Media Analytics for Personalization in Advertisement

Frank Rune Espeseth

Supervisor: Assoc. Prof. Dr. Mehdi Elahi
Co-supervisor: Chief Data Scientist Dr. Igor Pipkin

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University of Bergen

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Abstract

In the realm of advertising, strategic placement and presentation of advertisements are crucial for attracting potential clients. Media companies employ various tactics, such as visually appealing features and vibrant colors, to capture the attention of consumers. However, achieving this objective is not always straightforward, as some advertising strategies may be perceived as irrelevant or disturbing by recipients. This Master's thesis aims to explore the relationship between audience interaction and the perception of advertisements on media platforms, with the overarching goal of enhancing advertising effectiveness and addressing ethical concerns associated with targeted advertising. To delve into this topic comprehensively, this study utilizes real-time data provided by Amedia, one of the largest media companies in Norway. Through an extensive analysis of this real-world data, the research aims to explore the correlation between audience interaction and the perception of advertisements on media platforms. This investigation involves the extraction of relevant features from advertisement images, leading to the creation of a new dataset. Concurrently, predictive machine learning models are developed to gain insights into effective advertising strategies for media companies, with a focus on personalization. Furthermore, a comprehensive user study is conducted to gain insights into user behavior within media platform advertisements. By uncovering the interplay between visual features, user behavior, and advertising effectiveness, this research contributes to improving personalized advertising strategies in the context of media companies.

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Chapter 1

Introduction

1.1 Motivation

There exists a huge amount of media content available nowadays *Beheshti et al.* (2022). We upload more data to the Internet than ever before. With the rapid development of the media industry, advertisement has become an important source of income for media companies. Consider how we as consumers browse through the huge amount of media content available. Together with media content such as newspapers and articles, advertisements are present, and it has come to stay. In 2006, the total internet advertising expenditure in the US was estimated to exceed 17 billion dollars, demonstrating a growth rate of nearly 20% year after year *Chakrabarti et al.* (2008). The trend of using digital media platforms for advertisements is growing *Sama* (2019), one can only imagine the current magnitude of advertising spending in today's digital landscape. The question is, can we obtain more inside information on how the audience interacts with different types of content to further investigate if the advertisement is an effective form of communication to potential clients, in an attempt at growth? Is there anything we can learn to improve the experience of the audience but at the same time provide some more business value media companies?

My motivation behind this thesis is to investigate the correlation between audience interaction and the perception of advertisements on media platforms. By exploring how the audience engages with and feels about the advertisements shown, I aim to improve the overall advertising effectiveness and address ethical concerns associated with targeted advertising.

1.2 Problem Statement

In recent years, the advertising industry has experienced explosive growth, becoming a multibillion-dollar enterprise that can significantly boost business sales *Aggarwal et al.* (2016). However, the implementation of various advertising strategies has brought forth ethical concerns. Examples of such concerns include the presence of misleading or false information in advertising *Frith and Mueller* (2010) and the need to address ethical considerations related to cultural and political norms in specific contexts like Pakistan *Abbasi et al.* (2011); *Elahi et al.* (2022). These biases represent just a few instances of ethical issues that can arise in advertising. This can result in advertisements that struggle to capture the attention of potential target audiences or could be perceived as irrelevant and disruptive when displayed alongside the content. In this thesis, I explore the potential of analyzing and using feature extraction techniques to obtain a better representation of advertisements and improve their relevance to the audience. To address the research questions outlined in Section 1.3, a comprehensive analysis was conducted on a real-time dataset obtained from Amedia, one of Norway's largest media industries [1]. This dataset captured users' activity in online advertisements, providing valuable insights into user behavior. To enhance the understanding of the relationship between user behavior and advertisements, I applied feature extraction techniques to images associated with the data set, resulting in a new dataset. This new dataset served as the foundation for building predictive models, enabling a deeper exploration of the significance of personalization techniques. Additionally, I conducted a user study was further gain insights into user behavior within advertisements. Through these combined approaches, this research aimed to uncover the importance of personalization techniques while shedding light on user behavior dynamics.

1.3 Research Questions

Based upon the information provided in section 1.1 and 1.2, the following research questions are formulated:

RQ1: How to improve the experience of the audience by improving the relevance of contextualized advertisements with better personalization?

RQ2: How machine learning approaches can be employed to improve the personalization of advertisements on media platforms?

1.4 Contribution

The main contributions of the thesis are listed in the following:

- An extensive analysis of real-world data received from one of the largest media platforms in Norway Amedia, by exploring both visual features with audience behavioral data.

- Extracting a new dataset that contains the visual features from the images of advertisement campaigns. The implementation can be found in the MediaFutures Github repository[2].

- A predictive model with feature importance of the features in the new dataset. The implementation can be found in the repository.

- Conducting a real user study by using a new questionnaire designed in this thesis and performing both qualitative and quantitative analysis.

[1] www.amedia.no

[2] https://github.com/sfimediafutures/MA_Frank-Rune-Espeseth

1.5 Thesis outline

- **Chapter 2 Background:** This chapter provides an overview of previous works and concepts related to this thesis. Section 2.1 describe previous approaches to making advertisements more personalized, using different machine learning tools and artificial intelligence. Section 2.2 presents machine learning models and AI technologies. Section 2.3 describes personalization and how this is related to making advertisements more contextualized. Section 2.4 presents advertisements in the news article and Section 2.5 presents the ethical issues concerning advertising. Section 2.6 describe the differences between related work and this master thesis.

- **Chapter 3 Methodology:** Describes what methodology and methods have been used in this thesis and details the data set. Section 3.1 details an overview of the data set provided by Amedia. Section 3.2 presents the feature extraction and engineering methods, using object and emotion detection. Section 3.3 details the methods used to construct a predictive model. Section 3.4 presents the user study conducted.

- **Chapter 4 Evaluation and Results:** Presents and describes the results of the different experiments performed in this thesis. Section 4.1 presents the preliminary analysis and initial findings of the data. Section 4.2 presents the feature extraction results together with an offline evaluation. Section 4.3 details the user study conducted, and section 4.4 delves into the discussion of the study's findings and implications.

- **Chapter 5 Conclusion:** The concluding chapter summarizes the results in section 5.1, and the main contribution of the master thesis is presented in 5.2. The conclusion is provided in section 5.3 and in the last section 5.4, the limitations within this master thesis as well as future work is presented.

