DOI: https://doi.org/10.1145/3379157.3391305

Publisher: ACM

Mobile Consumer Behavior in Fashion m-Retail: An Eye Tracking Study to Understand Gender Differences

Zofija Tupikovskaja-Omovie
Manchester Metropolitan University
Manchester, United Kingdom
z.tupikovskaja-omovie@mmu.ac.uk

David Tyler
Manchester Metropolitan University
Manchester, United Kingdom
d.tyler@mmu.ac.uk

ABSTRACT

With exponential adoption of mobile devices, consumers increasingly use them for shopping. There is a need to understand the gender differences in mobile consumer behavior. This study used mobile eye tracking technology and mixed-method approach to analyze and compare how male and female mobile fashion consumers browse and shop on smartphones. Mobile eye tracking glasses recorded fashion consumers' shopping experiences using smartphones for browsing and shopping on the actual fashion retailer's website. 14 participants successfully completed this study, half of them were males and half females. Two different data analysis approaches were employed, namely a novel framework of the shopping journey, and semantic gaze mapping with 31 Areas of Interest (AOI) representing the elements of the shopping journey. The results showed that male and female users exhibited significantly different behavior patterns, which have implications for mobile website design and fashion m-retail. The shopping journey map framework proves useful for further application in market research.

CCS CONCEPTS

• **Human-centered computing → Smartphones**; **Empirical studies in ubiquitous and mobile computing**; **Empirical studies in interaction design**; • **Information systems → Online shopping**; • **Applied computing → Online shopping**; Marketing; Decision analysis; • **Social and professional topics** → User characteristics; **Men**; **Women**.

KEYWORDS

Online Shopping, Smartphones, Mobile Eye Tracking, Fashion Retail, Consumer Behavior, Mobile Consumer, Customer Shopping Journey, Website, Customer Journey, User Experience

ACM Reference Format:
Zofija Tupikovskaja-Omovie and David Tyler. 2020. Mobile Consumer Behavior in Fashion m-Retail: An Eye Tracking Study to Understand Gender Differences. In *Symposium on Eye Tracking Research and Applications (ETRA '20 Adjunct), June 2–5, 2020, Stuttgart, Germany*. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3379157.3391305

ETRA '20, June 2–5, 2020, Stuttgart, Germany

ACM ISBN 978-1-4503-7135-3/20/06.
https://doi.org/10.1145/3379157.3391305

1 INTRODUCTION

With the rapid adoption of mobile devices for shopping and growth of e-commerce, companies' website design becomes exceptionally crucial to attract and retain customers [Vera et al. 2017]. The companies need to focus on the process-tracing research on consumer decision-making [Shi et al. 2013; Zuschke 2019] and how consumers interact with dynamic stimuli such as websites or mobile apps [Schall 2016; Tupikovskaja-Omovie and Tyler 2020; Tupikovskaja-Omovie et al. 2015; Wedel 2013]. User experience (UX) is a form of user research which attracts practitioners and academics alike, but the development of UX evaluation methods is an emerging area of research requiring a mixed-methods approach, triangulation of multiple datasets [Hussain et al. 2018; Pfeiffer et al. 2016] and novel techniques of visual analysis of eye tracking data [Burch 2019; Eraslan et al. 2016; Kurzhals et al. 2016]. Researchers investigated how eye gaze behavior correlates with acceptance and perception, and perceived usefulness is linked to fixation duration [Tzafilkou and Protogeros 2017]. We selected eye tracking technology as it is the most suitable data gathering method in order to understand what fashion consumers actually do on smartphones and why. In this research, we documented the following three areas: eye tracking actual fashion mobile website on smartphone, tracking the whole shopping process through from initial search to the payment, and comparing male and female users' interaction with real smartphones.

2 BACKGROUND LITERATURE

2.1 Eye Tracking Research in e-Commerce

The use of mobile devices in stores can lead to increased purchases [Grewal et al. 2018], and eye tracking technology offers researchers an objective tool for data gathering about visual consumer behavior [King et al. 2019]. In order to analyze user experiences on mobile websites and apps, the settings of eye tracking experiments need to be designed in the most natural and least interrupting way. Often, the stimuli used for the experiments is overly manipulated and not dynamic as it is online or in-store [Huddleston et al. 2015]. Research with fashion websites [Guo et al. 2015] and groceries shopping online [Benn et al. 2015] tracked the shopping process excluding payment. Past studies used eye tracking to analyze the differences in behavior on different size screens [Kim et al. 2015; Tonkin et al. 2011] and the influence of the model's smile on consumers' attention and purchase intention [Wang et al. 2017]. Visual attention influences consumer evaluations of the product or service [Ladeira et al. 2019] and marketing ads online [Ahn et al. 2018; Chang and Chen 2017; Kaspar et al. 2019; Kong et al. 2019; Pfiffelmann et al. 2019]. Eye tracking technology has been used to capture user eye movements and attention to web design elements and images on e-commerce websites [Haesner et al. 2018; Jahanian et al. 2018; Lamberz and Litfin 2018; Sari et al. 2015; Vidyapu et al. 2019; Wang et al. 2014]. Eye tracking studies focusing on e-commerce search behaviour, especially mobile commerce, are limited [Ahn et al. 2018; Cortinas et al. 2019a,b; Hautala et al. 2018; Huddleston et al. 2018; Kessler and Zillich 2019]. Some eye tracking studies analyzed the effect of the background of a product image on consumer attention [Wang et al. 2019] and how consumers attend to and process reviews online [Fu et al. 2020; Maslowska et al. 2020].

