00:53	40.91%
6.		4	103 (12.80%)	00:01:13	41.41%
7.		6	96 (11.93%)	00:01:00	44.68%

Appendix 5. - Hour over device type

Page	Hour		Avg. Time on Page	Bounce Rate
All Users		805	00:01:01	40.37%
Desktop Traffic		270	00:01:04	35.04%
Tablet Traffic		224	00:01:06	37.10%
Mobile Traffic		311	00:00:53	46.98%
1.	**23**			
All Users		32 (3.98%)	00:01:32	30.00%
Desktop Traffic		11 (4.07%)	00:02:20	33.33%
Tablet Traffic		6 (2.68%)	00:00:46	16.67%
Mobile Traffic		15 (4.82%)	00:00:57	33.33%
2.	**22**			
All Users		70 (8.70%)	00:01:01	35.38%
Desktop Traffic		22 (8.15%)	00:01:04	28.57%
Tablet Traffic		20 (8.93%)	00:01:33	26.32%
Mobile Traffic		28 (9.00%)	00:00:36	48.00%
3.	**21**			
All Users		61 (7.58%)	00:00:59	41.07%
Desktop Traffic		20 (7.41%)	00:01:12	47.06%
Tablet Traffic		14 (6.25%)	00:01:15	35.71%
Mobile Traffic		27 (8.68%)	00:00:44	40.00%
4.	**20**			
All Users		61 (7.58%)	00:01:08	56.67%
Desktop Traffic		12 (4.44%)	00:00:15	72.73%
Tablet Traffic		20 (8.93%)	00:00:43	45.00%
Mobile Traffic		29 (9.32%)	00:01:50	58.62%

5.		19			
	All Users		65 (8.07%)	00:01:18	45.90%
	Desktop Traffic		11 (4.07%)	00:00:43	27.27%
	Tablet Traffic		16 (7.14%)	00:02:18	40.00%
	Mobile Traffic		38 (12.22%)	00:00:53	54.29%
6.		18			
	All Users		51 (6.34%)	00:00:39	45.65%
	Desktop Traffic		13 (4.81%)	00:00:50	40.00%
	Tablet Traffic		17 (7.59%)	00:00:36	37.50%
	Mobile Traffic		21 (6.75%)	00:00:32	55.00%
7.		17			
	All Users		56 (6.96%)	00:00:41	31.48%
	Desktop Traffic		21 (7.78%)	00:00:50	25.00%
	Tablet Traffic		18 (8.04%)	00:00:36	22.22%
	Mobile Traffic		17 (5.47%)	00:00:32	50.00%
8.		16			
	All Users		64 (7.95%)	00:00:48	33.33%
	Desktop Traffic		33 (12.22%)	00:00:44	33.33%
	Tablet Traffic		15 (6.70%)	00:00:59	26.67%
	Mobile Traffic		16 (5.14%)	00:00:51	40.00%
9.		15			
	All Users		44 (5.47%)	00:01:16	28.57%
	Desktop Traffic		14 (5.19%)	00:01:09	25.00%
	Tablet Traffic		11 (4.91%)	00:01:07	63.64%
	Mobile Traffic		19 (6.11%)	00:01:24	10.53%