Chapter 2

Background

In order to address the research questions formulated in section 1.3, previous topics that are of relevancy to this thesis are discussed in section 2.1. This section showcases previous work that has been done to improve the personalization of advertisements. Section 2.2 detail how *Artificial Intelligence* and *Machine learning* has previously been used to improve advertisements within the media industry. Section 2.3 presents the concepts of *personalization* and *contextualization*, highlighting their distinctions and providing a comprehensive understanding of these terms. One of the most important topics of the master thesis has been to investigate how advertisements can more personalized. This has been done by checking how advertisements in media platforms could affect user behavior, and how this has developed to become an important factor within media content during the last couple of decades. Section 2.4, therefore, details the influence advertisements have on media platforms such as news articles. Another major problem that is investigated through this master thesis is ethical issues considering how advertisers choose to promote their advertisements through media platforms. This is addressed in section 2.5. Lastly, section 2.6 will delve into what differs previous related work from mine. These are the main topics that will be introduced in the background section.

2.1 Related work

This chapter will provide an overview of existing literature that can be related to the research questions mentioned in section 1.3. Web advertising supports a large swath of today's Internet ecosystem. In 2006, the total advertising expenditure by internet advertisers in the United States surpassed 17 billion dollars, demonstrating a remarkable annual growth rate of nearly 20% *Broder et al.* (2007). In 2014, advertising expenditures reached 142 billion dollars in the United States and 467 billion dollars worldwide *Berger* (2020). Regarding the fact of this, it is evident that advertisements on the Internet have become a significant industry. Maximizing the economic benefits that advertisements can offer is a well-known challenge. Certain advertisements might exhibit bias and lack personalized relevance *Berger* (2020). Given the magnitude of this problem, a wide array of approaches naturally emerges to explore this well-known issue. There have been numerous previous works to make advertisements more personalized and appropriate for consumers. Some of the techniques that have been applied to improve the personalization of advertisements are *Content Match* and *Sponsored Search*.

The approach of content match refers to the placement of commercial textual advertisements within the content of a generic web page, while sponsored search advertising consists in placing ads on result pages from a web search engine, with ads driven by the originating query *Broder et al.* (2007).

Some of these methods are applied in a previous paper, where they attempt of making advertisements more contextualized in a more of a semantic approach: In the paper of *Broder et al.* (2007), this paper showcase the use of a combination of semantic and syntactic features. They believed that targeting mechanisms based solely on phrases found within the text of the page can lead to problems. Such as a page about a famous golfer named “John Maytag” may trigger an and for “Maytag dishwashers”. As a solution to this, this paper proposed a matching mechanism that combines a semantic phase with traditional keyword matching, that is, a synthetic phase. The semantic phase first and foremost classifies the page and the ads into a taxonomy of topics and then uses the proximity of the ad and page classes as a factor in the ad ranking formula. However, they still favor ads that are topically related to the page and thus avoid the pitfalls of purely syntactic approaches.

Meanwhile, the paper of *Chakrabarti et al.* (2008), showcases how user experience and revenue depend on the relevance of the displayed ads to the page content. Furthermore, they mention that relevance is provided by scoring the match between individual ads (the documents), and the content of the page (the query). Through this paper, they illustrate how this match can be improved significantly by augmenting the ad-page scoring function with extra parameters from a logistic regression model on the words in the pages and ads. A key property of the proposed model is that it can be mapped to standard cosine similarity matching and is suitable for efficient and scalable implementation over inverted indexes. The model parameter values are learned from logs that consist of ad impressions and clicks, which are also significant features included in my dataset analysis.

2.2 Machine learning

In recent decades, the rapid advancement of technology has brought forth numerous innovations that play a vital role in our interconnected world. Among these technologies, Artificial Intelligence (AI) stands out as a significant contributor. AI is often referred to as an Intelligent Agent, capable of interacting with its environment. Through its sensors, the agent perceives and comprehends the state of the environment, and subsequently, using its actuators, it can influence and modify that state *Das et al.* (2015). The concept of AI as an interactive agent is visually detailed in Figure 2.1.

Intelligence is defined as the “ability to think to imagine creating memorizing and understand, recognize patterns, make choices adapt to change, and learn from experience” *Khanzode and Sarode* (2020). This is what is concerned with the use of AI, by making it think and make decisions like a human. There is maybe therefore this paper also describes Artificial Intelligence as an integration of Physiology and Computer Science.

Machine Learning is a well-known technology. The paper of *Das et al.* (2015) defines this concept as follows: “Machine learning is defined as the field of study that gives computers the ability to learn without being explicitly programmed”. ML tech-

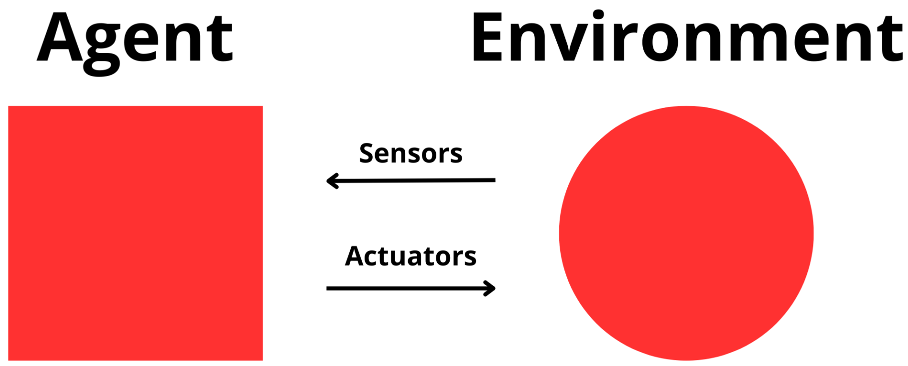


Figure 2.1: Perception Circle of AI Das et al. (2015)

niques exist in multiple applications users make use of each day. Whether you are using Google or Bing, web search engines are utilized to retrieve information from the internet. Those web search engines have implemented "learning-to-rank" algorithms that focus on ranking different web pages on the internet vs. a user query. Another example is the spam filter, where ML algorithms save people a lot of time from going through a huge amount of spam emails. Nevertheless, Machine learning played a big role in the battle against Coronavirus disease (COVID-19) where large-scale data of COVID-19 patients were integrated an analyzed by advanced machine learning algorithms. This is in order to understand the pattern of viral spread and to further improve the diagnostic speed and accuracy. *Alimadadi et al.* (2020). These examples mentioned above barely exemplify machine learning techniques around us in our daily life.