2.2 Gender in Eye Tracking Research

The evidence suggest that users' personal characteristics have an impact on the information processing, attention and user behavior [Toker et al. 2013]. Previous eye tracking studies identified that certain personal characteristics of the participants can influence how these participants view stimuli, namely comparison of younger and older users [Bergstrom et al. 2013], older adults with mild cognitive impairment (MCI) and without MCI [Haesner et al. 2018]. Past research studies suggest that there are potential differences in performance while navigating websites among users from different demographic groups [Bergstrom et al. 2013; Djamasbi et al. 2011]. Gender differences have been attracting researchers from various domains. Eye tracking technology used to analyze gender differences uncovered differences in gaze patterns in relation to viewing body of men and women [Hewig et al. 2008], solving text-and-diagram science problems [Huang and Chen 2016], passive indoor picture viewing [Abdi Sargezeh et al. 2019], visual attention and shopping attitudes online [Hwang and Lee 2018]. A number of studies investigating mobile device usage is limited, and often the users are presented with manipulated screens [Jeske et al. 2016] rather than original live digital platforms on their smartphones [Tupikovskaja-Omovie and Tyler 2019; Tupikovskaja-Omovie et al. 2015; Tupikovskaja-Omovie and Tyler 2018]. Furthermore, majority of eye tracking studies investigated online visual attention and gaze behavior within the sample of the same gender, either males or females only [Huang 2018]. There is a gap in research comparing male and females browsing behavior on the actual fashion retailers' websites accessed on smartphones. This study will analyze the gender differences in mobile consumer behavior using eye tracking technology with online stimuli from dynamic environments by tracking the actual shopping process online.

3 METHODOLOGY

3.1 Research Settings

For this research mobile eye tracking technology was used to record fashion consumers' behavior on smartphones while browsing and shopping on the fashion retailer's website. In order to eliminate bias, we needed to ensure the same conditions for all participants during the data collection, all participants of this research study were given the same smartphone, iPhone 8, connected to the same Wi-Fi. A major retailer of fashion leisurewear was involved in this research, and is anonymized for the analysis. In this paper, this fashion leisurewear company is called the fashion retailer. Its current online business has over 310K unique users per year, and over 52 percent of them use smartphones to access the website.

The analysis of the fashion retailer's customer database showed that the majority of the retailer's customers use iPhones for shopping on their website. Therefore, participants were recruited and selected based on the following criteria: own an iPhone and have experience shopping on smartphones on the fashion retailer's website. When selecting participants for this research study, it was important to recruit all participants with the same level of prior experience using smartphones for shopping and familiarity with the fashion retailer' website [Chrobot 2014]. A total of 14 participants successfully completed this study, aged 18 to 34 years old. All the participants of this study have gone through the pre-screening process with questions about the gender. Half of them identified themselves as males, and 50 percent as females. The gender remains one of the major categorisation factor in the fashion industry. This paper selected the participants of the two groups, mainly those who identified themselves as males or females. This gender variable was used to group the data about each gender group for analysis. All of these participants were working adults and they were given a promotional voucher code for the retailer's website as an incentive to join this study. SMI Eye Tracking Gasses 2.0 with smartphone-based recorder by SensoMotoric Instruments were used for this research, and SMI BeGaze 3.7 software was used to extract the data files for analysis and processing.

All the participants used the same smartphone to access the fashion retailer's website to browse and purchase up to 2 items within the set budget of £55 (max). for the purpose of this research, a natural and an unobtrusive interaction was required to create the shopping environment similar to the participants own shopping interaction. Therefore, the users of this research were allowed to browse freely any parts of the fashion retailer's website as they would normally do on their own. The researchers provided all participants with the checkout details, including the bank card to make payments. This ensured the security of personal information of our participants as well as allowing to track the whole shopping process from entering the website to completing the transaction.

3.2 Data Analysis

The analysis of mobile eye tracking data gathered using eye tracking glasses still remains challenging [Vansteenkiste et al. 2013] because data files produced are dynamic visualizations in a form of video files [Tupikovskaja-Omovie and Tyler 2018]. Instead of mapping of gaze data to a web page representation, it is proposed to identify fixed elements on web pages and combine user viewport screenshots in relation to fixed elements for an enhanced representation of the page [Menges et al. 2018]. However, this method might be problematic for actual live websites or mobile apps research when users interact with smartphones. The fashion retailer's website used for this research study has over 14,300 pages indexed on Google. Therefore, there is a vast diversity in the number and combination of web pages the participants can visit, and it is important to consider all elements of web pages visited by users [Eraslan et al. 2016]. Previous research highlights the need for an alternative method of mobile user behavior research. Therefore, a mixed-method approach was employed for this research study in order to compare data sets aggregated from eye tracking experiments for the best application

