UNIVERSITY OF TARTU

Faculty of Social Sciences

School of Economics and Business Administration

Hagigat Hasanova

CLUSTERING CUSTOMER GAZE BEHAVIOUR BASED ON REAL-LIFE EYE-TRACKING DATA

Master's Thesis

Supervisor: Junior Research Fellow Kristian Pentus (PhD)

Tartu 2022

I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

Table of contents

Abstract 3

Introduction 4

1. Literature Review 6
    1.1. Importance of Analysing Customer Behaviour in Retail Industry 6
    Neuromarketing 7
    Eye-tracking in research 10
    Importance of Clustering 12
    2. Methodology 17
    Participants and Equipment 17
    Data 17
    3. Results 19
    4. Discussion 25
    5. Limitations and Future Suggestions 27

Conclusion 28

List of references 29

APPENDICES 46
    APPENDIX A 46
    Questions asked in the store 46
    APPENDIX B 47
    Resümee 49

Abstract

This paper investigated gaze behaviour patterns of customers in Estonian supermarket based on the real-life eye-tracking data collected during their natural shopping experience, clustering customers based on the gaze behaviour metrics. For this purpose, real-life eye-movement data of 363 participants collected with The Tobii Pro Glasses 2 and K-means algorithm was used for clustering. Participants' demographic data was also collected during the experiment for checking the relationship. The results show there are very similar patterns between the demographic data of the clusters of customers based on their gaze behaviour and eye-tracking data can bring light to clustering practises of the retail stores as opposed to common practise of clustering based on demographics.

Keywords: Eye-tracking, clustering, K-means, gaze behaviour, retail marketing

Introduction

In the modern world, consumption is one of the key social factors, and producers will make any effort to persuade a customer to purchase their offering. In every shopping process, numerous elements influence a customer's decision in addition to their budget, like the positioning of the products in the stores, aesthetics of packaging like shape and color, graphics, company logo, and so on(Chynal *et.al.*, 2016). As 68% of purchases are made on the spur of the moment, retailers must assess the efficiency of their in-store marketing activities (Stahlberg&Maila, 2010). Successful presentations of products and some other promotional in-store attempts provide a chance to catch buyers' attention while also minimizing the burden of budget on their buying habits. Therefore, it is undeniable for stores to understand what attracts buyers' attention during shopping to be competitive. As Davenport and Beck (2001) said, "If you want to know to what people are paying attention, follow what they are looking at" also points out that identifying how shoppers perceive products will help with making decisions for surviving in the competitive environment. This creates a need for the producers to understand their customers and their preferences while their selection process for boosting their sales. It also leads to the emerging interest and motivation to research customer buying habits and selection traits using different technologies such as eye-tracking technology (ETT) studies in online and in-store environments (Behe *et.al.,* 2014).

Several methods have been proposed in prior works to better analyze buying behaviors. Interviews (Igarashi *et.al.,* 2017; Fawzy *et.al.,* 2008) and surveys (Kim et.al., 2016) with buyers have been the key research methodology used to discover users' behavioral tendencies. These procedures, unfortunately, are time-consuming while giving ambiguous results (Dood, *et.al.,* 2013). However, contemporary technological advancements have made it easier to follow and monitor the activities of clients. (Chandon *et.al.*, 2009). Eye-tracking provides valuable data to merchants because they define how individuals engage with their surroundings and make decisions (Bojko, 2013). Information about customers' undisclosed purchase patterns of behavior in stores may be revealed by determining their shopping journeys and purchasing habits. As a result, consumer behavior tendencies might be used as a viable solution for product marketing reasoning(Huddleston *et.al.,* 2015).

Eyetracking is a method for identifying where a customer is looking at (Jeon *et.al.,* 2021). It's commonly conducted using an infrared camera that detects the pupil's center and the corneal reflection, then measures the vector between them. The gadget can track and record the position of a person's visual attention (Farnsworth, 2019). Importantly, the spread of usage of eye trackers, which are glasses that participants may wear and walk in the stores, allowed similar research to be conducted everywhere, even in stores(Behe *et.al.*, 2013).

This paper aims to identify the clusters of customers based on their gaze behaviour according to their real-life eye-tracking data and to check any similarities between demographic characteristics of clusters. Considering that eye-tracking technologies are recently adopted by researchers to evaluate customer buying habits, the documentation on the use of this technology is limited in the literature. In the area of eye-tracking such as monitoring users' eye movements, some studies have been conducted. This allowed to gain a better understanding of what catches buyers' interest during shopping and also how their focus is being directed to the products on the shop's counter (Gidlöf *et.al.,* 2017; Folwarczny *et.al.,* 2019) Previous studies have been done to try clustering customers in an online environment by using eye-tracking technology or to investigate users' online shopping behavior patterns based on need-states. Although to understand consumer behaviors, the eye-tracking method has been studied theoretically and practically in previous literature, most of the studies have been conducted in the online environment (Wu *et.al.,* 2020) which is easier since the technology is enabling researchers to collect data without excess logistic costs with the help of webcams. Therefore examples of which using eye-tracking in the real-store environment are very scarce. One way of applying the technique to the customers and generating data from their experience is creating the simulation shelves of the stores such as images of the shelves taken from the real stores or creating the model of the real shelves in the stores. (Chynał *et.al.*, 2016; Chandon *et.al.,* 2009). Another way is providing consumers with eye-tracking glasses which are mainly used in the real store environment. Consumers who are participating in the studies are wearing eyeglasses and walking around the shelves, which brings advantages like allowing customers to get the real store experience and it also does not require any effort to set up special conditions to create a store environment (Khachatryan & Rihn, 2017). Although they have these advantages, they also have some limitations, such as not all eyes being tracked because of contact lenses, personal eyeglasses, or pupil eye color. Moreover, eye-tracking glasses can only collect data from one person at a time (Reisen *et.al.,* 2008; Tobii, 2014). On the other hand, most of the studies aim to investigate the effect of the labeling, packaging, or signage of prices on the customer decisions during shopping trips, but very few authors tried to identify the segments of customers according to their viewing patterns in a real store environment. So this research aims to close that gap in the literature by collecting data in the real store environment under natural shopping conditions in Estonian supermarket and clustering the customers based on their real-life viewing data.

CERCS code: S191

1. Literature Review

1.1. Importance of Analysing Customer Behaviour in Retail Industry

One of the questions that retail industry tries to find an answer is what triggers the repetitive shopping behaviour for customers and with this question they try to get the shopping patterns of the customers. Consumer behavior can be described as the decision process of individuals, groups, and organizations while selecting products, services, thoughts, or ideas to meet their needs and wants, how they prefer the gains, losses, and what they compromise during the process (Kotler, 2018). Detection of consumer behavior motivates companies to create effective strategies and guide customers, which also brings advantages for providers in dealing with rival companies in difficult market conditions (Ozmen, 2007).

Researchers also try to find out what the main cause is behind the customer selections; do they repurchase the same brand each time or do they purchase the product that has a discount. Research that has been done on this topic revealed that customer behavior has an effect on business profits in the retail industry context (Shah *et.al.,* 2014) and that a firm's marketing strategies should be aligned with the proven customer behavior records (Ailawadi *et.al.,* 2001). In other studies, Steinmann e*t.al.,*(2016) examined the importance of customer behavior and defined customer segments based on their analysis. In their study, Wästlund *et.al.,* (2015) examined customer behavior from the perspective of goal setting during their purchasing process and suggested its implications for the retail industry. One of the good illustration of involving smart technology in customer behavior analysis has been done by Caffè Nero. They went from the printed stamp vouchers of the previous decades to the innovative customer experience, which makes it possible to collect information about buyers such as the offers they prefer, their intensity, period, and venue of purchase. They may now specifically target clients with bonuses and incentives to encourage them to discover different items. (Hawtorne, 2017). Using several methods such as loyalty cards in the stores makes recording all kinds of information such as needs, interests, and preferences easier and more accessible (Magatef *et.al.,* 2015; Kannan *et.al.,* 2000). Making deep data analysis over the collected data and using the information correctly, companies can prepare themselves according to possible changes in customer behavior (Saarijärvi *et.al.,* 2013). It also helps stores distinguish between profitable and unprofitable customers and prepare specific campaigns for different segments (Kumar *et.al.,* 2006).

1.2. Neuromarketing

Since marketing became more information-based recently, it triggered the need to understand the way that the customer's brain is working. As a result, a strong desire to get a better understanding of human cognition and behavior has emerged (Heyes, 2012). There is now a new connection between the biological and social sciences. These combined study efforts of social and biological scientists have supported the advancement of key discoveries in social, behavioral, biological, and marketing research (Raquel & María, 2015). Consumer neuroscience is a new multidisciplinary topic that integrates sociology, neurology, and economics to investigate how advertising and marketing practices influence the brain physically (Agarwal *et.al.,* 2015). Over recent years, the area of consumer neuroscience has seen a remarkable improvement in terms of producing insights into marketing and consumer behavior.

In the literature, the interdisciplinary field between psychology and marketing is mentioned as consumer neuroscience or neuromarketing, which is being used interchangeably by researchers (Madan, 2010; Kenning & Linzmajer, 2010). While consumer neuroscience is being used for the academic relationship between the mentioned areas, neuromarketing refers to tools used for research such as eye-tracking, electroencephalography (EEG), functional magnetic resonance imaging (fMRI) that are used for marketing research (Agarwal *et.al.,* 2015; Plassman, 2011; Hubert & Kenning, 2008). In other words, neuromarketing is "the application of neuroscientific methods to analyze and understand human behavior in relation to markets and marketing exchanges" (Lee *et.al.,* 2007), which plays an important role in the decision-making of marketers. There is a noteworthy approach from The Neuromarketing Science and Business Association (NMSBA) that states the only techniques that are considered as neuromarketing research methods are neuroimaging and biometrics, while identifying participants' speculations such as how they are valuing the products or what their product preferences are, cannot be considered as neuromarketing activities (Ulman, *et.al.,* 2014). Consumer neuroscience gained popularity at the beginning of the 2000s when scholars revealed that advertisements, branding, and other marketing and promotion practices may have quantifiable effects on brain function (Venkatraman, 2015). In 2004, researchers offered two visually similar, but competitive soft drink samples to volunteers in an fMRI scanner (McClury, 2004). The researchers observed a similar brain response when the brands of beverages were not recognized by the participants. However, when respondents were informed about the brand of the drinks, the part of the brain linked to emotions and memories exhibited increased activity. As a result of that experience, with the usage of neuromarketing techniques, researchers confirmed that brand information has a significant effect on how customers perceive the product (Harrell, 2019). Another research has been done by Plassmann that examined the changes in the brains of the experiment participants while they were drinking three wines that have different price labels. The results from their brain signals indicated that participants are perceiving the most expensive wine as the best product and would prefer to buy it. While researchers have revealed this while tracking their brain signals, the reality was all the three wines were identical (Plassmann, 2008).

As we see from the previous experiments, neuromarketing techniques are opening the doors to the "black box" which is the human brain described by Camerer, 2005. It means they have the potential to bring valuable profits to retailers if they start to understand their customers. The data collected by real customers in stores can provide valuable information to understand the customers' shopping journey and improve their shopping experience by customization (Tianyi & Tuzhilin, 2009). Several elements in the stores can be affected by customer perception, which can be analyzed with neuromarketing. One of the factors that are being affected by customer perception is the orientation of the stores (Elbers, 2016; Pizzi & Scarpi, 2016). In the report shared by Deloitte which focused on the customer-centric shopping experience, it is highlighted that customers are creating the mental model of the stores in their brain according to their previous experience and when the real store design is not matching with their expectations it affects their buying triggers (Deloitte,2018) Neuromarketing can fill this gap with understanding the real-life experience and predicting expectations which can be handful especially when retail stores are trying to launch their new concepts (Gonchigjav, 2020). In addition to store layouts that can have a detectable effect on customer perception, the number of varieties in stores also matters and can be identified with neuromarketing techniques. Researchers have discovered that when there are too many varieties of products to pick from, consumers buy fewer of them (Tugend, 2010; Johnston, 2004). Pricing is another important trigger for customers while making decisions about purchasing (Suharso, 2020; Albari *et.al.,* 2018). Pricing has been studied by economics and marketing to help sellers determine pricing strategies for their business. Studies prove that, actually, it is not the price but the perception of the price that influences the purchasing decision (Suhaily *et.al.,* 2017; Widyastuti & Said, 2017). For example, Shiv (2005) used an fMRI method to reveal that customers are getting less pleasure from the products that they have bought at a discounted price compared with consumers who bought the products at a regular price.