There exist different types of machine learning. Those are *Supervised Learning*, *Unsupervised Learning*, and *Reinforcement Learning* as illustrated in figure 2.2. Supervised learning is based “on the comparison of computed output and expected output, that is learning refers to computing the error and adjusting the error for achieving the expected output” *Das et al.* (2015). An example of this could be a dataset that consists of a special brand of car where the price is given. The supervised model can now use this info to predict the market value of this type of car since it already has some prices to build on. Unsupervised learning is “termed as learned by its own by discovering and adopting, based on the input pattern” The learning data in this method is divided into clusters, and is therefore also called a clustering algorithm. *Das et al.* (2015). An example of this could be a dataset that consists of different attributes of cars, where the algorithm could figure out which of the cars share the same attributes such as color or mileage. Reinforcement learning is based on output with how an agent ought to take

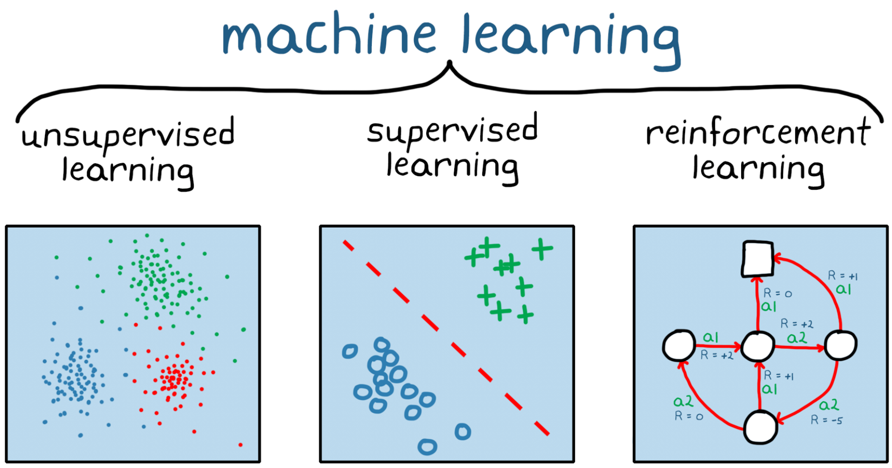


Figure 2.2: Different types of Machine LearningMathworks (2023)

actions in an environment so as to maximize some notion of long-term reward, where there is given a reward when the output is right and penalty else wise. *Das et al.* (2015).

As time goes by and those technologies are getting more and more advanced, they are also being used in all types of fields. As mentioned earlier, advertising has become a huge industry in recent years, and as a result, many marketers are turning their attention to the use of artificial intelligence to transform big data into valuable consumer insight. To gather such insight, they need to understand the consumer's journey. This journey might be complex, where the consumers express their attitudes, need and wants, and values in many different forms. Such as comments, through searching, likes, or videos. This takes place across different channels such as our mobile phones, the web, or face-to-face. When marketers are turning their attention to artificial intelligence to cope with these problems, they need to transform the big data flow into valuable consumer insight. They need to adapt the AI systems so that they can comply with new privacy standards. What this creates is opportunities for the advertisers and marketers to efficiently understand and reach out to the consumers in different phases of the consumer's journey *Kietzmann et al.* (2018).

To understand and transform the enormous flow of different types of data, often called big data, two different types of input are presented. Those are *structured data* and *unstructured data Beheshti et al.* (2022). These are the types of data that the artificial intelligence models deal with when they are assisting marketers and advertisers to optimize their advertising.

What are those structured and unstructured data, and what differentiates them from each other? *Kietzmann et al.* (2018), Gives a broad description of those two types. The biggest of them, unstructured data is the one data type that generates the most data in the world today. This paper states that about 80 percent of the daily user-generated data is unstructured data. Those data are provided as image files, speech, and written texts. The reason why AI might be a good technology for marketers and advertisers to use in order to optimize their consumer's insight is that AI has the ability to process large volumes of this type of data. In addition, it can do it quickly. This is what typically distinguishes it from other traditional computer systems.

Structured data can be seen as more of a traditional and standardized data set *Be-*

heshti et al. (2022). Those data could be web-browsing history or even transaction records of your bank account. What makes AI powerful when dealing with such data is that it enables complex computations on large volumes of structured or unstructured data. By using its robust computing power, it produces results in real-time. The importance of AI and machine learning are presented. The main question is, what are the real building blocks that allow advertisers and marketers to dig deep into the understanding of consumers and their journey?

There exists a majority of different building blocks, such as image recognition, Nature Language Processing (NLP), and Machine Learning as presented earlier. Using NLP, allows the AI systems to analyze the nuances of human language. This is in order to derive meaning from among others such as product reviews, Tweets from Twitter, Facebook posts, and also blog entries. For example, the Swedish bank, Swedbank, uses the virtual assistant with NLP to answer customer inquiries on their homepage, allowing customer-service employees to rather focus more on relevant tasks that promote revenue-generating sales instead of sacrificing their services to answer customers *Kietzmann et al.* (2018).

Another important building block is image recognition. This kind of technique is indeed a great help for advertisers to understand pictures and videos that people share on media platforms. The reason why, is that such a technique shows true consumer behavior. The consumers can identify important details about the offerings that are portrayed in the image, and the advertisers can benefit from contextual consumption details *Kietzmann et al.* (2018), cited from *Forsyth and Ponce* (2011). For example, “Selfies” can reveal brands, even when not mentioned in the post and the user’s personal details. So when a celebrity shares a photo that contains an unidentified product, the image recognition is still able to recognize both the potential social-media influencers and also the product *Kietzmann et al.* (2018). This technique is also used in brick-and-mortar retail, which accounts for the majority of all purchases. An example of this is the San Diego-based Cloverleaf. They use image recognition in their intelligent shelf-display platform. By using optical sensors, the display collects data on customer demographics. Those data could be such as age and gender and further scans the shoppers’ faces in order to gauge their emotional reaction to the product. The nearer the shoppers are to the display, the more personalized the content becomes *Kietzmann et al.* (2018).

Speech recognition is another technique that is frequently used. Not only using images, but speech recognition also allows AI to analyze the meaning of spoken words by using text. An example is the call-center service provider Sayint. They use speech recognition to monitor and analyze customer calls. By doing so, media companies are by applying speech recognition able to understand the customer needs, boost customer satisfaction and also improve the call-agent performance *Kietzmann et al.* (2018).