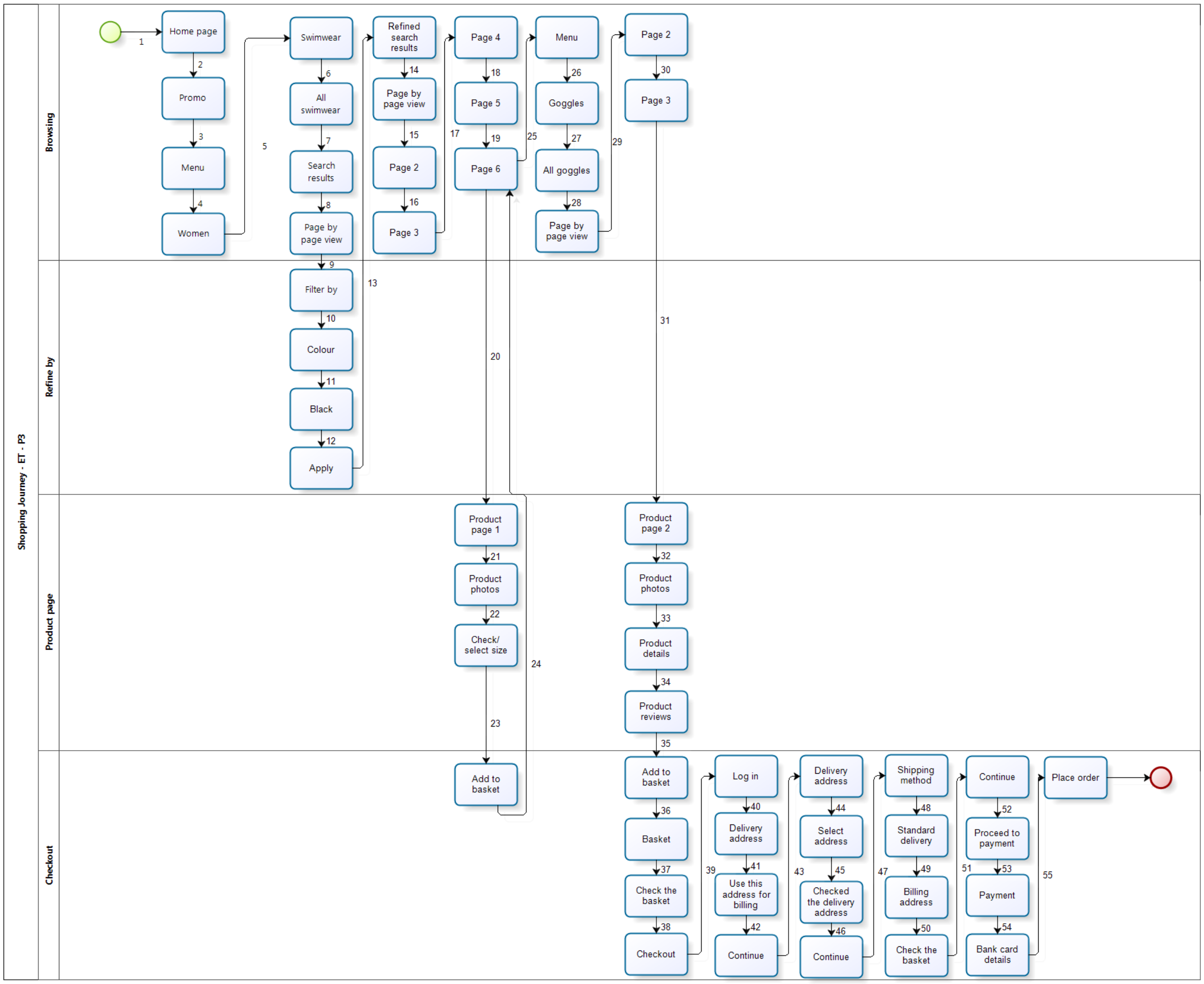

Figure 1: Mobile Fashion Consumer's Shopping Journey (Participant P3).

in market research. This paper makes use of Semantic Gaze Mapping (SGM) in combination with Areas of Interest (AOI) [Blascheck et al. 2016] and shopping journeys [Tupikovskaja-Omovie and Tyler 2018] as means to analyze and compare mobile consumers' behavior on the fashion retailer's website using smartphones.

In order to overcome these challenges along the traditional an alternative eye tracking data analysis method was employed based on the concept of shopping journeys [Tupikovskaja-Omovie and Tyler 2018]. This method helps to identify elements of the website used by the participants including areas users have looked at without clicking on anything. Using the shopping journeys framework, individual shopping journeys were developed for each participant based on scan path video files from the eye tracking experiments. This method allowed to count total number of steps and numbers of steps on separate stages of the shopping journey (Fig. 1).

The more traditional eye tracking data analysis method employed SGM with the AOIs that resemble the elements of the shopping journey for easier market research analysis and application. The SGM is the process of annotating eye gaze data onto the reference image with allocated areas of interest. This process was conducted using SMI BeGaze 3.7 software by manually mapping fixations into according AOIs going frame by frame through the whole video recording of the eye tracking experiment.The SGM is a time consuming process requiring precision in execution. The SGM reference image (Fig. 4) was created to reflect the major elements of the fashion retailer's website similar to the shopping journey framework which can be used to cluster eye tracking participants based on the elements used during the shopping journey [Tupikovskaja-Omovie and Tyler 2020].

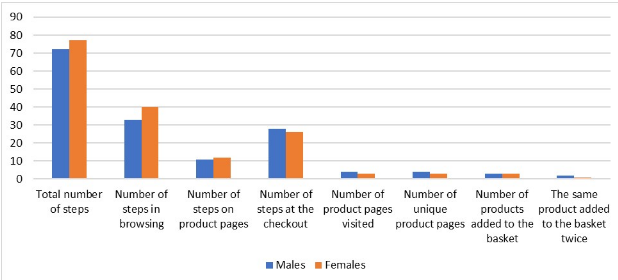

Figure 2: Average Number of Steps of the Shopping Journey.

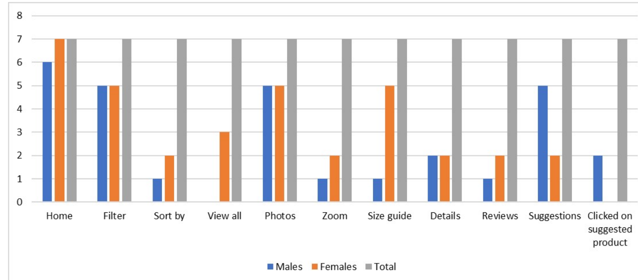

Figure 3: Elements Used during the Shopping Journey.

The following datasets were used to compare males and females using the fashion retailer's website on smartphones: the shopping journeys, the average number of steps during different stages of the shopping journey, the elements used during the shopping journeys, fixation count, revisits and the average fixation. Therefore, two major stages of data analysis are presented as follow: analysis of the data obtained through analysis of the shopping journeys and analysis of the data obtained through SGM.

4 RESULTS

4.1 Males vs Females: Findings based on Shopping Journeys Analysis

The shopping journeys concept for eye tracking data analysis can be used as means to analyze the user behavior differences on mobile apps and websites [Tupikovskaja-Omovie and Tyler 2018] and to cluster users based on the common patterns of these shopping journeys [Tupikovskaja-Omovie and Tyler 2020]. This analysis of the findings involves counting numbers of steps on five different stages of the shopping journey (Fig. 1), namely home page, refining activities, browsing, product page and checkout stages (Fig. 2).