13.		11			
	All Users		47 (5.84%)	00:01:09	46.67%
	Desktop Traffic		20 (7.41%)	00:01:31	27.78%
	Tablet Traffic		16 (7.14%)	00:00:52	56.25%
	Mobile Traffic		11 (3.54%)	00:00:28	63.64%
14.		10			
	All Users		38 (4.72%)	00:00:58	38.24%
	Desktop Traffic		15 (5.56%)	00:00:40	27.27%
	Tablet Traffic		12 (5.36%)	00:01:28	25.00%
	Mobile Traffic		11 (3.54%)	00:00:42	63.64%
15.		09			
	All Users		23 (2.86%)	00:01:24	33.33%
	Desktop Traffic		10 (3.70%)	00:02:10	25.00%
	Tablet Traffic		6 (2.68%)	00:00:36	16.67%
	Mobile Traffic		7 (2.25%)	00:00:53	57.14%
16.		08			
	All Users		19 (2.36%)	00:01:10	44.44%
	Desktop Traffic		3 (1.11%)	00:00:33	66.67%
	Tablet Traffic		7 (3.12%)	00:00:19	42.86%
	Mobile Traffic		9 (2.89%)	00:02:13	37.50%
17.		07			
	All Users		13 (1.61%)	00:00:27	53.85%
	Desktop Traffic		2 (0.74%)	00:00:05	50.00%
	Tablet Traffic		5 (2.23%)	00:00:42	60.00%
	Mobile Traffic		6 (1.93%)	00:00:20	50.00%
18.		06			
	All Users		2 (0.25%)	00:02:12	0.00%
	Desktop Traffic		1 (0.37%)	00:02:26	0.00%
	Tablet Traffic		0 (0.00%)	00:00:00	0.00%
	Mobile Traffic		1 (0.32%)	00:01:57	0.00%

Appendix 6. – Cross Tab – Problems in ecommerce

Answer Choices	Responses	
Te kleine productafbeeldingen	61.68%	169
Te grote productafbeeldingen	3.65%	10
Te veel tekst op de webpagina	12.77%	35
Niet genoeg tekst op de webpagina	16.06%	44
Te lange productbeschrijvingen	6.57%	18
Te korte productbeschrijvingen	50.00%	137
Langzame webpagina	67.15%	184
De vooraf ingestelde sortering van de producten	29.56%	81
Total Respondents: 274		

Appendix 7. Likert – Importance of Product Picture

Answer Choices	Responses	
Zeer eens	65.71%	184
Eens	28.57%	80
Neutraal	5.00%	14
Oneens	0.36%	1
Zeer oneens	0.00%	0
Geen Informatie	0.36%	1
Total		280

Appendix 8. – Likert – Importance Big over Small screen

Answer Choices	Responses	
Zeer eens	65.71%	184
Eens	28.57%	80
Neutraal	5.00%	14
Oneens	0.36%	1
Zeer oneens	0.00%	0
Geen Informatie	0.36%	1
Total		280

Exh. 1 Survey Questions

5%

1. Wat is je geslacht?

- Man
- Vrouw
- Geen informatie

2. Wat is je leeftijd?

- Jonger dan 25
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- Ouder dan 65

Volg.

10%

3. Heb je de website van (name) wel eens bezocht?

- Ja
- Nee

Vor. Volg.

15%

4. Met welk apparaat bezoek je het liefste de website van (name) (1= gebruik ik het liefst; 3= gebruik ik het minst liefst)

- Mobiele telefoon
- Tablet / IPad
- Computer / Laptop

Vor. Volg.

20%

5. Voor welke van onderstaande redenen zou je je mobiele telefoon gebruiken?

- Zoeken naar informatie
- Vergelijken van diensten
- Vergelijken van producten
- Het lezen van blogartikelen (Een informatief artikel op een website)
- Het kopen van producten
- Het bekijken van video's
- Spelletjes
- Luisteren naar muziek
- Social Media
- Geen van bovenstaande redenen

Vor. Volg.

25%

6. Voor welke van onderstaande redenen zou je je tablet / iPad gebruiken?

- Zoeken naar informatie
- Vergelijken van diensten
- Vergelijken van producten
- Het lezen van blogartikelen (Een informatief artikel op een website)
- Het kopen van producten
- Het bekijken van video's
- Spelletjes
- Luisteren naar muziek
- Social Media
- Geen van bovenstaande redenen

Vor. Volg.

30%

7. Voor welke van onderstaande redenen zou je je computer / laptop gebruiken?

- Zoeken naar informatie
- Vergelijken van diensten
- Vergelijken van producten
- Het lezen van blogartikelen (Een informatief artikel op een website)
- Het kopen van producten
- Het bekijken van video's
- Spelletjes
- Luisteren naar de muziek
- Social Media
- Geen van bovenstaande redenen

Vor. Volg.