Although neuromarketing has proved itself as a handful of methods to be used by retailers to open up the background of customer experiences, as with all new technologies, it also has some limitations and barriers to usage (Fortunato *et.al.,* 2014) To begin with, neuromarketing methods are time-consuming (Garczarek-Bąk, *et.al.,* 2021) and they are linked to ethical concerns(Nemorin, and Gandy, 2017, Steven *et.al.,* 2017). Customers' awareness, agreement, and comprehension of what may be perceived as a breach of their privacy rights are all potential moral dilemmas arising from neuroscience applications (Ulman *et.al.,* 2015). The danger is that marketing will employ brain scanning technology in such a way that privacy will be breached to an intolerable degree. We are currently witnessing big companies that have access to our personal information and selling this data to third parties which are being used in internet marketing activities. From this point, the question arises about who owns the personal data coming from neuromarketing experiments and who guarantees that respondents' information will not be shared with special interest parties (Ariely *et.al.,* 2010). For all these ethical concerns, Murphy *et.al.,* (2008) proposed that a code of ethics should be developed which will ensure safe research and development, entrepreneurship, and firm profitability via the use of neuromarketing technologies in a useful and safe way at all phases of creation, execution, and communication. Permission from authorized governmental institutions is also sometimes required while conducting neuromarketing studies, which creates legal problems (Voorhees, 2011). On the other hand, neuromarketing is unquestionably the best instrument for determining the best marketing efforts. Indeed, the high prices of neuromarketing services, such as fMRI, are a major reason for the scarcity of financing for long-term studies (Harrell, 2019). The number of completed neuromarketing research is likewise limited due to high expenditures (Mikic, 2016). As neuromarketing methods require time, the number of participants is lower than other studies (Vozzi *et.al.,* 2021). This also puts the reliability of the results under question as the sample is too small to retrieve meaningful information (Gang *et.al.,* 2012).

1.3.Importance of eye-tracking in research

Eye-tracking is one of the most widely used methods among neuromarketing research techniques(Iloka & Anukwe, 2020). With this technique, the pupils of the participants are followed by various methods during the test and the most used methods such are EEG and fMRI, which are frequently used when testing the usability of websites, shelf designs in shopping malls, and advertisements(Santos *et.al.,* 2015). It provides important findings such as the first point that participants looked at during the test, the areas they focused on, and the time it took to look at these areas. The peripheral nervous system is a communication network spread throughout our body, in which our brain communicates with organs and limbs. The reactions of this system occur in two basic ways. While autonomic responses affect pupil size, especially in the face of emotional stimuli, somatic responses maintain eye movements, focusing, and blink reflexes (Erdemir, 2017).

While eye-tracking technologies bring accuracy to the results with being so sensitive to eye movements, they can also be used in different environments. Table 1 below illustrates the overview of the literature about eyetracking. With the application of modern technology, the usability and accuracy of the process has been increased in recent years, the cost of the equipment has also become more affordable (Lahey *et.al.,* 2016). As mentioned in Table 1, as a result of the widening usage of eye-tracking systems, it has been used in different areas, such as learning (Shojaeizadeh *et.al.,* 2019; Alemdag & Cagiltay, 2018, Wang *et.al.,* 2020) psychology (Perez *et.al.,* 2015), health (Franchak *et.al.,* 2016; Gliga *et.al.,* 2016) marketing (Reijmersdal *et.al.,* 2020; Zuschke 2020;Venkatraman *et.al.,* 2015; Hui *et.al.,* 2013).

It measures:	It is used for:
● eye motion(Wedel and Pieters, 2017) ● gaze duration(Mak & Willems, 2019) ● visual attention (Li *et.al.,* 2016) ● diameter of the pupil(Hartmann and Fischer, 2014) ● reading time (Dirix *et.al.,* 2020) ● fixation count (Alemdag & Cagiltay, 2018). ● saccade (Stuart *et.al.,* 2019) ● pupil dilation(Cheval *et.al.,* 2020).	● fundamental cognitive processes and mechanisms involved in reading comprehension(Dirix *et.al.,* 2020) ● to investigate human–computer interactions(J.H. Goldberg *et.al.,* 2011) ● to investigate learning in different media platforms(Kruikemeier, 2018) ● studying the process of arithmetic problem solving(Shojaeizadeh,*et.al.,* 2019). ● to determine user engagement(Jung *et.al.,* 2021).
Advantages:	**Limitations:**
● helps complex decision-making process (Meißner *et.al.,* 2019). ● gives more experimental control(Meißner *et.al.,* 2019). ● provides validity because of naturalistic circumstances(Kroff *et.al.,* 2017) ● provides moment-to-moment data source(Conklin *et.al.,* 2016) ● provides nonreactive measurements(Eghbal-Azar *et.al.,* 2012)	● sample size is small and can cause unreliable results(Lim & Teo, 2020) ● equipments are too costly(Scott *et.al.,* 2017). ● it is difficult to analyze eye-tracking data(Kok and Jarodzka, 2017) ● it is difficult to mapping eye movement data to visualizations(Silva *et.al.,* 2019) ● brings up ethical and legal concerns(Meißner *et.al.,* 2019)

Table 1. Overview of eye-tracking in research
Source: the table was compiled by the author.

One of the applications of this method has been done by Chandon et.al., (2009) who tried using eye-tracking glasses in a real store environment to study the purchasing decisions of the customers and purchase conversion by focusing on the "First Moment of Truth". Wedel (2018) also used eye-tracking to find answers to the question of whether the graphic complexity of the visual marketing activities improves or degrades advertising performance. As Wedel (2018), Venkatraman et.al,. (2014) also found eye-tracking as a successful method to identify the success of advertising attempts. The insights gained through eye-tracking assist in the designing of a more pleasurable shopping environment (Klingensmith, 2013). Identifying the attention-grabbing potential of store elements is practical since the results gained from research lead stores to design more effective displays, resulting in a better shopping experience for customers and more revenue for shops. As highlighted among the advantages in Table 1, eye-tracking provides more validity because of usage in naturalistic circumstances such as while driving a car (Trösterer et.al., 2014), walking around a store

(Hendrickson & Ailawadi, 2014), measuring visual elements on large-screen televisions (Hennessey & Fiset, 2012) and smartphones (Valliappan et.al., 2020). Although the advent of affordable, lightweight eye-tracking technology presented an excellent opportunity to examine what attracts customers' focus in displays(Nőrdfalt, et.al., 2011), it also has some limitations. For example, as mentioned in Table 1, the pieces of equipment are expensive compared with other methods which hinder the wide usage of the method in the research(Scott et.al., 2017). It also can raise the questions about the consideration of ethical concerns during the process(Meißner et.al., 2019).

1.4. **Importance of Clustering**

Nowadays, with the advent of technology, it has become much easier for retailers to collect data about their customers. However, having only data does not give them the power to understand their customers and affect their decision-making. One of the methods that have been used for understanding the customers is using the customer data to extract patterns and understand the clusters in the dataset (Rajagopal, 2011).

Usage of clusters in the retail industry gained more importance recently and has been done by several researchers. For example, Dipanjan et.al., (2011) define customer clustering as the technique of dividing clients into homogeneous groups based on one or more criteria such as purchasing patterns, lifestyle, and food preferences. Dogan et.al., (2018) tried customer segmentation using clustering methods in the retail industry in Turkey and found two customer segments that brought valuable insights for decision making. A similar study has been conducted in Germany for a German multichannel retailer by clustering customers based on the data of their contact points (Steinmann et.al., 2016). Another very recent research has been done by Nguyen (2021) who was working on identifying the customer segments in the Vietnamese supermarkets and found four clusters. Behe (2014) also used clustering by using screen-based eye-tracking technology and found clusters of plant market customers based on their attention to plant display attributes. Studies in the retail industry covered m-retail also with clustering online shoppers (David et.al., 2021; Gehrt et.al., 2007). Tupikovskaja-Omovie et.al., (2020) did a study on the customer shopping journeys in the m-retail fashion industry and they found three clusters of customers according to their shopping behavior: “directed by the retailer’s website”, “efficient self-selected journey” and “challenging shopper."

Customers can be divided into clusters based on different variables. Demographic data of customers have been used for clustering and offering customized products. For example, Namvar et.al., (2010) analyzed the customers of the Iranian Bank wit using their demographic data to create the customer persona and address each of them with specific offerings. Hoegele et.al., (2016) segmented their customers based on their genders to identify differences between different gender groups. Lee et.al., (2011) also examined the gender-based clusters for the loyalty of the customers. Additional to gender-based clusters, Sargezeh et.al., (2019) conducted a study to see the differences between males and females in gaze behavior and found out that eye-tracking results change based on gender. Ruiz et.al., (2004) also did an exploratory study in which they segmented the customers based on their activities and then checked their demographic characteristics of them. On the other hand, the study in which the customer segmentation has been done among the customers of Nike and Sketchers based on gender revealed that demographic segmentation does not work alone for clustering and it can hide the reality if it is not merged with other behavioral clusterings (Urbany, 2016). Giering (2008) studied the possibilities of the sales prediction in retail stores based on the clustering of customers according to their demographic characteristics and suggested that it can result in increased sales. An et.al., (2018) also discussed the personas created based on the demographics of the customers and their implications for the offerings to customers. On the other hand, Chapman and Milham (2006) argue that customer personas are being created by insufficient information and they are not reliable enough to make decisions based on them. They also argue that the influence of other characteristics of the persona can affect the reliability of the decisions that have been made based on the defined personas. Thoma and Williams (2009) suggested that while segmenting customers other characteristics such as their shopping behavior should be taken into consideration in addition to their demographic data. Supporting previous criticism, Jung et.al., (2017) also argue that segmenting customer personas should consider customer behavior while making the decisions to prevent risks that may occur on the trust over personas created based on demographic or social characteristics.

In their work, Hume, and Mort (2010) found out that customer feelings have an effect on their decision-making process over purchases and customer behavior in the stores. The results of the research show that the feelings have an effect on the customer information processing process, their behavioral responses, and also their satisfaction levels (Hume & Mort, 2010). Gupta et.al., (2021) studied the effects of the mood on the people, clustered customers based on their mood, and offered them a customized selection of food and restaurants.

Another variable that can be used to cluster customers is the number of planned purchases of the customers. Previous studies suggested that goal-oriented exploration of customer journey maps can give information about the customer clusters and help in forecasting customer behavior (Bernard and Andritsos, 2017). Wu et.al., (2020) also suggested that the customers with goal-oriented shopping behavior have a simpler scan path than the customers who are not planned their shopping journey.

As discussed above, finding clusters of customers is already a proven method of improving sales in the retail industry. For clustering the data, the main component that is used by researchers is the scan path which is the sequence of fixations and saccades. For visualizing the scan path, nodes and arrows are being used in which nodes are representing the fixations and the diameter of the nodes shows the length of the fixation. Arrows are the saccades and their length is associated with the length of the saccade (Figure 1). Although these scan paths are very helpful for understanding data, for them to be more meaningful, Areas of Interest (AoI) need to be defined in the analyzed scenes. AoIs are determined depending on the focus of the task and triggers in the scene.

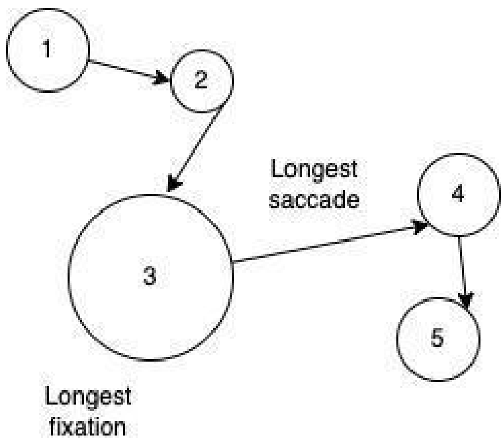


Figure 1. Scanpath
Source: the figure was compiled by the author.

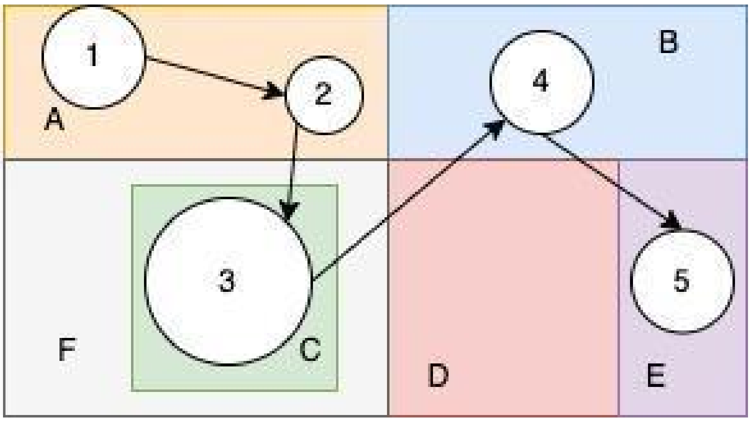


Figure 2. Scanpath over Areas of Interest
Source: the figure was compiled by the author.