The comparison of the average numbers of steps between males and females showed that females conducted more steps than males overall and during the browsing stage of the shopping journey. Male users made on average 33 steps at the browsing stage and females 40 steps. Whereby, it took more steps for male participants than female to complete the checkout stage (Fig. 2). It was interesting to note that male consumers visited more product pages than females, with 4 product pages on average visited by males compared to 3 by females. In regards to other variables, males and females were similar. Therefore, there is a need to compare what elements of the website were mainly used by males and females.

When analyzing the results of comparison of the elements of the website used during the shopping journey, males and females exhibited more significant differences (Fig. 3). Half of female users change the way products are displayed in the search results, 3 out of 7 females prefer the 'view all' option to viewing 'page by page' as in the default website mode. Whereby males did not make use of 'view all', but clicked through the search results pages in 'page by page' manner. Some categories had more than 13 pages of search results, and males who wanted to examine all products of that category have gone through all pages and then back until selecting the right product. The majority of both male and female participants have explored the 'home' page of the website, accounting for 6 out of 7 males and all females. This shows that mobile consumers might expect to find some attention capturing or promotional features on the home page. Furthermore, the majority of both groups used 'filter' option when browsing, accounting for 5 out of 7 males and the same number of females. The common use of 'filter' option suggests that mobile users are more time conscious and goal-oriented, they wish to find products matching their needs quicker. On product pages, 5 out of 7 participants of both groups viewed photos of the products, and about the third of each group spent time reading product 'details' and description.

However, when looking at the product photos, more females than males used the 'zoom' option and read product 'reviews'. The most significant differences between male and female mobile consumers were found in regards to the use of the 'size guide'. The majority of females checked the 'size guide' before selecting the size for their purchase, accounting for 5 out of 7 users. However, only one male participant has checked the 'size guide'. Whereby, the majority of males, 5 out of 7 participants, have checked the 'suggestions' on the product pages. The third of them have 'clicked on the suggested product', expecting to see the product similar to the one they were viewing. Only the third of females looked at the suggested products, with only 2 out of 7 female users, and none of the females have clicked on any suggestions.

To summarize, the analysis of the shopping journey can reveal the clear browsing differences when comparing groups of users [Tupikovskaja-Omovie and Tyler 2020], males and females in this case. The most informative dataset was based on the elements of the website the participants used during their shopping journeys (Fig. 3).

4.2 Males vs Females: Findings based on SGM and AOIs Analysis

A number of parameters can be extracted using SGM about AOIs, namely sequence, dwell time, hit ratio, revisits, average fixation, first fixation and fixation count. Taking into account that the fashion retailer's website has over 14,300 pages, and the participants of this study had a freedom to browse any parts of the website, just the way they would normally do on their own. Therefore, certain data parameters were dismissed, as these would not reflect the complexity of shopping behavior of live website.

Firstly, there was the need to compare the fixation count between males and females, as the number of fixations shows the amount of information a consumer extracts from visual stimuli

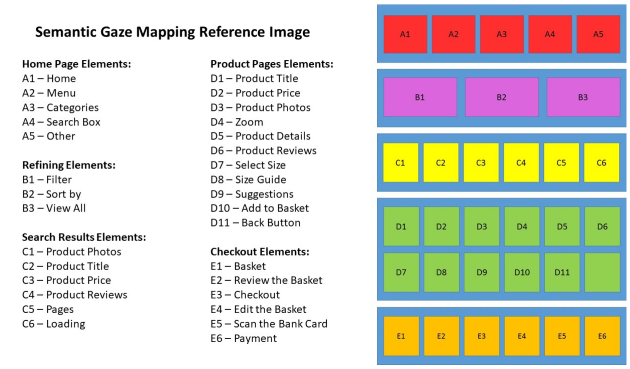

Figure 4: SGM Reference Image.

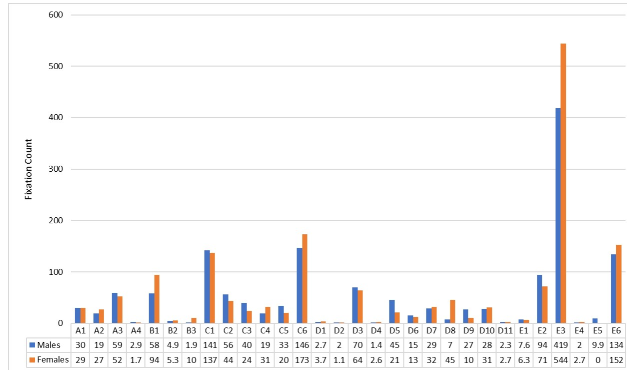

Figure 5: Fixation Count.

[Wedel and Pieters 2000]. Therefore, the comparison of the fixation count between males and females was conducted (Fig. 5). The highest fixation count was observed on AOI E3, which is the actual checkout process (Fig. 4). E3 involves typing users' contact details and selecting the delivery information. Although, in real shopping involvement these users might have saved their contact details on the retailer's website, this study was designed in the way that all participants needed to enter all contact details as a 'new' customer. This allowed to test how easy and usable is the checkout stage of the website. It can be seen that during the checkout users extract the highest amount of information as it requires a lot of their attention. Female participants exhibited 544 fixation counts on AOI of the checkout related activities, with 419 males retrospectively. This suggests that females extracted more information during the checkout than males. Other AOIs which captured mobile users' attention are the product photos in the search results with 141 fixation counts for males and 137 for female users. The payment stage of the checkout process AOI showed higher fixation count among females than males, with 152 and 134 for females and males respectively. The fixation count on B1 AOI for the filtering options showed the average fixation count of 94 among females compared with 58 for males, suggesting that females focused their attention more on the features of the filtering options in selecting the most appropriate combination in order to find the most suitable product quicker. In regards to the product photos on the product pages, both males and females had similar average fixation count, with 70 and 64 among males and females respectively. It is surprising how much attention went to 'look into void' while waiting for some pages to load, on average male users' fixation count on 'loading' AOI was 146 and 173 for females. This amount of attention could be diverted to the promotions or related products, but it is potentially lost on waiting for pages or products to load.