When advertisers in media companies make use of AI to investigate and gather insights that are hidden in user-generated content, they tend to narrowly define what kind of problem they want to solve, and how they will approach the data analysis. These processes give rise to all important detection of patterns in the data, by improving the ability to predict future behavior *Kietzmann et al.* (2018). Advertisers tend to segment their market on the basis of the psychographics of their base of customers. This is in order to determine who might be their best “customer”. Nevertheless, who might buy their offerings over other competitors? Important aspects here are one important term that AI models rely on, which are personality characteristic of the consumers

Braunhofer et al. (2015); *Mulyanegara et al.* (2009), where the AI is able to reason with how people interact on media platform as well as personal tendencies and values. The paper of *Kietzmann et al.* (2018) Mention that personality profiles depict an individual in term of the Big Five personality traits – Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism *Wiggins* (1996). From this, AI-based profiles that are derived from analyzing unstructured user-generated data can further inform future marketing decisions *Elahi and Qi* (2020). An example illustrating this is the renowned clothing brand Peak Performance, which employs similar techniques to identify the most suitable jackets for consumers based on available data regarding the specific usage scenarios and timing of jacket usage.

Another important building block is certainly machine learning (ML). By training on data and detecting patterns, AI models can propose the best options for consumers based on learned information. What makes ML techniques powerful, is that it stores their memories in a knowledge base, and then use ML to learn from the previous data. As mentioned earlier in this section, AI is frequently used to deal with unstructured data. The fact is that the more unstructured data the machine learning is "fed" with, the "smarter" it gets. The model gets more fine-grained and it provides insightful results for the advertisers *Kietzmann et al.* (2018). An example again provided by this paper is how the North Face business accumulates data from jacket searches and then combines this information with purchases that have been made by customers. By doing so, the model might be able to predict personalized recommendations and further refine the results to prioritize options that will satisfy the customer. Machine learning can also be used to analyze patterns and learn from past behavior to be able to the likeliness of a customer to purchase an item or to predict the future value. By building the models on unstructured data through personality analysis and sentiment analysis, such as emotions, AI help marketers in media companies reach out to consumers.

The building blocks mentioned above illustrate that AI has been of great help to advertisers and media companies to understand and guide consumers. In the future, there will be a main focus to find new ways of mining consumer-generated data that will drive consumer insight. By applying techniques such as machine learning, advertisers in media companies will have a better foundation to build on and be able to collect consumer data from many sources imperceptibly. How they will do this will be to combine data, and mine them to deliver on-the-spot consumer insights *Kietzmann et al.* (2018).

2.3 Personalization and Contextualization

Media companies and other services in these nowadays want to fit their information with the needs of specific users. They want to improve the content provided to meet the customers, and eliminate the communication gap with potential customers *Nuseir and Madanat* (2015). "Personalization is the use of technology and customer information to tailor electronic commerce interactions between a business and each individual customer. Using information either previously obtained or provided in real-time about the customer, the exchange between the parties is altered to fit that customer stated needs as well as needs perceived by media companies based on the available customer information" *Vesanen* (2007). It's worth mentioning that there exist different definitions of personalization, as this definition is more technology-based.

Today, there are numerous instances of personalized approaches in media platforms. Media companies try their best to personalize content for users. Streaming services such as Netflix uses personalization to further recommend relevant movies and series that match based on the user's previous watch history and preferences *Elahi et al.* (2018). Google at the same time, uses personalization to filter out irrelevant search results for the users. Examples of personalization are frequently encountered while browsing the Internet, making it challenging to escape its influence. When users search for specific items to purchase or plan holiday trips, their recent activities often result in personalized recommendations that persistently appear as advertisements on subsequent websites they visit. However, modern personalization seems to have different kinds of meanings, from location diagnosis, and fitting the visual layout of the message to data terminal equipment, to tailoring the content of the message and tailoring the product *Vesanen* (2007). This illustrates that there is no concrete answer to manifest how personalization should be performed by media companies or other services. Personalization often depends on what the users want to accomplish, but also the main goal of the companies and services. This leads to the fact that there exist multiple "faces" of personalization, and as a result of this, a lot of marketers are easily confused by the different meanings of personalization *Merisavo et al.* (2002). Two different companies might have different opinions about what personalization actually defines. The first company might think of personalization as where the customer is the active party, meanwhile, the other company thinks of personalization where the company is the active party *Kietzmann et al.* (2018). The problem is illustrated in 2.3

Figure 2.3: Two vievs on Personalization Merisavo et al. (2002)

	Company 1	**Company 2**
Personalization	The customer makes personalization after the company had done the customization.	The customer does the personalization first, then gives information to the company.
Customization	The company does the customization before the customer can do the personalization	--
Profilization	Equal to customization	The company does the profilization after the customer has done the personalization.

The diverse interpretations and perspectives surrounding the concept of personalization make it challenging to establish a universally accepted definition. This lack of a common framework can lead to confusion and a disconnect between customers and companies, hindering effective communication and understanding. The absence of a shared understanding of personalization poses a potential obstacle to the advancement of knowledge in the field of personalized marketing *Vesanen* (2007).

This illustrates that there is no certain definition of personalization or how it should be applied to media content. The paper of *Griffith-Jones* (2015) on the other side has divided personalization into four segments – triggered, behavioral, user set, and profiled personalization.

Triggered personalization is described as the action that results in certain contents being served to users. An example of this is when anyone who signs up for a newsletter now no longer sees the newsletter call to action. *Behavioral personalization* is a process where “points” are assigned based on the user’s cumulative behavior. This count towards the users being assigned a persona once there is a threshold that has been met. Furthermore, these different personas serve particular content which targets a specific group of people. One leading company within this sort of personalization is Amazon. They are analyzing the combination of different products users looked at, and they apply an algorithm to predict what you might be interested in. This reflects section 2.2 to showcase the influence AI systems might have. *User-set personalization* is the sort of personalization that is most common in applications where the users are encouraged to set preferences around content and notifications. By doing so, the user can provide personal and non-personal information. This approach typically carries less risk since the users are only permitting personalization based on information they are willing to share. *Profiled personalization* is the type of personalization that comes closest to involving personal data in the legal sense. The reason why, is that information that is known about users is usually held within a CRM system to serve specific content or to assign the user to a specific persona. Typical branches that use this sort of personalization are supermarkets that store data about a customer in-store, and further use this insight to the content they serve on their website.

The term "personalization" encompasses various meanings and interpretations. Furthermore, while closely related, there is another concept known as "contextualization" that differs in certain aspects. As mentioned earlier in the background section, the advertising industry has experienced significant growth in recent decades, with the primary objective of targeting specific audiences through personalized and contextualized approaches. Achieving personalized advertisements involves employing diverse strategies within the industry. Media companies aim to deliver personalized and contextualized advertisements, as these two terms are closely intertwined. Specifically, contextualization in the realm of advertising is commonly referred to as contextual advertising. This technique relies on various factors to determine the most relevant content to be placed alongside an advertisement, based on the current context. Advertisers leverage different contextual cues, such as the web page content, customer location, or even the weather forecast, to effectively reach potential consumers *IBM Watson Advertising* (2023). By leveraging contextualized advertisements, media companies are more robust to reach out to potential customers.