As it is visible from the Figure 2, when the scanpath is analyzed on the AoIs, taking the insights becomes easier. In Figure 2, the scanpath is AACBE where F is the background area. From this individual path, it can be derived that, in area A, there is a complexity of information or an important information that lead to the repetition of fixation. On the other hand, in Area D, there is a lack of attention which can also reveal some information for the researcher. There are different metrics that are being used for analysis such as the order of interest areas, the frequency and length of fixations in specific AoI, how long it takes to get to specific AoI. After having individual scanpaths of the multiple participants, specific algorithms are being used to compare them and cluster according to this comparison. These algorithms are primarily intended for quantitatively comparing two scanpaths, identifying trends within scanpaths, and determining a common scanpath for numerous scanpaths (Eraslan *et.al.,* 2016). One of the commonly used algorithms is the String-Edit Algorithm(SEA) which is also known as The Levenshtein Distance (Takeuchi *et.al.,* 2012; Räihä, 2010). This algorithm compares the number of operations to transform one string to another with operations of adding, substituting, or deleting(Fahimi *et.al.,* 2021) For example, if the paths are ABCD and ABCE, Levenshtein Distance is 1, because it is enough to replace E with D. Although Levenshtein Distance is a useful tool for scanpath comparison, it does not take into consideration the distance between AoIs which is one of the limitations of this method(Cristino *et.al.,* 2010). Another drawback of the SEA is it does not consider the fixation durations which also can give valuable insights(Eraslan *et.al.,* 2013) Cristino *et.al.* (2010) developed a new algorithm called ScanMatch, based on the Needleman-Wunsch algorithm, which addresses the drawbacks of the string-edit method and takes into consideration the AoIs distance and fixation durations. Needleman-Wunsch algorithm is used for comparing scanpath with using the substitution score and gap penalty (Needleman and Wunsch, 1970; Eraslan, 2016). Another method using string-edit method is developed by Heminghous and Duchowski (2006). They built iComp which is an open-source tool for visualizing and comparing scanpaths on Privitera and Stark's (2000) scanpath comparison method.

Additional to string-edit logic, some algorithms are based on the geometry of scanpath. One of these methods is MultiMatch developed by Dewhurst *et.al.,* (2011) which takes into consideration 5 factors when comparing scanpaths: shape, length, direction, position, duration. Taking saccades as vectors enables the algorithm to identify the shapes. However, the limitation of this method is it is hard to implement if the objects or AoI are not stable and moving during the experiment (Kang and Landry, 2015). Some other common scanpath comparison methods have been used in the previous literature. One of them is Shortest Common Supersequence which finds the shortest supersequesce of scanpaths. For example, paths ABC, ADC, AEC, AFC will have ABDEFC supersequence (Eraslan *et.al.,* 2016). Although it includes all the points that individual scanpath have, it is too long and makes it hard to implement to longer scenes. It also does not take into consideration the position and duration of the fixations (Eraslan *et.al.,* 2016). Dotplots method is also one of the common scanpath methods which use hierarchical clustering method to derive one scanpath out of multiple scanpaths. To do this, dotplot algorithm is being used to find two the most similar scanpath, merging these two, creating one scanpath from them and deleting the other two scanpaths. This process is being repeated until only one scanpath is found (Goldberg and Helfman, 2010). Additional to string-edit, geometry, and common scanpath methods, a probabilistic approach can also be used while comparing scanpaths. Markov models are one of the ways that focus on the probability of the AoI sequences (Coutrot *et.al.,* 2018). The commonly used algorithm of Markov's approach is the Hidden Markovs Model in which the only factor affecting the next sequence of points is the current state (Coutrot *et.al.,* 2018; Haji-Abolhassani&Clark, 2014). Another algorithm that addresses most drawbacks of the mentioned algorithms is Scanpath Trend Analysis(STA) developed by Eraslan *et.al.,* (2016). While clustering the data, their algorithm takes into account not only the elements that are visited in every individual scanpath but also analyzes the most common elements that have been visited in most individual paths. This method has been used in different fields such as detecting the patterns in code reading(Tablatin *et.al.*, 2018) or detecting autism (Eraslan *et.al.,* 2017).

It is undeniable and confirmed by previous research that clustering has an irreplaceable role for marketers to understand customer behavior in both online and offline retail stores, and eye-tracking is a successful method to collect data to understand the segments of the customers and address them with customized marketing activities

2. Methodology

2.1. Participants and Equipment

The study was conducted in one of the supermarkets in Estonia with the participation of 363 volunteers. Participants were aged between 8 and 89 years old with a number of 158 males and 195 females and 9 participants without reported gender. For getting the most accurate results from the experiment, and at the same time to ensure the diversity of the participants, only one point has been taken into consideration when choosing the customers to participate in the experiment. Since the experiment required participants to wear eyeglasses, the main requirement was not having obvious eye problems, such as having optic eyeglasses which would create problems for wearing experiment glasses. The Tobii Pro Glasses 2 was the main tool that was used for the data collection and the experiment has been conducted in a real-life set-up in the store under natural shopping conditions. Before the experiment, every participant was requested to complete the calibration process to ensure that eyeglasses were working with the best quality to collect data. For data analysis purposes and collecting the social and demographic data, participants were asked questions before and after the experiment. The questions that were asked are added to Appendix A.

2.2. Data

The data obtained by using Tobii Pro Glasses 2 have been exported from the Tobii Pro Lab program and the data consisted of 11421707 rows and 20 columns. The variables that were covered in the data are explained in Appendix B based on the Tobii Pro Lab user manual1. As a first step of the data analysis, data has been cleaned from the points which will not give any insight into the output. Firstly, “Eye movement type” column had the results of “EyesNotFound” which indicated that there was not any input from the eyeglasses to the data. So the rows that contain “EyesNotFound” of eye movement type have been dropped from the data. Before deleting these rows, the number of rows was 11421707 and after deleting the data had 8949938 rows which means 2471769 rows and overall 21% were not useful for the results. In the next step, “Eye movement type” column has been cleaned from the value “Unclassified”. Unclassified eye movement type is the ones that could not be classified either as fixation or saccade. After removing “Unclassified” eye movement type, the number of rows decreased from 8949938 to 8221460. In order to ensure the cleanness of the data, the dataset has been removed from the duplicates. After this step, in order to make the analysis easier, a copy of the original dataset has been generated and the columns that were not planned to be used in the data analysis have been removed. The removed columns were “Pupil diameter right [mm]”, "Pupil diameter left [mm]”, "Recording timestamp [μs]”, "Computer timestamp [μs]”, “Gaze point X [MCS px]”, “Gaze point Y [MCS px]”, "Validity left", "Validity right”. After removing these columns, duplicates have been again dropped to prevent any errors in the results.

Another data that had the social and demographic data of the participants has been collected by the experiment organizers during the experiment. Demographic data consisted of the answers to the questions mentioned in Appendix A and timestamps. Dataset was 363 rows and 18 columns, but since 2 columns were left empty without any answers, they were deleted before the analysis. As the main purpose of the work was to find the association between the clusters in the eye-tracking data and social-demographic data, the cross-checking has been done between two datasets based on “Participant name” column and both files have been cleaned. The reason for choosing the “Participant name” column as a basis was its being a common column between these two datasets and will be used for merging them. As a result of the cleaning, the data points that were used for clustering analysis and demographic data have been merged into one dataset which had 29 columns and 217 rows and the main reason for the decrease in the number of participants from 363 to 217 was the missing data points in the data sets. One version of the missing data was that the participant had the eye-tracking data, but the demographic data was missing, or the participant had the demographic data, but the eye-tracking was not successful. The tools that have been used for data analysis were Python 3 which was used in Jupyter Notebook and Excel to keep the merged data. The packages that have been used for analysis in Python were “pandas”, “matplotlib.pyplot”, “seaborn“, “gapminder”, ”defaultdict”, “numpy“, “statsmodels.api”, and “KMeans” to work on the data and for clustering.

For clustering, K-means method has been used to determine the clusters in the data. Previous research shows that the K-means algorithm is not only more stable in the clustering stage, but also reduces or even eliminates the effects of noise data in the database, resulting in a more reliable and effective final clustering result (Zhang and Fang, 2013). K-means algorithm uses an iterative way of clustering by using the Euclidean distance. As an output, this algorithm gives the K amount of clusters with centroids. Each data point belongs to the cluster with which it has a minimal distance to the centroid(Chong, 2021). The main reason that the K-means method has been used was it gives reliable results with the big data sets. On the other hand, the eye-tracking data that was collected was based on video visuals which made the analysis of the AoIs not possible and eliminated other clustering algorithm options. However, K-means also have some limitations such as not having the optimal number of clusters, so the K should be selected before analysis by the researcher. It also can understand the outliers as a separate cluster, so this needs to be taken into consideration during the interpretation of the results. However, as this method is flexible with changes in the data, and have good and easy interpretation as a result of the simple visual outputs, it is being used frequently with the eye-tracking data analysis.

3. Results

During the analysis, the focus was mainly on fixation points to understand how customers have different clusters over their fixation points and duration which will be a relevant measure for the gaze behavior. Figure 3 shows how the coordinates of fixation points are located in the area and what is the main focus of the participants. For this figure, matplotlib.pyplot, seaborn and gapminder packages, “Fixation point X [MCS px]”, Fixation point Y [MCS px], and “Gaze event duration [ms] as the plot size have been used. From the graph, it is visible that the main focus of the buyers has been on the center while the fixations become scarcer on the corners of the graph. Since the number of participants was too high, it was causing the overplotting problem in the graph and prevented getting valuable insights per participant. However, it is still visible that the main focus in the center with longer durations has the same pattern applies here that plots are getting smaller and scarcer going towards the corners.

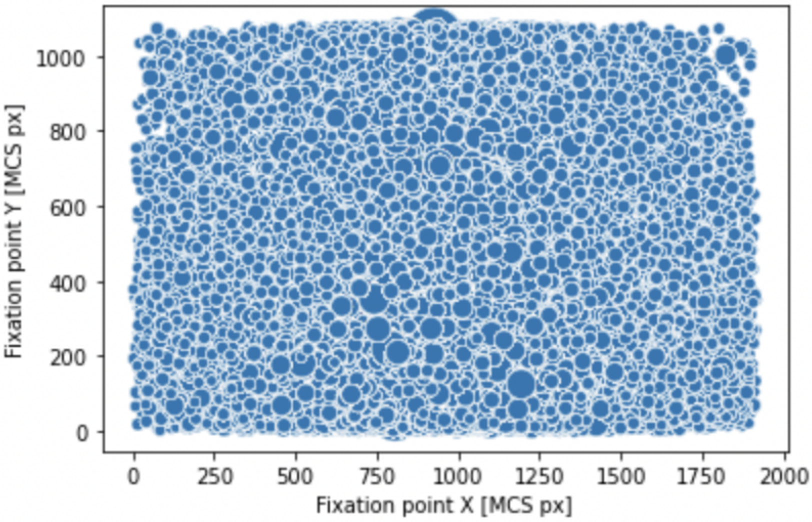


Figure 3. Fixation locations with “Gaze event duration [ms] as plot size
Source: calculations of author

One of the goals of the analysis was to check common patterns of the clusters in the data based on demographic factors. In order to be able to match data between demographic data and eye-tracking data, they should have a common column that will be used to merge the data which was “Participant name” as mentioned Methodology section. Table 2 shows the first 5 rows of the data that has been cleaned from the duplicates and will be used for analysis.As it is visible from Table 2, the 5 rows describe the same participant having the same recording duration which was the overall shopping journey duration.

	Sensor	Participant name	Recording name	Recording date	Recording start time	Recording duration [ms]	Recording Fixation filter name	Eye movement type	Gaze event duration [ms]	Eye movement type index	Fixation point X [MCS px]	Fixation point Y [MCS px]
0	Eye Tracker	kadi 37	Recording001	20.10.2020	10:59:32.160	1472351	Tobii I-VT (Attention)	Fixation	185	1	1077.0	353.0
19	Eye Tracker	kadi 37	Recording001	20.10.2020	10:59:32.160	1472351	Tobii I-VT (Attention)	Fixation	120	2	1073.0	347.0
39	Eye Tracker	kadi 37	Recording001	20.10.2020	10:59:32.160	1472351	Tobii I-VT (Attention)	Fixation	240	3	1068.0	341.0
65	Eye Tracker	kadi 37	Recording001	20.10.2020	10:59:32.160	1472351	Tobii I-VT (Attention)	Fixation	550	4	1070.0	356.0
305	Eye Tracker	kadi 37	Recording001	20.10.2020	10:59:32.160	1472351	Tobii I-VT (Attention)	Fixation	180	5	1025.0	387.0

Table 2. First 5 rows of data after cleaning
Source: calculations of author

However, all the rows have different fixation coordinates and every one of them is being calculated as unique fixations. After having all the participants cleaned in both datasets, the new variable “Number of fixations” has been extracted from the data. Since the data was cleaned from the duplicates, “Number of fixations” has been calculated as the count of unique fixation points per “Participant name”. Another variable that has been taken for the analysis was the “Average gaze duration” which has been taken as a mean of “Gaze Event Duration” per “Participant name”.