This study is mainly interested to compare males with females, and identify whether mobile consumers are similar or different in their shopping and browsing behavior. The similarities were identified in relation to the fixation count on the following elements of the shopping journey: viewing promotions on the home page, using menu and categories, sorting option, looking at the product photos in the search results and the product pages.

While browsing, females fixated more times on the filtering options, with the average fixation count of 94 compared to 58 among

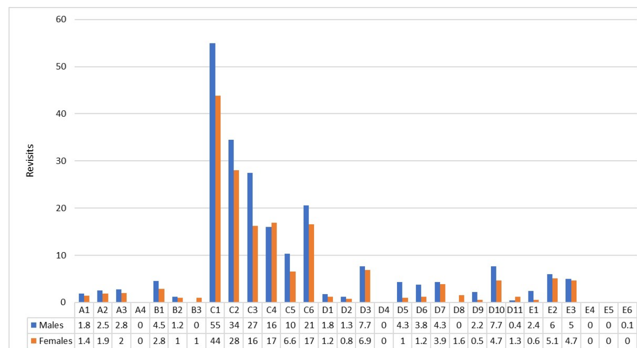

Figure 6: Revisits.

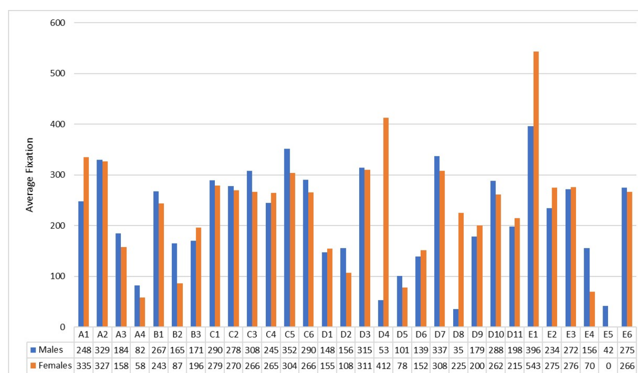

Figure 7: Average Fixation (ms).

females and males respectively. Female consumers exhibited higher average fixation count on AOI related to 'view all', accounting for 10 against 1.9 among females versus males. The AOI of product reviews' rating in the search results showed that females extracted more information from product ratings than males, accounting for 31 and 19 fixation counts among females and males respectively. On the product pages, females mostly fixated on the 'size guide', accounting for average fixation count of 45 for females versus only 7 for males. Females seemed to be more concerned at the checkout than males, as they fixated more when filling in the contact information, delivery and payment details.

The products' price in both the search results and the product pages attracted more attention of male consumers (Fig. 5), accounting for average fixation count of 40 for males versus 24 for females. They fixated more on categories, product photos, product title and page numbers in the search results. On the product pages, male users fixated mostly on product details, with fixation count of 45 among males compared to only 21 among females. Male users exhibited higher average fixation count on AOI of 'suggestions', accounting for 27 and 10 among males and females respectively. Other AOIs with higher fixation count than females were related to product photos and product reviews. Male consumers also reviewed the basket contents more carefully than females, accounting for fixation count of 94 versus 71 for males and females respectively.

Although, the fixation count shows the users' visual attention, it was needed to compare these users' revisits to all AOIs of this study. The data about the revisits might reveal which AOIs were more routinely gazed on (Fig. 6). The highest number of the revisits were related to the AOIs of the 'search results elements' of the browsing stage of the shopping journey, accounting for 55 and 44 average revisits to product photos, 34 and 28 revisits to product title, 27 and 16 to product price, and 16 and 17 to product reviews among males and females respectively. During this browsing stage users were looking for the right products to purchase, and it is not surprising that elements of the browsing stage of the shopping journey attracted the highest number of revisits to AOIs. Most strikingly, male users have made higher number of revisits to almost all AOIs than females.

Taking into account that the participants have gazed on 31 AOIs during the eye tracking experiments, it was interesting to evaluate which of these AOIs received the highest average fixations (Fig. 7). The comparison between males and females in regards to the average fixation on each AOI was conducted. Female users fixated longer than male users on a number of AOIs, namely the 'zoom' of the product photos, accounting for 412 ms among females compared to 53 ms by males. The average fixation duration on the 'size guide' was more than 6 times longer among females than males, accounting for 225 ms and 35 ms respectively. Females and males fixated the longest on the 'basket' AOI, accounting for 543 ms and 396 ms on average among females and males. Whereby, male group of consumers fixated longer than females on the page numbers within the search results, the product price, selecting size and adding to the basket. Interestingly, male consumers fixated longer on the AOI of 'editing the basket', accounting for 156 ms on average among males compared to 70 ms among females. This finding is linked to the data about the average number of steps of the shopping journey (Fig. 2) about the number of products added to the basket. It is apparent, indeed, that 2 out of 7 males have added the same product to the basket twice. Having these distinct datasets in parallel, based on shopping journey analysis and on SGM and AOI analysis, can help in explaining certain behaviour differences between males and females when shopping for fashion products on smartphones.

The analysis of SGM data about the selected AOIs showed that, indeed, male and female mobile fashion consumers exhibit diverse browsing and shopping patterns on smartphones. Further to shopping journeys' data analysis, SGM provided knowledge about eye gaze data in relation to AOIs of this study. These findings are in agreement with most of the findings of shopping journey maps analysis (Section 4.1.), and allowed to analyze not only the browsing behavior of mobile fashion consumers, but also the search behavior and detailed inspection of the product pages. The findings of this study make practical and intellectual contribution to the area of consumer behavior and design of websites with the reference to gender impact on mobile shopping behavior differences.