The approach where advertisers traditionally use customers’ data surrounding their browsing and shopping habits is no longer problem-free. This raises concerns about privacy issues which have led the advertisers to find alternative options. They can no longer rely on behavioral signals or cookies to provide relevant ads. Instead, by using insights that are surrounded by the context of the advertisement, the companies can provide relevant advertisements *IBM Watson Advertising* (2023). This paper also states that companies are starting to attempt this approach to advertising and that the contextual advertising project is estimated to reach over USD 376 billion by 2027.

The new trend that has become increasingly common for media companies is to personalize or contextualize the digital customer experience. By optimizing the online messaging for a specific audience or context, media companies avoid spamming the same audience with the same products, but instead make the experience more targeted and because of this, it could increase sales *Griffith-Jones* (2015). Figure 2.4 provides an illustration of the distinction between personalization and contextualization.

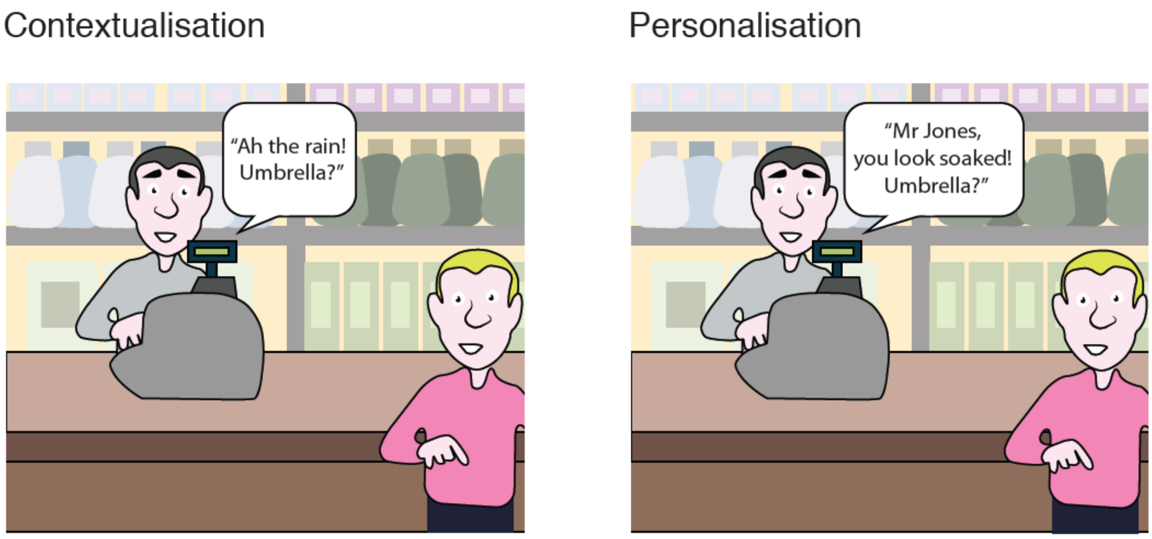


Figure 2.4: Personalization vs Contextualization IBM Watson Advertising (2023)

While personalization focuses on tailoring content based on specific user attributes, contextualization operates differently by relying on the surrounding context of the user. Unlike personalization, which requires specific user information, contextualization simply considers the user's presence within a particular context *Griffith-Jones* (2015). This approach has recently gained popularity, with numerous media companies incorporating contextual elements into their websites. For instance, certain companies dynamically adjust their homepage features based on the weather forecast. Figure 2.5 provides an example where the brand Topshop integrates a weather feed to showcase how to use contextualization.

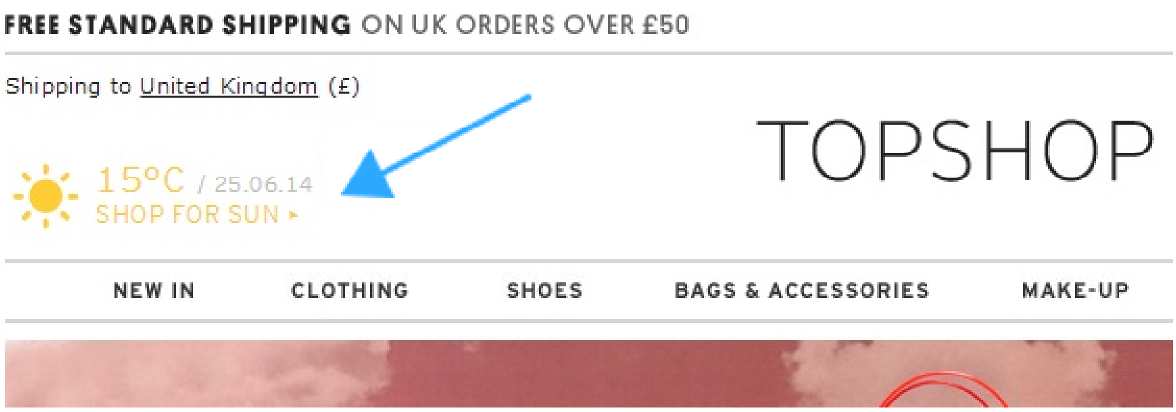


Figure 2.5: Contextualization example IBM Watson Advertising (2023)

When it comes to privacy, consumers are nowadays a lot more sensitive about their personal information than any other type of information. It is then appropriate to mention from a privacy perspective to say that contextualization is a safer option to apply since it doesn't rely on personal information, but rather on the actual context. According to *Griffith-Jones* (2015), personal information is: "Data which relates to a living individual who can be identified from those data or those data and other information". However, it is worth mentioning that approaching both personalization and contextualization is a good approach, but one should keep the customer response the mind so that the brand is deploying targeted messaging that feels relevant without being intrusive.

In today's digital landscape, consumers are increasingly concerned about the privacy of their personal information *Jacobson et al.* (2020). Given this heightened sensitivity, it is important to consider contextualization as a privacy-friendly approach. Unlike personalization, which relies on personal information, contextualization is based on the immediate context in which users find themselves. According to *Griffith-Jones* (2015), personal information refers to data that can identify a living individual. By adopting contextualization, businesses can respect privacy concerns while still delivering relevant messaging. However, it is worth mentioning that approaching both personalization and contextualization techniques are good approaches, but one should keep the customer response the mind so that the brand is deploying targeted messaging that feels relevant without being intrusive.