For further analysis and clustering, a new dataset has been created in which the data that will be used for further analysis has been collected. Columns included in that dataset were these: “Participant name”, “Average gaze event duration”, “Number of fixations”, “Recording duration [ms]”,“Recording duration [sec]”. Since the shopping journeys has different lengths, using “Number of fixations” was not a reliable measure for clustering, therefore new variables called “Number of fixations per X seconds” have been added to the sheet. For testing purposes, “Number of 30 sec during recording”, “Number of fixations per 30 sec”, “Number of 20 sec during recording”, “Number of fixations per 20 sec”, “Number of 10 sec during recording”, “Number of fixations per 10 sec”,“Number of 5 sec during recording”, “Number of fixations per 5 sec” have been added to the dataset. Table 3 displays the first 5 rows of the dataset after new variables have been added. Then this data has been added to Python to get clusters and by using “sklearn.clusters-Kmeans” package clustering algorithm has been applied. As mentioned above for testing purposes K-means clustering has been done between 4 different pairs:

1.” Number of fixations per 30 sec” and “Average gaze event duration”
2. ” Number of fixations per 20 sec” and “Average gaze event duration”
3.” Number of fixations per 10 sec” and “Average gaze event duration”
4.” Number of fixations per 5 sec” and “Average gaze event duration”

	Participant name	Average gaze event duration	Number of fixations	Recording duration [ms]	Recording duration [sec]	Number of 30 sec during recording	Number of fixations per 30 sec	Number of 20 sec during recording	Number of fixations per 20 sec	Number of 10 sec during recording	Number of fixations per 10 sec	Number of 5 sec during recording	Number of fixations per 5 sec
0	22tina	262.943005	1158	501968.0	501.968	16.732267	172.122526	25.09840	46.138399	50.1968	23.069200	100.3936	11.534600
1	Alan32	256.311281	1436	612210.0	612.210	20.407000	180.232273	30.61050	46.912007	61.2210	23.456004	122.4420	11.728002
2	ALAN 37	243.234104	1038	363575.0	363.575	12.119167	174.847005	18.17875	57.099636	36.3575	28.549818	72.7150	14.274909
3	Aleks46	274.976190	336	145901.0	145.901	4.863367	166.962529	7.29505	46.058629	14.5901	23.029314	29.1802	11.514657
4	alexa44	291.775168	1192	484885.0	484.885	16.162833	117.491776	24.24425	49.166297	48.4885	24.583149	96.9770	12.291574

Table 3. First 5 variables of new dataset with new variables
Source: Based on calculations of author on eye-tracking data

For all clustering tests, K, which demonstrates the number of clusters has been determined as 3 taken from the elbow method applied to the data (Figure 4). Figure 5 below shows the results from the first pair of variables which were ”Number of fixations per 30 sec” and “Average gaze event duration”. It shows that when the number of fixations per 30 seconds increases, the average gaze event duration decreases which means when people change the focus of their eyes more, as the number of their fixation increases. In the next 3 tests, the results have been the same which located the participants in the same clusters. Although the results of all of them were identical for clusters, they were different from the first test. Figure 6 (a), 6(b) and 6(c) shows the last three test results and visualize the clusters with 3 different colors which indicates different clusters.

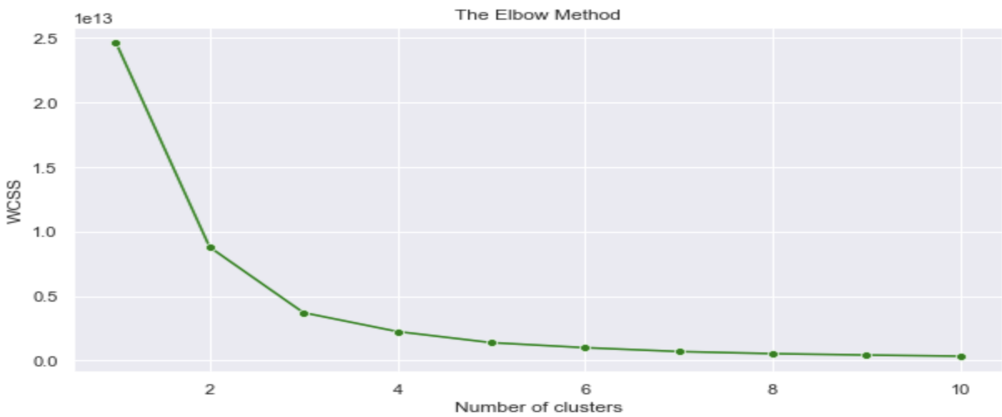


Figure 4. Elbow method to determine number of clusters: K
Source: Based on calculations of author on eye-tracking data

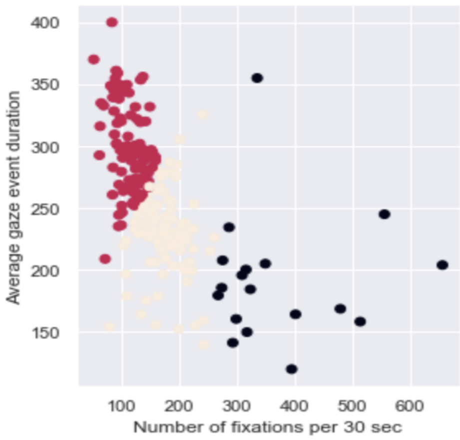
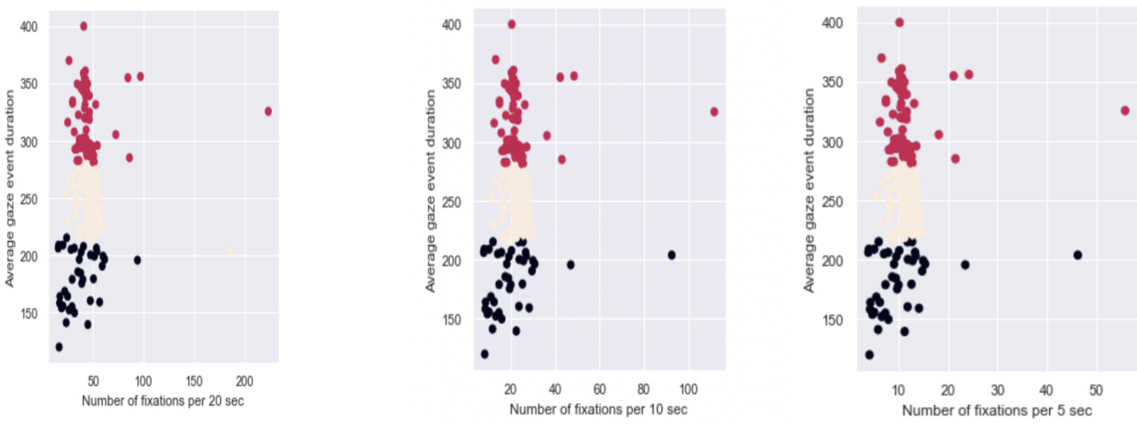


Figure 5. Clusters based on “Number of fixations per 30 sec” and “Average gaze event duration”
Source: calculations of author



(a) (b) (c)

Figure 6

(a)Clusters based on “Number of fixations per 20 sec” and “Average gaze event duration”

(b) Clusters based on “Number of fixations per 10 sec” and “Average gaze event duration”

(c) Clusters based on “Number of fixations per 5 sec” and “Average gaze event duration”

Source: calculations of author

Figure 6 (a), 6(b) and 6(c) illustrate the clusters based on pairs of valiables of “Number of fixations per 20 sec” and “Average gaze event duration”, Number of fixations per 10 sec” and “Average gaze event duration” and Number of fixations per 5 sec” and “Average gaze event duration”. It show that most participants have around 40-60 fixations per 20 seconds, around 20-30 fixations per 10 seconds, and around 10-15 fixations per 5 seconds accordingly. From Figure 6, it is reliable to think that people who have more fixation points than the abovementioned ranges are outliers in the data. The number of outliers can be taken as 7 participants in all three tests if we take 60,40 and 20 fixations as thresholds accordingly. For getting more accurate results, outliers have been removed from the dataset and clusters has been analyzed with 211 participants.

After checking clusters with the K-means algorithm, clusters in which variables were ”Number of fixations per 20 sec” and “Average gaze event duration” has been taken as valid results. One reason for this is this result was repeated in following three tests of different pairs of variables repeated after it. Additionally, the data that we used for analysing clusters has been used previously in other study by Orgusaar (2021) to understand purchase behaviour based on time to make a purchase. In that study the amount of time spent choosing three different types of products: tea, dairy products, and joghurt has been investigated. As a result, 42 % of participants took 16-30 seconds to make a purchase decision. Since the data of that study is same with the data of this thesis and the purchase times belongs to the same participants, we can say that for customers it usually takes 16-30 seconds to make decisions and “Number of fixations per 20 sec” can be selected for clustering since 20 is located in that range. In the next step, demographic data, eye-tracking data, and cluster numbers have been added to one dataset which will be used for taking demographic and social statistics for the clusters that have been identified as a result of the test. Merged data consisted of these columns: 'Participant name', 'Average gaze event duration', 'Number of fixations', 'Recording duration [ms]', 'Recording duration [sec]', 'Number of 30 sec during recording', 'Number of fixations per 30 sec', 'Number of 20 sec during recording', 'Number of fixations per 20 sec', 'Number of 10 sec during recording', 'Number of fixations per 10 sec', 'Number of 5 sec during recording', 'Number of fixations per 5 sec', 'cluster', 'Gender', 'Age', 'Poekülastuse eesmärk/põhjus', 'Number of planned purchases', 'Any unplanned purchase', 'Did notice the screens', 'If noticed, what do you remember about the screen ad', 'Did any advertisement affect purchases?', 'Type of checkout', 'Why did you choose remote control / cash register/self-service', 'Calibration', 'Mood rating', 'Fatigue rating'.

	Clusters	Average age	Percentage of female in cluster	Percentage of male in cluster	Average mood rating	Average fatigue rating	Average number of planned purchases
Cluster 1	Cluster 1	34.09	50.85%	49.15%	4.50	2.21	6.71
Cluster 2	Cluster 2	36.15	35.00%	65.00%	4.35	2.25	5.80
Cluster 3	Cluster 3	35.52	47.95%	52.05%	4.36	2.23	5.84

Table 4. Clusters based on their demographic data
Source: calculations of author

As a result of merging data, descriptive statistics of the social and demographic data have been taken for the clusters based on the eye-tracking data. Table 4 above describes the results for descriptive statistics. The first variable in the descriptive statistics is the average age of the participants which is very similar in all the clusters and changes between 34 to 35.5. For the second variable - gender distribution in the clusters, female and male division is very similar especially in Clusters 1 and 3. 50.85% of participants in Cluster 1 and 47.95% of participants in Cluster 3 are female while 49.15% of participants in Cluster 1 and 52.05% of participants in Cluster 3 are male. However, in Cluster 2, the percentage of females is 35.00%

while 65.00% are male participants.The next variable is the average mood rating which was the data taken after the shopping experience and indicates how the participants were feeling on the day of the experiment. As visible from Table 4, all clusters have a very close average mood rating which is 4.50 for Cluster 1, 4.35 for Cluster 2, and 4,36 for Cluster 3 out of a 1-5 scale. The average fatigue rating is also based on the data collected after the shopping experience and shows similar results in all clusters as the average mood rating. While Cluster 1 has an average fatigue rating of 2.21, Cluster 2 has 2.25, and Cluster 3 has 2.23 out of a 1-5 scale.An average number of planned purchases was also a variable which was indicating how many products participants are planning to buy before the experiment which had a minimum of 1 product and a maximum of 10 products. It shows how planned a participant is about the shopping journey and how possible it is that the advertisement can affect their purchases. Results show very similar numbers for all clusters while Cluster 1 had an average of 6.71 products, Cluster 2 had 5.80 products and Cluster 3 had 5.84 products planned to buy. Figure 7 visually illustrates the steps explained above to have a better understanding of the flow. As mentioned above, all the analysis has been done in Python 3 and the codes used for analysis were added to Github repository[1] dedicated for this study.

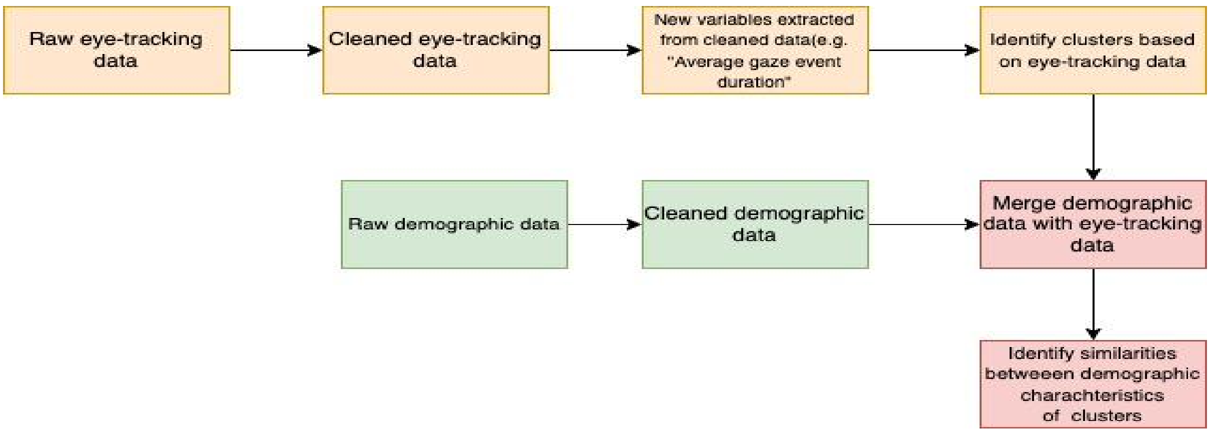


Figure 7. Visualised flow of analysis

4. Discussion

This study contributes to the current literature on the clustering of customers based on the gaze behavior taken from eye-tracking data by conducting a segmentation analysis of 211 journeys. By merging two datasets, we found three clusters from the pair of variables of "Number of fixations per 20 sec" and "Average gaze event duration". Since the clusters were

[1] https://github.com/HagigatH/MasterThesis.git

identified based on the “Average gaze event duration”, they can be labeled as “Customers with short fixations”, “Customers with middling fixations” and Cluster 3 as “Customers with long fixations”.