5 CONCLUSIONS AND FUTURE WORK

The data analysis showed that in relation to a number of parameters, namely viewing the product photos and overall search related activities, both male and female consumers tend to revisit the AOIs specifically linked to the search results elements much more than any other elements. This closely links with the previous research suggesting that consumers spend more time assessing purchase options than the actual purchase process [Cortinas et al. 2019a]. The web pages of a low-complexity [Liu et al. 2019] and with concise designs [Hsu et al. 2018] attract users' attention more, and consumers shift their attention between brand, price and visual information about the products shown within the search results, with image information being the most important [Cortinas et al. 2019b]. Past research found that females inspect images faster than males [Abdi Sargezeh et al. 2019], in our research both males and females attended to the product photos in a similar way. Previous study suggested that females tend to attend visually to most elements of the website, compared with males who focused their attention on consumer opinion areas [Hwang and Lee 2018]. Current study found that in most cases females, indeed, placed more attention on the product reviews than males. Furthermore, males made use of the suggested products and product details far more than females. Although, the product related information on product pages is most important for consumers, some consumers spend time reading product reviews [Maslowska et al. 2020], which create a safety perception when shopping online [Fu et al. 2020]. The current study identified and highlighted some significant differences from previous studies, which might be explained by the use of mobile eye tracking technology with the live fashion retailer's website on smartphones.

The gender differences identified in this study can be explained through the understanding of the products these users have viewed and purchased. Female fashion products, in this case leisurewear product, require more knowledge about the size as female body shape is different from males. Having in mind that fashion industry is gender focused, the fashion retailer in this study has products for both male and female consumers. The knowledge of the gender differences when shopping for leisurewear products on smartphones is crucial. This study was conducted with 14 participants, and the differences observed suggest that the understanding of the gender differences can be used to improve the UX of the fashion retailer's website to offer satisfactory and personalised shopping experiences. This research provides a new insight to mobile consumer behavior research with potential for further developments using other retailers' websites and mobile apps. There is a possibility to cluster users based on their behavior viewing search results' elements online [Hautala et al. 2018] or browsing digital retailers' shopping platforms [Tupikovskaja-Omovie and Tyler 2019, 2020].

The findings from eye tracking data analysis and shopping journeys showed that certain eye tracking data types produce very similar results to the ones identified through the shopping journeys data analysis. Although, all the stages of the analysis, even the shopping journeys, were developed from eye tracking experiments recordings, the data types have impact on the types of the findings possible. This paper attempted to compare male and female fashion consumers shopping on their smartphones, and all the data types used have proved that there were obvious behavior differences in regards to the gender. In order to increase user engagement, e-commerce companies can offer the personalization process for their users based on combining the eye tracking research with the web usage logs [Velasquez 2013], Google Analytics [Tupikovskaja-Omovie and Tyler 2020] and visual gaze activity accounting for pupil dilation changes [Loyola et al. 2015]. The findings form this study have practical implications for fashion retail, UX and website developers. As knowing what are the differences in shopping behavior, fashion retailers can better design their shopping platforms to accommodate mobile consumers' diverse needs.

ACKNOWLEDGMENTS

The authors would like to thank the anonymous referees for their valuable comments and helpful suggestions.

REFERENCES

B. Abdi Sargezeh, N. Tavakoli, and M. R. Daliri. 2019. Gender-based eye movement differences in passive indoor picture viewing: An eye-tracking study. *Physiology & Behavior* 206 (2019), 43–50.

J.-H. Ahn, Y.-S. Bae, J. Ju, and W. Oh. 2018. Attention Adjustment, Renewal, and Equilibrium Seeking in Online Search: An Eye-Tracking Approach. *Journal of Management Information Systems* 35, 4 (2018), 1218–1250.

Yael Benn, Thomas L Webb, Betty P. I. Chang, and John Reidy. 2015. What information do consumers consider, and how do they look for it, when shopping for groceries online? *Appetite* 89, 1 (2015), 265–273.

Romano Bergstrom, J. C., E. L. Olmsted-Hawala, and M. E. Jans. 2013. Age-Related Differences in Eye Tracking and Usability Performance: Website Usability for Older Adults. *International Journal of Human-Computer Interaction* 29, 8 (2013), 541–548.

T. Blascheck, K. Kurzhals, M. Raschke, S. Strohmaier, D. Weiskopf, and T. Ertl. 2016. AOI hierarchies for visual exploration of fixation sequences. In *Proceedings of the Ninth Biennial ACM Symposium on eye tracking research & applications*. ACM, 2016, 111–118.

M. Burch. 2019. Interaction graphs: visual analysis of eye movement data from interactive stimuli. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*. Association for Computing Machinery, Article 89, Denver, Colorado.

C.-T. Chang and P.-C. Chen. 2017. Cause-related marketing ads in the eye tracker: it depends on how you present, who sees the ad, and what you promote. *International Journal of Advertising* 36, 2 (2017), 336–355.

N. Chrobot. 2014. The role of processing fluency in online consumer behavior: evaluating fluency by tracking eye movements. In *Proceedings of the Symposium on Eye Tracking Research and Applications*. Association for Computing Machinery, Safety Harbor, Florida, 387–388.

M. Cortinas, R. Cabeza, R. Chocarro, and A. Villanueva. 2019a. Attention to online channels across the path to purchase: An eye-tracking study. *Electronic Commerce Research and Applications* 36 (2019).

M. Cortinas, R. Chocarro, and A. Villanueva. 2019b. Image, brand and price info: do they always matter the same?. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*. Association for Computing Machinery, Article 92, Denver, Colorado.

S. Djamasbi, M. Siegel, J. Skorinko, and T. Tullis. 2011. Online Viewing and Aesthetic Preferences of Generation Y and the Baby Boom Generation: Testing User Web Site Experience Through Eye Tracking. *International Journal of Electronic Commerce* 15, 4 (2011), 121–158.

S. Eraslan, Y. Yesilada, and S. Harper. 2016. Scanpath Trend Analysis on Web Pages: Clustering Eye Tracking Scanpaths. *ACM Transactions on the Web (TWEB)* 10, 4 (2016), 1–35.

H. Fu, G. Manogaran, K. Wu, M. Cao, S. Jiang, and A. Yang. 2020. Intelligent decision-making of online shopping behavior based on internet of things. *International Journal of Information Management* 50 (2020), 515–525.