2.4 Advertisements in News Articles

Interactive communication technology has grown during the last couple of decades and has become a significant role in all aspects of modern society *Roztocki et al.* (2019). Since the Internet is always available, it has become a major source of news. Before the Internet made its entrance into our world, the news was only available through physical newspapers. Today, we find them everywhere online. To attract a higher volume of traffic to their websites, these online portals are increasingly adopting recommender systems to improve user experience on their sites *Elahi et al.* (2021); *Raza and Ding* (2021).

In the recommendation and personalization domain, we'll often refer to user experience as usefulness, usability, and satisfaction for the user while interacting with the system, as well as how effective it is *Braunhofer et al.* (2014). Responsibility, fairness, and bias mitigation in the recommendation are among other important factors that have recently drawn a lot of attention *Elahi et al.* (2022); *Klimashevskaia et al.* (2022); *Wang et al.* (2023). Within different websites, one can see a huge amount of different advertisements. Some of them may be of relevance to the reader, while some of them not. It is almost impossible to read a news article without being offered to buy something. New curtains for your living room or a booking for your next holidays are just some examples of what you may be shown. Sometimes, it can seem like the advertisements can read your brain. It may seem like they know what your next step is, or what you are looking for. The personalization systems out there play a major role in what is to be shown and not within the websites and news articles. The major question is if the advertisements that are shown are of relevance to the user.

2.5 Ethics in Advertising

The issue of ethical considerations in contextualizing advertisements on media platforms is becoming increasingly important in today's society. With the rise of social media and the increasing use of data analytics, advertisers are able to target consumers with personalized advertisements. However, this raises ethical concerns regarding privacy and the use of personal information. The paper by *Abbasi et al.* (2011) sheds light on the ethical issues related to advertising in Pakistan. The author highlights the importance of ethical considerations in advertising and suggests that advertisers should avoid using false or misleading information, unfair tactics, and offensive material in their advertisements. The paper also emphasizes the need for advertisers to consider the cultural and religious sensitivities of their target audience. This is particularly important in countries like Pakistan, where cultural and religious norms play a significant role in shaping the attitudes and behaviors of consumers. In this context, it is important for advertisers to be aware of these cultural and religious sensitivities, and to tailor their advertisements accordingly. Under the Islamic ethical system, it is not allowed to use emotional appeal or romantic language when advisers promote their advertisements. This paper provides useful insights for addressing the ethical considerations in contextualizing advertisements on media platforms, particularly regarding the importance of respecting privacy, avoiding misleading information, and considering the cultural and religious sensitivities of the target audience *Abbasi et al.* (2011).

However, the success of any organization depends on the effectiveness of advertising practices, and this might be the reason why they use different kinds of approaches to "lure" consumers. In other industries such as healthcare, the development of marketing strategies has led to the emergence of advertising and promotion as part of the strategy aimed at developing and maintaining relationships with the targeted audience. The healthcare industry requires ethical rules of healthcare marketing to ensure the content of promotional messages is truthful and does not create unjustified expectations. The doctor or healthcare unit must be able to provide the services claimed in the advertisement, and marketing communication should be consistent with reality even if its purpose is to shed light on more attractive issues. A study published in the Romanian Journal of Ophthalmology, mentions that: "Those responsible for marketing in the healthcare field must keep in mind the ethics code of the medical profession, must maintain an honest marketing communication, which does not create inaccurate expectations, must not denigrate other colleagues, and must use a message whose content should respect the dignity of the profession" *Solomon et al.* (2016). From an ethical point of view, the information presented must not alter reality and should not give false hopes to patients. Vulnerable groups and patients with serious suffering can be easily influenced and will tend to trust any promise easily, with the desire to heal. Ethically, the information presented must not alter reality and should not give false hopes to patients. Healthcare providers should be careful when creating promotional messages and make sure that the language used is truthful and honest, as it is often necessary to shorten and compress the message. Any paid advertisement should be identified as such, as required by *Solomon et al.* (2016).

2.6 Key Differences from Previous Work

The primary distinguishing factors of my work compared to previous studies are twofold: the inclusion of online evaluations alongside offline evaluations, and the utilization of a user study for investigating user behavior towards advertisements. In the online evaluation, a user study was conducted on a representative sample of individuals across Norway, specifically focusing on their perceptions and attitudes toward advertisements. Scenarios were designed where participants were presented with different advertisements alongside news articles and asked to indicate their preferred choice. This approach aimed to gain insights into people's preferences and provide valuable business insights to advertisers.

Regarding the offline evaluation, extensive prior research has been conducted in this area. In the case of this thesis, a comprehensive dataset from Amedia AS was obtained, consisting of user data encompassing individuals aged 18 to 75, specifically, click data on advertisements. The data were processed and cleaned, uncovering observations among the users. Furthermore, feature extraction was applied to identify objects present in the clicked advertisement images from the dataset. Additionally, if a person was detected in the image, the associated emotions were extracted. The aim of this process was to determine whether these extracted features could potentially contribute to the improvement of personalization efforts.

This process resulted in the creation of a novel dataset, which was subsequently utilized in the application of a predictive model, specifically a random forest algorithm, combined with feature importance analysis to further explore the research questions at hand. While related works have primarily focused on Sponsored Search and Content-matching techniques as mentioned in section2.1, the study of this thesis diverged in its emphasis on online evaluations, user behavior in the user study, and the utilization of real user data obtained from Amedia AS. Overall, the inclusion of both online and offline evaluations, along with the unique dataset and feature extraction techniques employed, sets the research of this thesis apart from previous studies in the field.

Chapter 3

Methodology

This chapter presents the methodologies and techniques employed to address the research questions outlined in the thesis. Section 3.1 provides a concise overview of the dataset provided by the media company Amedia. Section 3.2 outlines the feature extraction methods utilized for extracting features from the advertisement images. The section also elaborates on how the images were manually labeled to evaluate object detection, utilizing a pre-trained model from *You Only Live Once (YOLO)* - specifically, YOLOv5 was employed to perform object detection, and the *DeepFace* library was used to detect emotions in the images. These techniques enabled the detection of objects within the advertisement images, which were then encoded as features for further analysis. This analysis leads to Section 3.3, which describes the process of building a predictive model that identifies and predicts key features from the dataset, along with the metrics used. Finally, Section 3.4 presents the user study that was conducted.