The findings of this study do not intend to rule out all potential crossings between ET and retail decisions. Instead, further methods are required to comprehend the relationship between the brain, the neurological system of the body, and, lastly, users' visual awareness and self-assessments. Results of this study show that the demographic characteristics of the clusters have similarities. For example, Table 4 indicates that the average age of the customers in all segments is very close to each other. On the other hand, the gender division of the clusters also shows similar patterns in the results. In the literature, previous researchers have done studies on clustering based on demographic characteristics. As the literature review indicated, while some studies have been focused on the clustering customers based on demographic characteristics (Hoegele et.al., 2016; Sargezeh et.al., 2019), some studies (Urbany, 2016; Chapman & Milham, 2006; Thoma & Williams, 2009) also indicate the need for further research on gaze behaviour to get more insights about the customer personas. Results also show similar social characteristics for three clusters which include average mood rating, average fatigue rating and amount of planned purchases. As discussed in the literature review, these variables are being used for clustering customers and addressing them with different offerings. However, our results show that there can be other patterns which could add more value to these clustering studies if eye-tracking data is taken into account in addition to mentioned variables. As mentioned above, Gupta et.al.,(2021) discusses the effects of the mood on people while making decisions about consuming food in restaurants, adding eye-tracking results can be useful to understand what exactly people are interested in while making a decision in the restaurants. Additionally, for example, as it was added to the literature review Bernard & Andritsos (2017) suggested that goal-oriented exploration of customer journey maps can give information about the customer clusters and help in forecasting customer behavior.

From the results in Table 4, we can conclude that the clusters that have been taken from the eye-tracking data are not explained by the demographic data which is an indicator that eye-tracking data can contain the information that cannot be revealed by only analyzing the demographic data. Relying on the contradicting and overlapping results of our study and literature, it is undeniable that demographic clustering has the potential to bring light to the decisions of retail stores. In the studies that have been done in-store environments, demographic data has been used to explain clusters based on the data collected from shopping behaviour. While it gives insights to the retailers about the shopping patterns of the customers, it does not cover the way that customers pay attention to the in-store determinants such as the design of the store, product details, advertisement placements, etc. Having information about these variables can give retailers extra confidence to arrange the stores in a way that fits different clusters of people who have different ways of attention during shopping. For example, in our results, clusters based on “Number of fixations per 30 sec” and “Average gaze event duration” showed that customers who have a shorter average fixation duration tend to have more number of fixations. Although the topic and literature of this study do not cover the analysis of this relationship, this thesis can be an inspiration to understand the reasons for this pattern. For example, it can be analysed whether people who have more and shorter fixation points are less goal-oriented customers than those who have longer fixations and can be more planned customers. All the results of this study support that retail stores can take the advantage of the eye-tracking method and use them in tandem with other methods such as social clustering or demographic clustering to understand what gets the attention of the customer to make a purchase decision.

5. Limitations and Future Suggestions

One of the main limitations was the lack of possibility to use other clustering algorithms because of missing Areas of Interest in the data. Data was collected by the eyeglasses that were carried by the moving participants which means the recordings were moving frames. For future analysis of the data, Areas of Interest can be plotted in the moving frames with using the program of the glasses however it was not possible in this study because of time limitation. After having the AoIs plotting the fixation locations on them, it can give more insights for further researches. Another limitation was not having available standards for the metrics in the literature that can be used for eye-tracking data analysis. For example, for analyzing the average gaze event duration, there was no standard range to label the clusters. There might be more articles about standards for labeling length of average gaze event duration that our search keywords didn't find or that published in papers that weren't well linked to the digital libraries we looked at. Results of this study has been built on the clusters based on eye-tracking data and checking the demographic data of these clusters. However, this research can be extended to identifying clusters based on the demographic data. It will give a chance to see the similarities between clusters based on demographic data and clusters based on eye-tracking data. Moreover, this research has been done on the data which was collected in only one supermarket in Estonia and participants were local people. Adding participants from diverse backgrounds can add more insights for the data for further research. Finally, a small number of research have been conducted in-store environments.

Conclusion

As stores are not identical, the consumers who are an important part of those stores are also diverse in their choices and the emphasis they put on various store components. This thesis is one of the few examples of studies that identified the clusters based on real-life eye-tracking data of the customers and checked the similarities of the demographic and social characteristics of the clusters. Results revealed three clusters based on their fixation duration which can be labeled as "Customers with short fixations", "Customers with middling fixations" and "Customers with long fixations". However the clusters which have different gaze characteristics have very similar demographic and social indicators, so the clusters could not be explained by demographic data which showed that eye-tracking analysis can have additional insights to offer to retailers in addition to demographic clustering.It also showed that analysis of eye-tracking data has a potential usage for retailers to know their customers better and to have deeper information of what the customers are looking at during their shopping journey. These insights can be useful when retail stores want to improve their sales, have special offerings to their customers, or improve the customer experience and keep the retention rate high. Combining data based on personal characteristics, economic conditions, lifestyle, and shopping habits with eye behavior and exploring common patterns can be used to formulate the retailer's customer personas. The marketing teams of retail stores will be better equipped to reach out to their customers and provide a customized consumer experience that meets the demands of consumers if they add eye-tracking data to their analysis while making data-driven decisions.

List of references

1. Agarwal, S., & Dutta, T. (2015). Neuromarketing and consumer neuroscience: current understanding and the way forward. Decision, 42(4), 457–462. doi:10.1007/s40622-015-0113-1
2. Ailawadi, Kusum L., Donald R. Lehmann, and Scott A. Neslin (2001), "Market Response to a Major Policy Change in the Marketing Mix: Learning from Procter & Gamble's Value Pricing Strategy," Journal of Marketing, 65 (January), 44–61.
3. Albari, Safitri I (2018). The Influence of Product Price on Consumers' Purchasing Decisions
4. Alemdag, E., & Cagiltay, K. (2018). A systematic review of eye tracking research on multimedia learning. Computers & Education, 125, 413-428.
5. An, J., Kwak, H., Jung, Sg. et al.(2018) Customer segmentation using online platforms: isolating behavioral and demographic segments for persona creation via aggregated user data. Soc. Netw. Anal. Min. 8, 54 https://doi.org/10.1007/s13278-018-0531-0
6. Ariely, D., and G. Berns (2010). Neuromarketing: the hope and hype of neuroimaging in Business. Nature Review Science. Http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2875927/.
7. Artun and Omer (1969). Predictive marketing : easy ways every marketer can use customer analytics and big data.CH 1, p. 3
8. Bagozzi, R. P., & Dholakia, U. (1999). Goal Setting and Goal Striving in Consumer Behavior. Journal of Marketing, 63, 19. doi:10.2307/1252098
9. Bao Chong. K-means clustering algorithm: a brief review. Academic Journal of Computing & Information Science (2021), Vol. 4, Issue 5: 37-40. https://doi.org/10.25236/AJCIS.2021.040506.
10. Barz, M., Poller, P., & Sonntag, D. (2017). Evaluating Remote and Head-worn Eye Trackers in Multi-modal Speech-based HRI. Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17. doi:10.1145/3029798.3038367
11. Behe, B. K., Fernandez, R. T., Huddleston, P. T., Minahan, S., Getter, K. L., Sage, L., & Jones, A. M. (2013). Practical Field Use of Eye-tracking Devices for Consumer Research in the Retail Environment, HortTechnology hortte, 23(4), 517-524.

Retrieved Jan 29, 2022, from https://journals.ashs.org/horttech/view/journals/horttech/23/4/article-p517.xml

12. Behe, Bridget & Campbell, Ben & Khachatryan, Hayk & Hall, Charles &Dennis, Jennifer & Huddleston, Patricia & Fernandez, Rodney. (2014).Incorporating Eye Tracking Technology and Conjoint Analysis to Better Understand the Green Industry. Consumer. HortScience: a publication of the American Society for Horticultural Science. 49. 1550-1557.10.21273/HORTSCI.49.12.1550
13. Bello-Morales Raquel, Delgado-García José María(2015). The social neuroscience and the theory of integrative levels.Frontiers in Integrative Neuroscience.Vol https://www.frontiersin.org/article/10.3389/fnint.2015.00054. DOI=10.3389/fnint.2015.00054
14. Bercea, M. D. (2013). "Anatomy Of Methodologies For Measuring Consumer Behavior İn. Neuromarketing Research" http://www.lcbr-online.com/index_files/proceedingsemc12/12emc023.pdf
15. Bernard, Gaël & Andritsos, Periklis. (2017). CJM-ex: Goal-oriented Exploration of Customer Journey Maps using Event Logs and Data Analytics.
16. Bojko, A. (2013). Eye tracking the user experience: A practical guide to research. Rosenfeld Media.
17. Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics.Journal of Economic Literature, 43, 9–64
18. Chandon, P., Hutchinson, J. W., Bradlow, E. T., & Young, S. H. (2009). Does In-Store Marketing Work? Effects of the Number and Position of Shelf Facings on Brand Attention and Evaluation at the Point of Purchase. Journal of Marketing, 73(6), 1–17. http://www.jstor.org/stable/20619055
19. Chapman, CN & Milham, RP (2006), 'The Personas' New Clothes: Methodological and Practical. Arguments against a Popular Method', Proceedings of the Human Factors and Ergonomics. Society Annual Meeting, vol. 50, no. 5, pp. 634–636.
20. Conklin, K., & Pellicer-Sánchez, A.(2016). Using eye-tracking in applied linguistics and second language research.Second Language Research, 32(3), 453–467. doi:10.1177/0267658316637401
21. Coutrot, A., Hsiao, J.H. & Chan, A.B (2018). Scanpath modeling and classification with hidden Markov models. Behav Res 50, 362–379). https://doi.org/10.3758/s13428-017-0876-8

22. Cowen, L., Ball, L. J., & Delin, J. (2002). An eye-movement analysis of web-page usability. In X. Faulkner, J. Finlay, & F. Détienne (Eds.), People and Computer XVI—Memorable yet Invisible: Proceedings of HCI 2002 (pp. 317-335)
23. Cristino, F., Mathôt, S., Theeuwes, J., & Gilchrist, I. D. (2010). ScanMatch: A novel method for comparing fixation sequences. Behavior Research Methods, 42(3), 692–700. doi:10.3758/brm.42.3.692
24. Davenport, T.H. and Beck, J.C. (2001), The Attention Economy: Understanding the Currency ofBusiness, Harvard Business Press, Boston, MA
25. Dewhurst, Richard & Jarodzka, Halszka & Holmqvist, Kenneth & Foulsham, Tom & Nyström, Marcus. (2011). A new method for comparing scanpaths based on vectors and dimensions. Journal of Vision. 11. 10.1167/11.11.502.
26. Dipanjan, D., Satish, G., & Goutam, C (2011). Comparison of Probabilistic-D and k-Means Clustering in Segment. Profiles for B2B. Markets. SAS Global Forum.
27. Dirix, N., Vander Beken, H., De Bruyne, E., Brysbaert, M., & Duyck, W. (2019). Reading Text When Studying in a Second Language: An Eye‐Tracking Study. Reading Research Quarterly. doi:10.1002/rrq.277
28. Doody, O., & Noonan, M. (2013). Preparing and conducting interviews to collect data. Nurse researcher, 20(5).)
29. Eben Harrell, 2019. Neuromarketing: What You Need to Know. https://hbr.org/2019/01/neuromarketing-what-you-need-to-know
30. Eghbal-Azar, K., & Widlok, T. (2012).Potentials and Limitations of Mobile Eye Tracking in Visitor Studies. Social Science Computer Review, 31(1), 103–118. doi:10.1177/0894439312453565
31. Elbers, T. (2016). The effects of in-store layout- and shelf designs on consumer behaviour. Retrieved from https://edepot.wur.nl/369091
32. Eraslan, S., Yesilada, Y., & Harper, S. (2016). Scanpath Trend Analysis on Web Pages: Clustering Eye Tracking. Scanpaths. ACM Transactions on the Web. https://doi.org/10.1145/2970818
33. Eraslan, S., Yesilada, Y., & Harper, S. (2013).eMINE Scanpath Analysis Algorithm https://zenodo.org/record/11997/files/D5.pdf
34. Eraslan, S., Yesilada, Y., and Harper, S. (2016).Eye Tracking Scanpath Analysis Techniques on Web Pages: A Survey, Evaluation and Comparison