D. Grewal, C.-P. Ahlbom, L. Beitelspacher, S. M. Noble, and J. Nordfält. 2018. In-Store Mobile Phone Use and Customer Shopping Behavior: Evidence from the Field. *Journal of Marketing* 82, 4 (2018), 102–126.

Fu Guo, Yaqin Cao, Yi Ding, Weilin Liu, and Xuefeng Zhang. 2015. A Multimodal Measurement Method of Users' Emotional Experiences Shopping Online. *Human Factors and Ergonomics in Manufacturing and Service Industries* 25, 5 (2015), 585–598.

M. Haesner, J. Chandra, A. Steinert, and E. Steinhagen-Thiessen. 2018. An eye movement analysis of web usability: Differences between older adults with and without mild cognitive impairment. *Assistive Technology* 30, 2 (2018), 66–73.

J. Hautala, C. Kiili, Y. Kammerer, O. Loberg, S. Hokkanen, and P. H. T. Leppänen. 2018. 'Sixth graders' evaluation strategies when reading Internet search results: an eye-tracking study. *Behaviour & Information Technology* 37, 8 (2018), 761–773.

J. Hewig, R. H. Trippe, H. Hecht, T. Straube, and W. H. R. Miltner. 2008. Gender Differences for Specific Body Regions When Looking at Men and Women. *Journal of Nonverbal Behavior* 32, 2 (2008), 67–78.

T.-C. Hsu, S.-C. Chang, and N.-C. Liu. 2018. Peer Assessment of Webpage Design: Behavioral Sequential Analysis Based on Eye Tracking Evidence. *Journal of Educational Technology & Society* 21, 2 (2018), 305–321.

P.-S. Huang and H.-C. Chen. 2016. Gender Differences in Eye Movements in Solving Text-and-Diagram Science Problems. *International Journal of Science and Mathematics Education* 14, S2 (2016), 327–346.

Y.-T. Huang. 2018. The female gaze: Content composition and slot position in personalized banner ads, and how they influence visual attention in online shoppers. *Computers in Human Behavior* 82 (2018), 1–15.

Patricia Huddleston, Bridget K Behe, Stella Minahan, and R. Thomas Fernandez. 2015. Seeking attention: an eye tracking study of in-store merchandise displays. *International Journal of Retail and Distribution Management* 43, 6 (2015), 561–574.

P. T. Huddleston, B. K. Behe, C. Driesener, and S. Minahan. 2018. Inside-outside: Using eye-tracking to investigate search-choice processes in the retail environment. *Journal of Retailing and Consumer Services* 43 (2018), 85–93.

J. Hussain, W. A. Khan, T. Hur, H. S. M. Bilal, J. Bang, A. U. Hassan, M. Afzal, and S. Lee. 2018. A Multimodal Deep Log-Based User Experience (UX) Platform for UX Evaluation. *Sensors (Basel, Switzerland)* 18, 5 (2018), 1622.

Y. M. Hwang and K. C. Lee. 2018. Using an Eye-Tracking Approach to Explore Gender Differences in Visual Attention and Shopping Attitudes in an Online Shopping Environment. *International Journal of Human-Computer Interaction* 34, 1 (2018), 15–24.

A. Jahanian, S. Keshvari, and R. Rosenholtz. 2018. Web pages: What can you see in a single fixation? *Cognitive Research: Principles and Implications* 3, 1 (2018), 1–15.

D. Jeske, P. Briggs, and L. Coventry. 2016. Exploring the relationship between impulsivity and decision-making on mobile devices. *Personal and Ubiquitous Computing* 20, 4 (2016), 545–557.

K. Kaspar, S. L. Weber, and A.-K. Wilbers. 2019. Personally relevant online advertisements: Effects of demographic targeting on visual attention and brand evaluation. *PloS one* 14, 2 (2019).

S. H. Kessler and A. F. Zillich. 2019. Searching Online for Information About Vaccination: Assessing the Influence of User-Specific Cognitive Factors Using Eye-Tracking. *Health Communication* 34, 10 (2019), 1150–1158.

J. Kim, P. Thomas, R. Sankaranarayana, T. Gedeon, and H. J. Yoon. 2015. Eye-tracking analysis of user behavior and performance in web search on large and small screens. *Journal of the Association for Information Science and Technology* 66, 3 (2015), 526–544.

A. J. King, N. Bol, R. G. Cummins, and K. K. John. 2019. Improving Visual Behavior Research in Communication Science: An Overview, Review, and Reporting Recommendations for Using Eye-Tracking Methods. *Communication Methods and Measures* 13, 3 (2019), 149–177.

S. Kong, Z. Huang, N. Scott, Z. a. Zhang, and Z. Shen. 2019. Web advertisement effectiveness evaluation: Attention and memory. *Journal of Vacation Marketing* 25, 1 (2019), 130–146.

K. Kurzhals, M. Hlawatsch, M. Burch, and D. Weiskopf. 2016. Fixation-image charts. In *Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications*, ACM (Ed.). Association for Computing Machinery, Charleston, South Carolina, 11–18.

W. J. Ladeira, V. A. M. Nardi, F. d. O. Santini, and W. C. Jardim. 2019. Factors influencing visual attention: a meta-analysis. *Journal of Marketing Management* 35, 17-18 (2019), 1710–1740.

J. Lamberz and T. Litfin. 2018. Teckert, Ö. and Meeh-Bunse, G. 2018. 'Still Searching or Have You Found It Already? – Usability and Web Design of an Educational Website'. *Business Systems Research Journal* 9, 1 (2018), 19–30.

W. Liu, X. Liang, and F. Liu. 2019. The Effect of Webpage Complexity and Banner Animation on Banner Effectiveness in a Free Browsing Task. *International Journal of Human-Computer Interaction* 35, 13 (2019), 1192–1202.