3.1 Data set

This section presents certain details about the data set analyzed in this thesis. The data is provided by Amedia, one of the largest media companies in Norway. As shown in figure 3.1, the dataset contains user behavior in online advertisement. Each row represents an observation of a user who clicked on an advertisement, presenting the audience's behavior and the characteristics of the advertisement. This includes the content type of the ad (cat_20maxlabel) and the advertiser responsible for presenting the ad (annonsornavn). There are in total 685553 observations and 19 different features in the dataset. The data had to be cleaned and pre-processed before further analysis. This process is covered in the preliminary analysis in section 4.1. However, each row of the data set contains one person's characteristics such as age and gender. It is also possible from each row to investigate if the advertisements actually were clicked, and how many viewers the ad actually had received by checking the features: "n_impressions_measurable". The data has both numerical and categorical data types, as shown in the figure 3.1. Amedia describes the features as listed:

- **page_type:** This is whether the advertisement is present on the homepage or a content page. The homepage is the main page all audiences will first see when visiting a newspaper site and is where they can scroll through to get to content pages.

annonsornavn	industry	n_impressions_measurable	format	gender	ctr	age_group	cat20_maxlabel	n_click
Coop Extra - Konsern	Øvrige	2	netboard	F	0,50	65-69	Politikk	1
Coop Extra - Konsern	Øvrige	4	netboard	F	0,50	65-69	Økonomi og næringsliv	2
Coop Extra - Konsern	Øvrige	2	midtbanner	F	0,50	70-74	Politikk	1
Coop Extra - Konsern	Øvrige	2	midtbanner	F	0,50	70-74	Økonomi og næringsliv	1
Coop Extra - Konsern	Øvrige	2	midtbanner	F	0,50	75+	Kriminalitet og rettsvesen	1
Coop Extra - Konsern	Øvrige	2	midtbanner	M	0,50	30-34	Utdanning	1
Coop Extra - Konsern	Øvrige	2	midtbanner	M	0,50	35-39	Fritid	1
Coop Extra - Konsern	Øvrige	2	midtbanner	M	0,50	65-69	Økonomi og næringsliv	1
Coop Extra - Konsern	Øvrige	2	midtbanner	M	0,50	65-69		1
Coop Extra - Konsern	Øvrige	2	netboard	M	0,50	70-74	Samferdsel	1
Coop Extra - Konsern	Øvrige	2	netboard	M	0,50	75+	Sport	1
Coop Extra - Konsern	Øvrige	7	midtbanner	M	0,43	75+	Ulykker og naturkatastrofer	3
Coop Extra - Konsern	Øvrige	5	netboard	F	0,40	75+	Kriminalitet og rettsvesen	2
Coop Extra - Konsern	Øvrige	3	midtbanner	F	0,33	30-34	Økonomi og næringsliv	1
Coop Extra - Konsern	Øvrige	3	netboard	F	0,33	45-49	Økonomi og næringsliv	1
Coop Extra - Konsern	Øvrige	6	midtbanner	F	0,33	50-54	Bolig og eiendom	2
Coop Extra - Konsern	Øvrige	3	midtbanner	F	0,33	50-54	Økonomi og næringsliv	1

Figure 3.1: Dataset sample

- **annonsornavn:** The name of the company running a campaign with Amedia.
- **industry:** The type of industry the advertisement belongs in, which is related to the company running the campaign.
- **CreativeId:** The id of each of the images of the advertisements.
- **format:** The placement of the advertisement on the web page. For example, "toppbanner" is the top section of the web page.
- **hb_size:** The size of the advertisement image.
- **gender:** The target gender of the advertisement, can be either male or female.
- **age_group:** The target age group of the advertisement in 5-year increments from 18-25 to 75+.
- **cat20_maxlabel:** The category of the advertisement, and determines what different sections of content the advertisement will be shown in.
- **word_count:** The number of words in an article.
- **n_obs:** Number of observations the audience has had of the advertisement.
- **n_impressions _measurable:** The number of measurable impressions as defined by Amedia, meaning the system detected that the advertisement was on the screen of the audience.
- **n_impressions _viewable:** The number of the audience where 50% of the advertisement was visible for at least two seconds.
- **n_click:** The number of the audience who clicked on the advertisement.

Table 3.1: Data Types

Column Name	Data Types
LineItemId	Int64
page_type	object
annonsornavn	object
industry	Object
CreativeId	int64
format	object
hb_size	object
gender	object
age_group	object
cat20_maxlabel	object
word_count	float64
n_content_ids	int64
n_obs	int64
n_impressions_measurable	int64
n_impressions_viewable	int64
n_click	Int64
ctr	float64
n_obs_total	int64

- **ctr:** Represents *click-through rate*. This term is defined by *Google* as the number of clicks that your ad received by the number of times your ad is shown. It is a ratio showing how often people who see your ad end up clicking it. It can be used as a performance metric to measure how well keywords and advertisements perform. The formula to compute the CTR is presented by *Google* as such:

$$CTR = \frac{\text{Clicks}}{\text{Impressions}} \tag{3.1}$$

  Due to the uneven distribution of users in the dataset after the aggregation and cleaning of the data, the computation of CTR values required the use of weighted averages, as determined by the following formula provided by *Fost* (2023):

$$\text{Weighted Average CTR for each age-group} = \frac{\text{Clicks} \times \text{Users}}{\sum \text{Users}} \tag{3.2}$$

  In this case for the dataset, features like n_clicks could be used for clicks, and n_impressions _measurable could be used for impressions.

- **n_obs_total:** The total number of observations audience members have of the advertisement for the whole campaign.

- **ctr_total:** The total click-through rate for each observation.

3.2 Feature Extraction and Engineering

This section presents the feature extraction methods used in the thesis. Object and emotion detection models were employed to extract objects and emotions from the dataset's advertisement images (see Table 3.1). The model construction involved utilizing a pre-trained YOLO (You Only Look Once) model for object detection and DeepFace libraries for emotion detection. To evaluate the object detection, manual labeling was performed using the tool *Makesense* together with *Intersection over Union*.

3.2.1 Object Detection

Object detection is described as: "one of the primary tasks in computer vision which consists of determining the location on the image where certain objects are present, as well as classifying those objects" *Thuan* (2021). An example of this is illustrated in figure 3.2. To be able to detect objects from the provided dataset, a popular deep learning algorithm for object detection was conducted. The model used is You Only Look Once version 5 (YOLOV5), available from [1]. YOLOv5 is described as: "YOLOv5 is a family of compound-scaled object detection models trained on the COCO dataset, and includes simple functionality for Test Time Augmentation (TTA), model ensembling, hyperparameter evolution". The COCO dataset consists of approximately 80 labels, including people, bicycles, cars, trucks, etc.