35. Eraslan, S., Yaneva, V., Yesilada, Y., & Harper, S. (2017, April). Do web users with autism experience barriers when searching for information within web pages?. In Proceedings of the 14th International Web for All Conference (pp. 1-4).
36. Fang, C.; Liu, H. (2021) Eye tracking technology to audit google analytics: Analysing digital consumer shopping journey in fashion m-retail,. Research and Application of Improved Clustering Algorithm in Retail Customer Classification.
37. Fahimi, R., Bruce, N.D.B. On metrics for measuring scanpath similarity. Behav Res 53, 609–628 (2021). https://doi.org/10.3758/s13428-020-01441-0
38. Farnsworth, 2019, What is Eye Tracking and How Does it Work? https://imotions.com/blog/eye-tracking/
39. Fawzy, A., & Samra, Y. A. (2008). A Conceptual Model for Understanding Associations' Site Selection Processes: An Organizational Buyer Behavior Perspective. Journal of Convention & Event Tourism, 9(2), 119–136. doi:10.1080/15470140802195027
40. Fortunato, V. C. R., Giraldi, J. D. M. E., & De Oliveira, J. H. C. (2014). A Review of Studies on Neuromarketing: Practical Results, Techniques, Contributions and Limitations. Journal of Management Research, 6(2), 201. doi:10.5296/jmr.v6i2.5446
41. Franchak, J. M., Kretch, K. S., Soska, K. C., & Adolph, K. E. (2011). Head-Mounted Eye Tracking: A New Method to Describe Infant Looking. Child Development, 82(6), 1738–1750. http://www.jstor.org/stable/41289878
42. Franco-Watkins, A. M., & Johnson, J. G. (2011). Decision moving window: using interactive eye tracking to examine decision processes. Behavior Research Methods, 43(3), 853–863.doi:10.3758/s13428-011-0083-y
43. G. Öquist, A. Hein, J. Ygge, M. Goldstein. Eye movement study of reading on a mobile device using the page and RSVP text presentation formats. S. Brewster, M. Dunlop (Eds.), Mobile human computer Interaction – Mobile HCI 2004, LNCS 3160, Springer, Berlin/Heidelberg, Germany(2004), pp. 108-119
44. Garczarek-Bąk, U., Szymkowiak, A., Gaczek, P., & Disterheft, A. (2021). A comparative analysis of neuromarketing methods for brand purchasing predictions among young adults. Journal of Brand Management, 1–15. Advance online publication. https://doi.org/10.1057/s41262-020-00221-7
45. Gehrt, K. C., Onzo, N., Fujita, K., & Rajan, M. N. (2007). The Emergence of Internet Shopping in Japan: Identification of Shopping Orientation-Defined Segments. Journal

of Marketing Theory an Practice, 15(2), 167–177. http://www.jstor.org/stable/40470289

46. Giering, M. (2008). Retail sales prediction and item recommendations using customer demographics at store level. ACM SIGKDD Explorations Newsletter, 10(2), 84. doi:10.1145/1540276.1540301
47. Gliga, T., Elsabbagh, M., Hudry, K., Charman, T., Johnson, M. H., & The BASIS Team. (2012). Gaze Following, Gaze Reading, and Word Learning in Children at Risk for Autism. Child Development,83(3), 926–938. http://www.jstor.org/stable/23255733
48. Gonchigjav, Boldbaatar. (2020). Results of neuromarketing study of visual attention and emotions of buyers in retail store environment. Proceedings of the Mongolian Academy of Sciences. 52-64.10.5564/pmas.v60i1.1337.
49. Goldberg, J. H., & Helfman, J. I. (2010). Scanpath clustering and aggregation. Proceedings of the 2010 Symposium on Eye-Tracking Research & Applications - ETRA '10. doi:10.1145/1743666.1743721
50. Gupta, M., Mourila, S., Kotte, S., & Chandra, K. B. (2021, August). Mood Based Food Recommendation System. In 2021 Asian Conference on Innovation in Technology (ASIANCON) (pp. 1-6). IEEE.
51. Haji-Abolhassani, A., & Clark, J. J. (2014). An inverse Yarbus process: Predicting observers' task from eye movement patterns. Vision Research, 103, 127–142.
52. Hayk Khachatryan and Alicia L. Rihn, 2017. Eye-tracking Methodology And Applications In Consumer Research. https://edis.ifas.ufl.edu/publication/FE947#FOOTNOTE_1
53. Heminghous, J., & Duchowski, A.T. (2006). iComp: a tool for scanpath visualization and comparison. SIGGRAPH '06.
54. Hendrickson, K., & Ailawadi, K. L. (2014). Six Lessons for In-Store Marketing from Six Years of Mobile Eye-Tracking Research. Shopper Marketing and the Role of In-Store Marketing, 57–74. doi:10.1108/s1548-643520140000011002
55. Hennessey, C., & Fiset, J. (2012).Long range eye tracking. Proceedings of the Symposium on Eye Tracking Research and Applications - ETRA '12. doi:10.1145/2168556.2168608
56. Heyes C. (2012). New thinking: the evolution of human cognition. Philosophical transactions of the Royal Society of London. Series B, Biological sciences, 367(1599), 2091–2096. https://doi.org/10.1098/rstb.2012.0111

57. https://www2.deloitte.com/content/dam/Deloitte/de/Documents/Innovation/Customer-Centric-Shopping-Experience-Neuroscience-Deloitte-2018.pdf
58. Hoegele, D., Schmidt, S.L. & Torgler, B. The importance of key celebrity characteristics for customer segmentation by age and gender: Does beauty matter in professional football?. Rev Manag Sci 10, 601–627 (2016). https://doi.org/10.1007/s11846-015-0172-x
59. Hubert, M., & Kenning, P. (2008). Acurrent overview of consumer neuroscience. Journal of Consumer Behaviour,7(4–5), 272–292.
60. Huddleston, Patricia & Behe, Bridget& Minahan, Stella & Fernandez, Rodney. (2015). Seeking attention: Aneye tracking study of in-store merchandise displays. International Journal of Retail & Distribution Management. 43. 561-574. 10.1108/IJRDM-06-2013-0120.
61. Hui, S. K., Huang, Y., Suher, J., & Inman,J. J. (2013). Deconstructing the “First Moment of Truth”: Understanding Unplanned Consideration and Purchase Conversion Using In-Store Video Tracking. Journal of Marketing Research, 50(4), 445–462. doi:10.1509/jmr.12.0065
62. Hume, Margaret & Sullivan Mort, Gillian. (2010). The Consequence of Appraisal Emotion, Service Quality, Perceived Value and Customer Satisfaction on Repurchase Intent in the Performing Arts. Journal of Services Marketing. 24. 10.1108/08876041011031136.
63. Jacob R.J., Karn S.K (2003). Eye tracking in human-computer interaction and usability research: Ready to deliver the promises. J. Hyönä, R. Radach, H. Deubel (Eds.), The mind’s eye: Cognitive and applied aspects of eye movement research, Elsevier Science, Amsterdam , pp. 573-60
64. Jeon, Y., Cho, M.S. and Oh, J. (2021), "A study of customer perception of visual information in food stands through eye-tracking", British Food Journal, Vol. 123 No. 12, pp. 4436-4450. https://doi.org/10.1108/BFJ-12-2020-1082
65. Igarashi, M., Boer, L.d. and Pfuhl, G. (2017), "Analyzing buyer behavior when selecting green criteria in public procurement", Journal of Public Procurement, Vol. 17 No. 2, pp. 141-186. https://doi.org/10.1108/JOPP-17-02-2017-B001
66. Iloka, B. C., & Anukwe, G. I. (2020). Review of eye-tracking: A neuromarketing technique. Neuroscience Research Notes, 3(4), 29-34.

67. J.H. Goldberg, J.I. Helfman. Eye tracking for visualization evaluation: reading values on linear versus radial graphs.Information Visualization, 10 (3) (2011), pp. 182-195,International Journal of Information Management, Volume 59,2021,102294, ISSN 0268-4012,https://doi.org/10.1016/j.ijinfomgt.2020.102294.
68. Johnson, S. P., Amso, D., & Slemmer, J. A. (2003). Development of Object Concepts in Infancy: Evidence for Early Learning in an Eye-Tracking Paradigm. Proceedings of the National Academy of Sciences of the United States of America, 100(18), 10568–10573. http://www.jstor.org/stable/3147757
69. Johnston, T.(2004) Research: too Much Choice Can Hurt Brand Performance.
70. Jung, S-G, An, J, Kwak, H, Ahmad, M, Nielsen, L & Jansen, BJ 2017, ‘Persona Generation from Aggregated Social Media Data’, in Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems, CHI EA ’17, pp. 1748–1755
71. Jung, S. G., Salminen, J., & Jansen, B. (2021, May). Implementing eye-tracking for persona analytics. In ACM Symposium on Eye Tracking Research and Applications (pp. 1-4).
72. K. Rayner, K.H. Chace, T.J. Slattery, J.Ashby.(2006) Eye movements as reflections of comprehension process in reading. Scientific Studies of Reading, 10 (3) pp. 241-255
73. K. Rayner.(2009) Eye movements and attention in reading, scene perception, and visual search. The Quarterly Journal of Experimental Psychology, 62 (8), pp. 1457-1506
74. Kang, Z., & Landry, S. J. (2015). An Eye Movement Analysis Algorithm for a Multielement Target Tracking Task: Maximum Transition-Based Agglomerative Hierarchical Clustering. IEEE Transactions on Human-Machine Systems, 45(1), 13–24. doi:10.1109/thms.2014.2363121
75. Kannan P. K. & Bramlett Matthew D.(2000) “Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value”, Journal of the Academy of Marketing Science.Volume 28, No. 1, pages 95-108
76. Kenning, Peter & Linzmajer, Marc.(2010). Consumer neuroscience: An overview of an emerging discipline with implications for consumer policy. Journal für Verbraucherschutz und Lebensmittelsicherheit. 6. 111-125. 10.1007/s00003-010-0652-5.

77. Kerstin Gidlöf,et.al.,2017. Looking is buying. How visual attention and choice are affected by consumer preferences and properties of the supermarket shelf, Appetite, Volume 116,Pages 29-38,ISSN 0195-6663,https://doi.org/10.1016/j.appet.2017.04.020.
78. Kılınç Orhan Erdemir, Brand Map, Haziran 2017.Eye Tracking ve Nöropazarlama AlanındakiKullanımı.https://neurodiscover.com/bilim-ve-teknoloji/noropazarlamada-eye-tracking-arastirmasi/
79. Kim, C., & Takashima, K. (2016). Retail buyer control systems: Implications of buyer behavior strategies for performance. Australasian Marketing Journal (AMJ), 24(2), 171–178. doi:10.1016/j.ausmj.2016.02.00
80. Klein, C., & Ettinger, U. (Eds.). (2019). Eye Movement Research. Studies in Neuroscience, Psychology and Behavioral Economics. doi:10.1007/978-3-030-20085-5
81. Klingensmith, D. (2013), "Behavioural science: in-store eye-tracking", Path to Purchase Institute, available at: www.prsresearch.com/prs-insights/article/behavioral-science-in-store-eyetracking/
82. Knoepfle, D. T., Camerer, C. F., & Wang, J. T. (2009). Studying Learning in Games Using Eye-Tracking. Journal of the European Economic Association, 7(2/3), 388–398. http://www.jstor.org/stable/40282757
83. Kok, E. M., & Jarodzka, H. (2017).Before your very eyes: The value and limitations of eye tracking in medical education. Medical education, 51(1), 114-122.
84. Krajnovic, A., Sikiric, D., & Jasic, D. (2012). Neuromarketing and customers' free will. In Proceedings of the 13 th Management Internetional Conference.-Budapest (pp. 1143-1163).
85. Kruikemeier, S., Lecheler, S., & Boyer, M. M. (2018). Learning from news on different media platforms: An eye-tracking experiment. Political Communication, 35(1), 75-96.
86. Kumar, V. & Shah, Denish & Venkatesan, Rajkumar. (2006). Managing retailer profitability—one customer at a time!. Journal of Retailing. 82. 277-294. 10.1016/j.jretai.2006.08.002.
87. Lahey, J. N., & Oxley, D. (2016). The Power of Eye Tracking in Economics Experiments. The American Economic Review 106(5), 309–313. http://www.jstor.org/stable/43861034

88. Lee, N., Broderick, A. J., &Chamberlain, L. (2007). What is “neuromarketing”? A discussion and agenda for future research. International Journal of Psychophysiology, 63(2), 199–204.doi:10.1016/j.ijpsycho.2006.03.007
89. Lee J-H, Kim H-D, Ko Y. K., Sagas M(2011), The influence of service quality on satisfaction and intention: A gender segmentation strategy, Sport Management Review, Volume 14, Issue 1,Pages 54-63, ISSN 1441-3523,https://doi.org/10.1016/j.smr.2010.02.002.
90. Leow, R. P., Grey, S., Marijuan, S., &Moorman, C. (2014). Concurrent data elicitation procedures, processes, and the early stages of L2 learning: A critical overview. Second Language Research. 30(2), 111–127. http://www.jstor.org/stable/4428013
91. Li, Q., Huang, Z. (Joy), & Christianson, K. (2016). Visual attention toward tourism photographs with text:An eye-tracking study. Tourism Management, 54, 243–258.doi:10.1016/j.tourman.2015.11
92. Lim, J. Z., Mountstephens, J., & Teo, J. (2020). Emotion recognition using eye-tracking: taxonomy, review and current challenges. Sensors, 20(8), 2384.
93. Lorigo, L., Haridasan, M., Brynjarsdóttir, H., Xia, L., Joachims, T., Gay, G., Pan, B. (2008). Eye tracking and online search: Lessons learned and challenges ahead. Journal of the American Society for Information Science and Technology, 59(7), 1041–1052. doi:10.1002/asi.20794
94. MacInnes, J. J., Iqbal, S., Pearson, J., & Johnson, E. N. (2018). Wearable Eye-tracking for Research: Automated dynamic gaze mapping and accuracy/precision comparisons across devices.
95. MacInnes, Jeff & Iqbal, Shariq &Pearson, John & Johnson, Elizabeth. (2018). Wearable Eye-tracking for Research: Automated dynamic gaze mapping and accuracy/precision comparisonsacross devices. 10.1101/299925.
96. Madan, Christopher. (2010).Neuromarketing: the next step in market research?. Eureka. 1. 34-42.10.29173/eureka7786.
97. Magatef, Sima. (2015). The Impact of Customer Loyalty Programs on Customer Retention
98. Marketing management/Philip Kotler, Kevin Lane Keller. — 14th ed. p. Cm. ISBN 978-0-13-210292-6

99. Marloes Mak & Roel M. Willems (2019) Mental simulation during literary reading: Individual differences revealed with eye-tracking, Language, Cognition and Neuroscience, 34:4, 511-535, DOI: 10.1080/23273798.2018.1552007

100. McClure SM, Li J, Tomlin D, Cypert KS, Montague LM, Montague PR. Neural correlates of behavioral preference for culturally familiar drinks. Neuron. 2004 Oct 14;44(2):379-87. doi: 10.1016/j.neuron.2004.09.019.PMID: 15473974.