35%

8. Lees je wel eens blogartikelen? (Een informatief artikel op een website)

- Ja
- Nee

Vor. Volg.

40%

9. Het liefste lees ik blogartikelen (informatief artikel op een website) op: (1= gebruik ik het liefst; 3= gebruik ik het minst liefst)

- Mijn mobiele telefoon
- Mijn tablet / iPad
- Mijn computer / laptop

Vor. Volg.

45%

10. Stel je voor dat je een blogartikel leest op een website. Welke van de volgende punten is volgens jou het meest storend?

- ☐ De tekstgrootte is te klein
- ☐ De tekstgrootte is te groot
- ☐ Niet genoeg afbeeldingen / foto's
- ☐ Te veel afbeeldingen / foto's
- ☐ Er is een video aanwezig
- ☐ Er is geen video aanwezig
- ☐ Er is te veel tekst
- ☐ Er is te weinig tekst
- ☐ Te veel reclame
- ☐ Langzame webpagina

Vor. Volg.

50%

11. Koop je wel eens producten online?

- ○ Ja
- ○ Nee

Vor. Volg.

55%

12. Tijdens het online shoppen gebruik ik het liefste: (1= gebruik ik het liefst; 3= gebruik ik het minst liefst)

- Mijn mobiele telefoon
- Mijn tablet / IPad
- Mijn computer / laptop

Vor. Volg.

60%

13. Stel je voor dat je aan het surfen (internetten) bent en je een product ziet welke je graag zou willen kopen. Welke apparaten gebruik je bij het bestellen van je product het liefste? (1= gebruik ik het liefst; 3= gebruik ik het minst liefst)

- Mijn mobiele telefoon
- Mijn tablet / IPad
- Mijn computer / laptop

Vor. Volg.

65%

14. Stel je voor dat je aan het winkelen bent bij een webwinkel. Welke van de volgende kenmerken van de webpagina is volgens jou het meest storend?

- ☐ Te kleine productafbeeldingen
- ☐ Te grote productafbeeldingen
- ☐ Te veel tekst op de webpagina
- ☐ Niet genoeg tekst op de webpagina
- ☐ Te lange productbeschrijvingen
- ☐ Te korte productbeschrijvingen
- ☐ Langzame webpagina
- ☐ De vooraf ingestelde sortering van de producten

Vor. Volg.

70%

15. Wat is de maximale tijd die je zou besteden aan het lezen van een blogartikel? (Een informatief artikel op een website)

- ○ 1-2min
- ○ 3-4min
- ○ 5-6min
- ○ 7-8min
- ○ 8-10min
- ○ Ik lees geen blogartikelen

Vor. Volg.

75%

16. Een goede productafbeelding is belangrijk voor het kopen van een product online?

- ○ Zeer eens
- ○ Eens
- ○ Neutraal
- ○ Oneens
- ○ Zeer oneens
- ○ Geen Informatie

Vor. Volg.

80%

17. Blog artikelen (Een informatief artikel op een website) zouden (ook) een video moeten bevatten?

- ○ Zeer eens
- ○ Eens
- ○ Neutraal
- ○ Oneens
- ○ Zeer oneens
- ○ Geen Informatie

Vor. Volg.

85%

18. Wanneer je aan het surfen bent op het internet, zijn apparaten met een groter scherm (tablet/computer) comfortabeler dan apparaten met een kleiner scherm (mobiele telefoon).

- ○ Zeer eens
- ○ Eens
- ○ Neutraal
- ○ Oneens
- ○ Zeer Oneens
- ○ Geen Informatie

Vor. Volg.

90%

19. Een samenvattende infographic (de inhoud van een artikel weergegeven in een afbeelding) is het meest nuttig...

- ○ ...in het begin van een artikel
- ○ ...in het midden van een artikel
- ○ ...in het eind van een artikel

Vor. Volg.