P. Loyola, G. Martinez, K. Muñoz, J. D. Velásquez, P. Maldonado, and A. Couve. 2015. Combining eye tracking and pupillary dilation analysis to identify Website Key Objects. *Neurocomputing* 168 (2015), 179–189.

E. Maslowska, C. M. Segijn, K. A. Vakeel, and V. Viswanathan. 2020. How consumers attend to online reviews: an eye-tracking and network analysis approach. *International Journal of Advertising* 39, 2 (2020), 282–306.

R. Menges, H. Tamimi, C. Kumar, T. Walber, C. Schaefer, and S. Staab. 2018. Enhanced representation of web pages for usability analysis with eye tracking. In *Proceedings of the 2018 ACM Symposium on Eye Tracking Research & Applications*. Association for Computing Machinery, Article 96, Warsaw, Poland.

T. Pfeiffer, P. Renner, and N. Pfeiffer-Leßmann. 2016. EyeSee3D 2.0: model-based real-time analysis of mobile eye-tracking in static and dynamic three-dimensional scenes. In *Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications*, ACM (Ed.). Association for Computing Machinery, Charleston, South Carolina, 189–196.

J. Pfiffelmann, N. Dens, and S. Soulez. 2019. Personalized advertisements with integration of names and photographs: An eye-tracking experiment. (2019).

J. N. Sari, R. Ferdiana, P. I. Santosa, and L. E. Nugroho. 2015. An eye tracking study: exploration customer behavior on web design. In *Proceedings of the International HCI and UX Conference in Indonesia*. Association for Computing Machinery, Bandung, Indonesia, 69–72.

A. Schall. 2016. Eyes on the Go: Using Eye Tracking to Understand How Mobile Users Consume Online Content. In *Proceedings of the 34th ACM International Conference on the Design of Communication*. Association for Computing Machinery, Article 33, Silver Spring, MD, USA.

S. W. Shi, M. Wedel, and F. G. M. Pieters. 2013. Information Acquisition During Online Decision Making: A Model-Based Exploration Using Eye-Tracking Data. *Management Science* 59, 5 (2013), 1009–1026.

D. Toker, C. Conati, B. Steichen, and G. Carenini. 2013. Individual user characteristics and information visualization: connecting the dots through eye tracking. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, Paris, France, 295–304.

C. Tonkin, A. T. Duchowski, J. Kahue, P. Schiffgens, and F. Rischner. 2011. Eye tracking over small and large shopping displays. In *Proceedings of the 1st international workshop on pervasive eye tracking & mobile eye-based interaction*. Association for Computing Machinery, Beijing, China, 49–52.

Z. Tupikovskaja-Omovie and D. Tyler. 2019. Mobile Consumers' Shopping Journey Types: Eye Tracking Digital User Behaviour Patterns in Fashion m-Retail. In *Proceedings of AM2019: The 52nd Academy of keting Conference 'When you tire of marketing you tire of life'*. London, UK.

Z. Tupikovskaja-Omovie and D. Tyler. 2020. Clustering Consumers' Shopping Journeys: Eye Tracking Fashion m-Retail. *Journal of Fashion Marketing and Management: An International Journal* (2020). https://doi.org/DOI:10.1108/JFMM-09-2019-0195.

Zofija Tupikovskaja-Omovie, David Tyler, Sam Chandrasekara, and Steve Hayes. 2015. Mobile App versus Website: A Comparative Eye-Tracking Case Study of Topshop. *International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering* 9, 10 (2015), 3251–3258.

Z. Tupikovskaja-Omovie and D. J. Tyler. 2018. Mobile Consumer Shopping Journey in Fashion Retail: Eye Tracking Mobile Apps and Websites. (2018).

K. Tzafilkou and N. Protogeros. 2017. Diagnosing user perception and acceptance using eye tracking in web-based end-user development. *Computers in Human Behavior* 72 (2017), 23–37.

P. Vansteenkiste, G. Cardon, and M. Lenoir. 2013. Dealing with head-mounted eye-tracking data: comparison of a frame-by-frame and a fixation-based analysis. In *Proceedings of the 2013 Conference on eye tracking south africa*. ACM, 2013, 55–57.

J. D. Velasquez. 2013. Combining eye-tracking technologies with web usage mining for identifying Website Keyobjects. *Engineering Applications of Artificial Intelligence* 26, 5-6 (2013), 1469–1478.

F. Vera, V. D. Cortes, G. Iturrra, J. D. Velasquez, P. Maldonado, and A. Couve. 2017. Akori: A Tool Based in Eye-Tracking Techniques for Analyzing Web User Behaviour on a Web Site. *IEEE* (2017), 635–640.

S. Vidyapu, V. S. Vedula, and S. Bhattacharya. 2019. Quantitative visual attention prediction on webpage images using multiclass SVM. In *Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications*. Association for Computing Machinery, Article 90, Denver, Colorado.

Q. Wang, D. Ma, H. Chen, X. Ye, and Q. Xu. 2019. Effects of background complexity on consumer visual processing: An eye-tracking study. *Journal of Business Research* (2019).

Q. Wang, Z. Xu, X. Cui, L. Wang, and C. Ouyang. 2017. Does a big Duchenne smile really matter on e-commerce websites? An eye-tracking study in China. *Electronic Commerce Research* 17, 4 (2017), 609–626.

Qiuzhen Z Wang, Sa Yang, Manlu L Liu, Zike K Cao, and Qingguo G Ma. 2014. An eye-tracking study of website complexity from cognitive load perspective. *Decision support systems* 62, 1 (2014), 1–10.

M. Wedel. 2013. *Attention Research in Marketing: A Review of Eye Tracking Studies (December 1, 2013). Robert H.* Research Paper. Robert H. Smith School Research Paper No. RHS 2460289. ed.

M. Wedel and R. Pieters. 2000. Eye Fixations on Advertisements and Memory for Brands: A Model and Findings. *Marketing Science* 19, 4 (2000), 297–312.

N. Zuschke. 2019. An analysis of process-tracing research on consumer decision-making. *Journal of Business Research* (2019).