101. Meißner, M., Pfeiffer, J., Pfeiffer, T., & Oppewal, H. (2019). Combining virtual reality and mobile eye tracking to provide a naturalistic experimental environment for shopper research. Journal of Business Research, 100, 445-458.

102. Mikic, A. (2016). Neuromarketing as a New Paradigm for Understanding Consumer Behavior. In: Proceedings of ICSD 2016, Innovation, Competitiveness and Sustainable Development. Belgrade, 25 May 2016.Belgrade: Metropolitan University.

103. Milica & Popovic Sevic, Slijepčević, Nevenka & Radojevic, Ivana. (2019). Limit aspects of neuromarketing research. Journal of Innovative Business and Management. 11.72-83. 10.32015/JIMB/2019-11-1-8.

104. Mohamed, Abdallahi & Perreira Da Silva, Matthieu & Courboulay, Vincent. (2007). A history of eye gaze tracking.

105. Murphy, E., J. Illes and P. Reiner. 2008.Neuroethics of neuromarketing. Journal ofconsumerbehaviour.Http://www.neuroethics.ubc.ca/National_Core_for_Neuroethics/Publications_files/Murphy%20et%20al.,%202008%5B1%5D.pdf.

106. Namvar, M., Gholamian R. and KhakAbi S. (2010) "A Two Phase Clustering Method for Intelligent Customer Segmentation," International Conference on Intelligent Systems, Modelling and Simulation, doi: 10.1109/ISMS.2010.48.

107. Needleman S.B. and Wunsch C.D.. (1970). A General Method Applicable to the Search for Similarities in the Amino Acid Sequence of Two Proteins. Journal of Molecular Biology 48, 3,443–453

108. Nemorin, S., & Gandy Jr, O. H. (2017). Exploring neuromarketing and its reliance on remote sensing: Social and ethical concerns. International Journal of Communication, 11, 21.

109. Nguyen, S. P. (2021). Deep customer segmentation with applications to a Vietnamese supermarkets' data. Soft Computing, 25(12), 7785–7793. doi:10.1007/s00500-021-05796-0

110. Nőrdfalt, J. (2011), “Improving the attention-capturing ability of special displays with thecombination effect and the design effect”,Journal of Retailing and Consumer Services,Vol. 18, pp. 169-173.

111. Doğan N,Ayçin E., Bulut Z. Customer Segmentation By Using Rfm. Model And Clustering Methods: A Case Study In Retail Industry. International Journal of Contemporary Economics and Administrative Sciences ISSN: 1925 – 4423. Volume :8, Issue: 1, Year:2018, pp.1-19

112. Orgusaar, T. (2021). Kliendi ostuotsuse kujunemine maiustuste, leivatoodete, jogurtite ja tee kaubagruppide näitel (Master’s Thesis, Universiry of Tartu, Tartu, Estonia). Retrieved from http://dspace.ut.ee/handle/10062/72178

113. Özmen, R.(2007). Tüketici Hakları Mevzuatı. Ankara: Seçkin Yayıncılık.

114. P. Chynał, J. Sobecki, M. Rymarz and B. Kilijańska(2016), "Shopping behaviour analysis using eyetracking and EEG," 2016 9th International Conference on Human System Interactions (HSI), pp. 458-464, doi: 10.1109/HSI.2016.7529674.

115. Park, S., Aksan, E., Zhang, X., & Hilliges, O. (2020). Towards end-to-end video-based eye-tracking. In European Conference on Computer Vision (pp. 747-763). Springer, Cham.

116. Perez, M. M., Desmet, P., & Peters, E. (2015). Enhancing Vocabulary Learning Through Captioned Video: An Eye-Tracking Study. The Modern Language Journal, 99(2), 308–328. http://www.jstor.org/stable/4365002

117. Pieters, R., & Wedel, M. (2004).Attention Capture and Transfer in Advertising: Brand, Pictorial, and Text-Size Effects. Journal of Marketing, 68(2), 36–50. http://www.jstor.org/stable/30161988

118. Pieters, R., Wedel, M., & Batra, R. (2010). The Stopping Power of Advertising: Measures and Effects of VisualComplexity. Journal of Marketing, 74(5), 48–60. doi:10.1509/jmkg.74.5.48

119. Pizzi, Gabriele & Scarpi, Daniele. (2016). The effect of shelf layout on satisfaction and perceived assortment size: An empirical assessment. Journal of Retailing and Consumer Services. 28.67-77. 10.1016/j.jretconser.2015.08.012.

120. Plassmann H, Yoon C, Feinberg F, Shiv B (2011) Consumer neuroscience. In: Bagozzi RP, Ruvio A (eds) Wiley international encyclopedia of marketing. Wiley, West Sussex, UK

121. Plassmann H., O'Doherty J., Shiv B., Range A., Proceedings of the National Academy of Sciences Jan 2008, 105 (3) 1050-1054; DOI: 10.1073/pnas.0706929105

122. Poole, A., Ball, L. J., & Phillips, P. (2004). In search of salience: A response time and eye movement analysis of bookmark recognition. In S. Fincher, P. Markopolous, D. Moore, & R. Ruddle (Eds.), People and Computers XVIII-Design for Life: Proceedings

123. Privitera C. M. and Stark L. W.(2000), "Algorithms for defining visual regions-of-interest: comparison with eye fixations," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no. 9, pp. 970-982. doi: 10.1109/34.877520.

124. Punde, P. A., Jadhav, M. E., & Manza, R. R. (2017). A study of eye tracking technology and its applications. 2017 1st International Conference on Intelligent Systems and Information Management (ICISIM). doi:10.1109/icisim.2017.812215

125. Rajagopal S.(2011) Customer Data Clustering Using Data Mining Technique. International Journal of Database Management Systems (IJDMS) Vol.3, No.4. DOI: 10.5121/ijdms.2011.3401

126. Räihä KJ. (2010) Some Applications of String Algorithms in Human-Computer Interaction. In: Elomaa T., Mannila H., Orponen P. (eds) Algorithms and Applications. Lecture Notes in Computer Science, vol 6060. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-12476-1_14

127. Reisen, N., U. Hoffrage, and F.W. Mast. (2008). Identifying decision strategies in a consumer choice situation. Judgment and Decision Making 3(8):641–658.

128. Ruiz J, Chebat J , Hansen P. (2004). Another trip to the mall: a segmentation study of customers based on their activities. Journal of Retailing and Consumer Services, Volume 11, Issue 6, Pages 333-350, ISSN 0969-6989, https://doi.org/10.1016/j.jretconser.2003.12.002.

129. Russo, J. E., & Leclerc, F. (1994). An Eye-Fixation Analysis of Choice Processes for Consumer Nondurables. Journal of Consumer Research, 21(2), 274. doi:10.1086/209397

130. Russo, J. E., & Leclerc, F. (1994). An Eye-Fixation Analysis of Choice Processes for Consumer Nondurables. Journal of Consumer Research, 21(2), 274–290. http://www.jstor.org/stable/2489820

131. Ruyter, K. and Bloemer, J. (1999), "Customer loyalty in extended service settings: The interaction between satisfaction, value attainment and positive mood", International Journal of Service Industry Management, Vol. 10 No. 3, pp. 320-336. https://doi.org/10.1108/09564239910276917

132. S.P. Liversedge, J.M. Findlay (2000). Saccadic eye movements and cognition. Trends in Cognitive Sciences, 4 (1), pp. 6-14

133. Liversedge S.P., Paterson K.B., Pickering M.J (1998). Eye movements and measures of reading time. G. Underwood (Ed.), Eye guidance in reading and scene perception, Elsevier Science Ltd, Amsterdam, pp. 55-75

134. Saarijärvi, H., Karjaluoto, H., & Kuusela, H. (2013). Customer relationship management: the evolving role of customer data. Marketing Intelligence & Planning, 31(6), 584–600. doi:10.1108/mip-05-2012-0055

135. Santos, Rene & Oliveira, Jorge & Rocha, Jessica & Giraldi, Janaina. (2015). Eye Tracking in Neuromarketing: A Research Agenda for Marketing Studies. International Journal of Psychological Studies. 7. 10.5539/ijps.v7n1p32.

136. Sargezeh B.A, Tavakoli N, Daliri M.R (2019) Gender-based eye movement differences in passive indoor picture viewing: An eye-tracking study, Physiology & Behavior, Volume 206, ISSN 0031-9384, https://doi.org/10.1016/j.physbeh.2019.03.023.

137. Schiffman, L., Hansen H. and Kanuk L. (2007) “Consumer Behaviour: A European Outlook”, London: Pearson Education

138. Scott, N., Zhang, R., Le, D., & Moyle, B. (2017). A review of eye-tracking research in tourism. Current Issues in Tourism, 1–18. doi:10.1080/13683500.2017.1367

139. Shah, D., Kumar, V., & Kim, K. H. (2014). Managing Customer Profits: The Power of Habits. Journal of Marketing Research, 51(6), 726–741. http://www.jstor.org/stable/43832330

140. Shiv B., Carmon Z., Ariely . Placebo Effects of Marketing Actions :Consumers May Get What They Pay For[J]. Journal of Marketing Research,2005(11):383-393

141. Shojaeizadeh, M., Djamasbi, S., Paffenroth, R. C., & Trapp, A. C. (2019). Detecting task demand via an eye tracking machine learning system. Decision Support Systems, 116, 91-101.

142. Silva, N., Blascheck, T., Jianu, R., Rodrigues, N., Weiskopf, D., Raubal, M., & Schreck, T. (2019, June). Eye tracking support for visual analytics systems: foundations, current applications, and research challenges. In Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications (pp. 1-10).
143. Stahlberg, M. and Maila, V. (2010), Shopper Marketing: How to Increase Purchase Decisions at thePoint of Sale, Kogan Page, Philadelphia, PA
144. Steinmann, S., Schramm-Klein, H., Mau, G., & Wagner, G. (2016). An ExploratoryInvestigation of Multidimensional Customer Contact Sequences – Insights into Customer Behaviour in Multichannel Retailing. Marketing: ZFP – Journal of Research and Management, 38(2), 75–91. https://www.jstor.org/stable/26426809
145. Steven J.S & Walter S-A & Scott A. Huettel, (2017). "Neuromarketing: Ethical Implications of its Use and Potential Misuse," Journal of Business Ethics, Springer, vol. 144(4), pages 799-811, September.
146. Stuart, S., Hickey, A., Vitorio, R., Welman, K., Foo, S., Keen, D., & Godfrey, A. (2019). Eye-tracker algorithms to detect saccades during static and dynamic tasks: a structured review. Physiological measurement, 40(2), 02TR01.
147. Suhaily, L., & Darmoyo, S. (2017). Effect of product quality, perceived price and brand image on purchase decision mediated by customer trust (study on japanese brand electronic product). Jurnal Manajemen, 21(2), 179-194.
148. Suharso, A. (2020). The Effect of Products and Prices on Purchasing Decisions of Health Food. Management and Economic Journal (MEC-J). 4. 175-184. 10.18860/mec-j.v4i2.9209
149. T.van Gog, K. Scheiter (2010). Eye tracking as a tool to study and enhance multimedia learning. Learning and Instruction, 20 , pp. 95-99
150. Tablatin, C. L., & Rodrigo, M. M. (2018). Identifying common code reading patterns using scanpath trend analysis with a tolerance. In Proceedings of thee 26th International Conference for Computers in Education (ICCE 2018), Metro Manila, Philippines.
151. Thoma, V & Williams, B (2009), 'Developing and Validating Personas in e-Commerce: A Heuristic Approach', in Human-Computer Interaction – INTERACT 2009, Lecture Notes in Computer Science, Springer, Berlin, Heidelberg, pp. 524–527, retrieved 29 October 2018 from https://link.springer.com/chapter/10.1007/978-3-642-03658-3_56

152. Takeuchi, H., & Matsuda, N. (2012). Scan-path analysis by the string-edit method considering fixation duration. The 6th International Conference on Soft Computing and Intelligent Systems, and The 13th International Symposium on Advanced Intelligence Systems. doi:10.1109/scis-isis.2012.6505116

153. Tianyi Jiang, & Tuzhilin, A. (2009). Improving Personalization Solutions through Optimal Segmentation of Customer Bases. IEEE Transactions on Knowledge and Data Engineering, 21(3), 305–320. doi:10.1109/tkde.2008.163

154. Tobii. 2014. Tobii Website. http://www.tobii.com.

155. Trösterer, S., Meschtscherjakov, A., Wilfinger, D., & Tscheligi, M. (2014). Eye Tracking in the Car. Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications - AutomotiveUI '14. doi:10.1145/2667239.2667277

156. Tugend A. 2010. Too Many Choices: A Problem That Can Paralyze. https://www.nytimes.com/2010/02/27/your-money/27shortcuts.html

157. Tupikovskaja-Omovie, Z., & Tyler, D. (2020). Clustering consumers' shopping journeys: eye tracking fashion m-retail. Journal of Fashion Marketing and Management: An International Journal, 24(3), 381–398. doi:10.1108/jfmm-09-2019-0195

158. Ulman, Y. I., Cakar, T., & Yildiz, G. (2014). Ethical Issues in Neuromarketing: "I Consume, Therefore I am!" Science and Engineering Ethics, 21(5), 1271–1284. doi:10.1007/s11948-014-9581-5

159. Urbany, J. (2016). Demographic Segmentation Can Cover Up Real Customer Differences: A Case Study. Retrieved May 15, 2022 from https://www.vennli.com/blog/demographic-segmentation-can-cover-up-real-customer-differences-a-case-s tudy

160. Valdés Kroff, J. R., Guzzardo Tamargo, R. E., & Dussias, P. E. (2017). Experimental contributions of eye-tracking to the understanding of comprehension processes while hearing and reading code-switches. Methodologies for Intra-Sentential Code-Switching Research, 8(1), 98–133. doi:10.1075/lab.16011.val

161. van Reijmersdal, E. A., Rozendaal, E., Hudders, L., Vanwesenbeeck, I., Cauberghe, V., & van Berlo, Z. M. (2020). Effects of disclosing influencer marketing in videos: An eye tracking study among children in early adolescence. Journal of Interactive Marketing, 49, 94-106.

162. Venkatraman, V., Dimoka, A., Pavlou, P. A., Vo, K., Hampton, W., Bollinger, B., Hershfield, H. E., Ishihara, M., & Winer, R. S. (2015). Predicting Advertising success beyond Traditional Measures: New Insights from Neurophysiological Methods and Market Response Modeling. Journal of Marketing Research, 52(4), 436–452. https://doi.org/10.1509/jmr.13.0593

163. Venkatraman, V., Dimoka, A., Pavlou, P. A., Vo, K., Hampton, W., Bollinger, B., Hershfield, H. E., Ishihara, M., & Winer, R. S. (2015). Predicting Advertising Success Beyond Traditional Measures: New Insights from Neurophysiological Methods and Market Response Modeling. Journal of Marketing Research, 52(4), 436–452. http://www.jstor.org/stable/43832373

164. Venkatraman, Vinod & Dimoka, Angelika & Pavlou, Paul & Võ, Khôi & Hampton, William & Bollinger, Bryan & Hershfield, Hal & Ishihara, Masakazu & Winer, Russell. (2014). Predicting Advertising Success Beyond Traditional Measures: New Insights from Neurophysiological Methods and Market Response Modeling. Journal of Marketing Research. 52. 150619071651008. 10.1509/jmr.13.0593.

165. Voorhees, T, Spieegel D, Cooper D. (2011). "NEUROMARKETING: LEGAL POLICY ISSUES". Retrieved from: https://www.yumpu.com/en/document/read/12990311/neuromarketing-legal-policy-issues

166. Vozzi, A., Ronca, V., Aricò, P., Borghini, G., Sciaraffa, N., Cherubino, P., Trettel, A., et al. (2021). The Sample Size Matters: To What Extent the Participant Reduction Affects the Outcomes of a Neuroscientific Research. A Case-Study in Neuromarketing Field. Sensors, 21(18), 6088. MDPI AG. Retrieved from http://dx.doi.org/10.3390/s21186088

167. Wang, J., Antonenko, P., & Dawson, K. (2020). Does visual attention to the instructor in online video affect learning and learner perceptions? An eye-tracking analysis. Computers & Education, 146, 103779.

168. Wästlund, E., Otterbring, T., Gustafsson, A., & Shams, P. (2015). Heuristics and resource depletion: eye-tracking customers' in situ gaze behavior in the field. Journal of Business Research, 68(1), 95-101.

169. Wedel, M., & Pieters, R. (2017). A review of eye-tracking research in marketing. Review of marketing research, 123-147

170. Wedel, M. (2018). Improving ad interfaces with eye tracking. In K. L. Norman & J. Kirakowski (Eds.), The Wiley handbook of human computer interaction (pp. 889–907). Wiley Blackwell.
171. Widyastuti, S., & Said, M. (2017). Consumer consideration in purchase decision of SPECS sports shoes product through brand image, product design and price perception. International Journal of Supply Chain Management, 6(4), 199-207.
172. Wu, I.-C., & Yu, H.-K. (2020). Sequential analysis and clustering to investigate users' online shopping behaviors based on need-states. Information Processing & Management, 57(6), 102323. doi:10.1016/j.ipm.2020.102323
173. Yoseph, F., & Heikkila, M. (2018). Segmenting Retail Customers with an Enhanced RFM and a Hybrid Regression/Clustering Method. 2018 International Conference on Machine Learning and Data Engineering (iCMLDE). doi:10.1109/icmlde.2018.00029
174. Zofija, Tupikovskaja-Omovie, David Tyler, Zurawicki, L. (2010). Neuromarketing: Exploring the brain of the consumer. Springer Science & Business Media.
175. Zhang, C. & Fang, Z.. (2013). An improved K-means clustering algorithm. Journal of Information and Computational Science. 10. 193-199.
176. Zuschke, N. (2020). The impact of task complexity and task motivation on in-store marketing effectiveness: An eye tracking analysis. Journal of Business Research, 116, 337-350.

APPENDIX A

Questions asked in the store

The questions that they were asked before the experiment started were below:

1. How would you describe your gender?
2. What is your name?
3. What is your age?
4. What is your purpose for visiting the store?
5. How many item purchases are you planning?

The questions that they were asked after the experiment started were below:

1. Did you buy anything unplanned?
2. Did you notice the screens in the store?
3. If you noticed, what do you remember about the advertisement on the screen?
4. Were your purchases affected by any advertisement?
5. Which check-out method did you use?
6. Why did you choose the remote control/cash register / self-service method?
7. How would you evaluate your mood on a 1-5 scale?
8. How would you rate your tiredness level on a 1-5 scale?

APPENDIX B

Data name	**Description**
Recording timestamp [μs]	The Recording timestamp in the eye tracker clock.
Computer timestamp [μs]	The value of the win32 clock "QueryPerformanceCounter" (QPC) in microseconds.
Sensor	Rotation along the X, Y, and Z axes.
Participant name	The name that was entered in the Participant Name field in Pro Lab when the recording was created.
Recording name	The name that was entered in the Recording Name input field in Pro Lab when the recording was created. In Glasses projects, the recording name is generated automatically when the recording is created.
Recording date	Date when the Recording was performed in this time zone.
Recording start time	Start time of the Recording in this time zone
Recording Fixation filter name	The name of the Fixation Filter applied to the Recording eye-tracking data in the export.
Recording duration [ms]	Total duration of the recording
Gaze point X [MCS px]	This is the x-coordinate for each sampled gaze point.
Gaze point Y [MCS px]	The y-coordinates for each sampled gaze point.
Pupil diameter left [mm]	Estimated size of the pupils.
Pupil diameter right [mm]	Estimated size of the pupils.
Validity left	The validity of the event of the row, either whole or partial.
Validity right	Indicates if the eyes have been correctly identified.

Eye movement type	Type of eye movement event is classified by the selected Fixation filter for mapped gaze data.
Gaze event duration [ms]	The duration of the currently active eye movement.
Eye movement type index	Represents the order in which an eye movement was recorded. An index is an auto-increment number starting with 1 for each eye movement type.
Fixation point X [MCS px]	This is the x-coordinate of the fixations determined by the currently used Gaze Filter
Fixation point Y [MCS px]	This is the y-coordinate of the fixations determined by the currently used Gaze Filter

Description of data points
Source: Tobii Pro Lab user manual

Resümee

Kaasaegses ühiskonnas on tarbimine üks peamisi sotsiaalseid tegureid ja tootjad teevad kõik endast oleneva, et veenda klienti nende toodet ostma. Seepärast on oluline, et tootjad mõistaksid oma kliente ja nende eelistusi otsustusprotsessis, et suurendada müüki. See toob kaasa ka tärkava huvi ja motivatsiooni uurida klientide ostuharjumusi ja valikuomadusi, kasutades erinevaid tehnoloogiaid, näiteks pilgujälgimise uuringuid veebi- ja poekeskkondades. Enamike sellisete uuringute eesmärk on uurida märgistuse, pakendi või hindade mõju klientide otsustele ostuteekonnal, kuid vähesed autorid on püüdnud eristada reaalses poekeskkonnas erinevaid klientide segmente nende vaatamisharjumuste põhjal. Seega on käesoleva uurimistöö eesmärk täita see lünk kirjanduses, kogudes andmeid reaalses poekeskkonnas Eesti supermarketis ja eristades kliendid tegelike vaatamisandmete põhjal. Käesolev lõputöö eristas kliendid klastritesse nende pilgujälgimise põhjal, lähtudes kogutud pilgujälgimise andmetest ja kontrollis klastrite demograafiliste tunnuste sarnasusi. Uuring viidi läbi ühes Eesti supermarketis ja valimiks osutus 363 inimest. Osalejad olid vanuses 8–89 aastat, seejuures 158 meest ja 195 naist ning 9 osalejat, kelle sugu ei olnud märgitud. Tobii Pro Glasses 2 oli peamiseks tehnoloogiliseks tööriistaks, mida kasutati andmete kogumisel, sest katse viidi läbi loomulikes poetingimustes. Tulemuste saamiseks analüüsiti kahte andmekogumit, millest üks koguti pilgujälgimisprillidest ja sisaldas osalejate visuaalseid andmeid. Teiseks kogusid katse läbiviijad uuringu käigus osalejate sotsiaalseid ja demograafilisi andmeid. Klastrite moodustamisel kasutati andmetes K-keskmiste meetodit. Analüüsi käigus keskenduti peamiselt fikseeringutele, et mõista, kuidas kliendid erinevad klastrite lõikes fikseeringute ja selle kestuse põhjal. Analüüsi tulemusena, mis põhines muutujatel "Fikseerimiste arv 20 sekundi jooksul" ja "Keskmine fikseeringute kestus" identifitseeriti 3 klastrit: "Lühikese fikseeringuga kliendid", "Keskmise fikseeringuga kliendid" ja "Kliendid, kellel on pikad fikseeringud”. Klastrite demograafiliste ja sotsiaalsete tunnuste analüüs näitab, et pilgujälgimise andmetest leitud klastrid ei seleta demograafilised andmed, mis tõendab, et pilgujälgimise andmed võivad sisaldada teavet, mida pelgalt analüüsides ei ole võimalik tuvastada. Kõik selle uuringu tulemused kinnitavad, et jaekauplused saavad kasutada pilgujälgimise meetodit koos teiste meetoditega, nagu sotsiaalne või demograafiline klasterdamine, et mõista, mis pälvib kliendi tähelepanu ostuotsuse tegemisel.

Non-exclusive licence to reproduce thesis and make thesis public

Hagigat Hasanova,
(*author's name*)

herewith grant the University of Tartu a free permit (non-exclusive licence) to

reproduce, for the purpose of preservation, including for adding to the DSpace digital archives until the expiry of the term of copyright,

CLUSTERING CUSTOMER GAZE BEHAVIOUR BASED ON REAL-LIFE EYE-TRACKING DATA

(*title of thesis*)

supervised by

Kristian Pentus
(*supervisor's name*)

2. I grant the University of Tartu a permit to make the work specified in p. 1 available to the public via the web environment of the University of Tartu, including via the DSpace digital archives, under the Creative Commons licence CC BY NC ND 3.0, which allows, by giving appropriate credit to the author, to reproduce, distribute the work and communicate it to the public, and prohibits the creation of derivative works and any commercial use of the work until the expiry of the term of copyright.

3. I am aware of the fact that the author retains the rights specified in p. 1 and 2.

4. I certify that granting the non-exclusive licence does not infringe other persons' intellectual property rights or rights arising from the personal data protection legislation.

Hagigat Hasanova

18.05.2022