The custom model was loaded and implemented through a PyTorch framework [2]. To be able to handle the images, the Python Imaging Library (PIL) was used. The custom-trained model was initialized using the load() function and passed each image through the model using the model() function. The output of the model was a set of bounding boxes and confidence scores for each detected object. An example of an advertisement with its bounding boxes is illustrated in Figure 3.2. The bounding boxes from each image were used to determine whether a person was present in the image. If a person was detected, the DeepFace library was used to analyze their facial expressions and detect the dominant emotion. If no person was detected, the first object detected (if any) was recorded as the "object" in the results. If there was no person detected, the column for dominant emotion was set to "no person". Finally, the results of the emotion analysis and object detection were merged into a single data frame, which made it possible to explore the relationship between visual features, emotional responses, and object types in advertisements. This analysis can provide insights into the effectiveness of different visual features and object types in capturing viewers' attention and eliciting emotional responses. It is important to note that certain images in the dataset were blank, resulting in some rows containing NaN values in the object and dominant emotion columns. To address this, the NaN values were replaced with "no object" and "no person," as illustrated in Figure 4.5.

The YOLO version 5 family consists of 5 models in total, as shown in Table 3.2. Starting from YOLOv4 Nano, which is the smallest and fastest, to YOLOv5 extra-large, the largest. A broad description of the models by *Rath* (2022) is detailed. A comparison of the YOLOv5 models is shown in Table 3.2.

[1] https://docs.ultralytics.com/yolov5/

[2] https://pytorch.org/hub/ultralytics_yolov5/

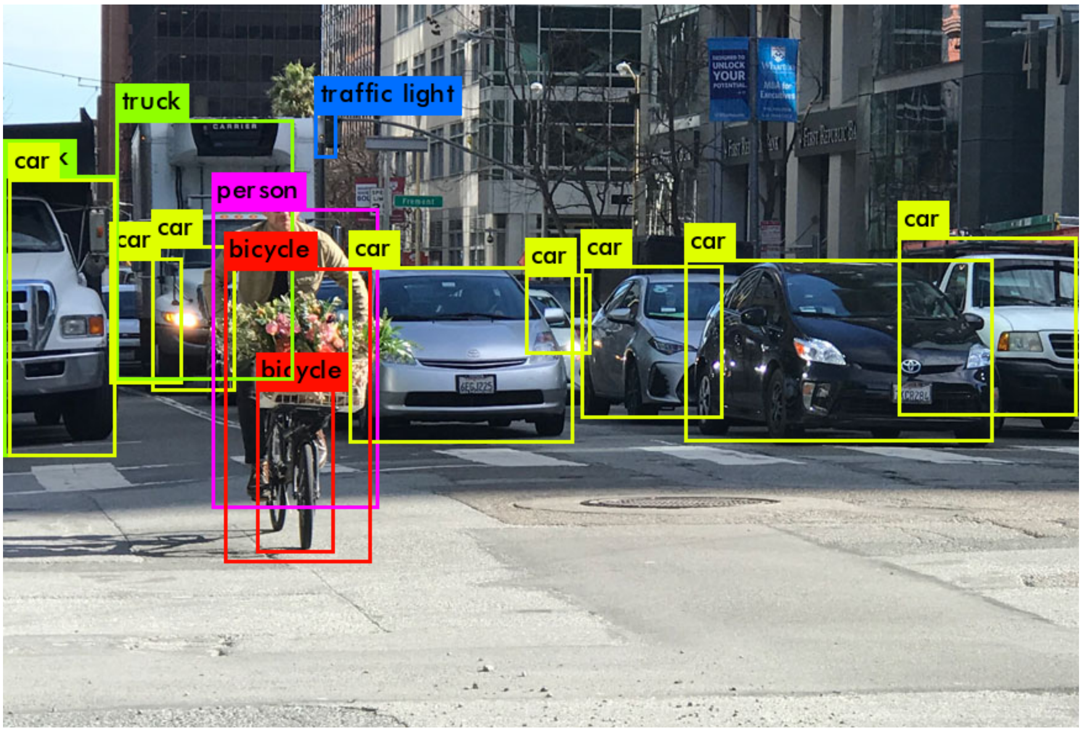


Figure 3.2: Real-time object detection example using YOLO

- YOLOv5n: It is a newly introduced nano model, which is the smallest in the family and meant for the edge, IoT devices, and with OpenCV DNN support as well. It is less than 2.5 MB in INT8 format and around 4 MB in FP32 format. It is ideal for mobile solutions.
- YOLOv5s: It is a small model in the family with around 7.2 million parameters and is ideal for running inference on the CPU.
- YOLOv5m: This is a medium-sized model with 21.2 million parameters. It is perhaps the best-suited model for many datasets and training as it provides a good balance between speed and accuracy.
- YOLOv5l: It is the large model of the YOLOv5 family with 46.5 million parameters. It is ideal for datasets where we need to detect smaller objects.
- YYOLOv5x: It is the largest among the five models and has the highest mAP among the 5 as well. Although it is slower compared to the others and has 86.7 million parameters.

For object detection in this thesis, the YOLOv5s model from the models presented in Table 3.2 was employed. The selection of the YOLOv5s model was based on the dataset used for training, which comprised approximately 200 images. Considering the relatively small size of the dataset, opting for a smaller model was intended to mitigate overfitting risks and enhance training efficiency.

There exist two different types of object detection models. Those are two-stage object detectors and single-stage object detectors. Single-stage object detectors (like YOLO) architecture are composed of three components: Backbone, Neck, and a Head

Table 3.2: Comparison of YOLOv5 models, Rath (2022)

Model	Backbone	Input Size	Params (million)	CPU Time (ms)	Accuracy (mAP 0.5)
YOLOv5n	CSPDarknet53	640x640	1.9M	45	45.7
YOLOv5s	CSPDarknet53	640x640	7.2M	98	56.8
YOLOv5m	CSPDarknet53	640x640	21.2M	225	64.1
YOLOv5l	CSPDarknet53	640x640	46.5M	430	67.3
YOLOv5x	CSPDarknet53	640x640	86.7M	766	68.9

to make dense predictions. The backbone model is a pre-trained network that extracts rich feature representations for images. By doing so, it reduced the spatial resolution of the image and increases the feature resolution. The neck of the model helps to generalize well to objects of different sizes and scales. The model head is used to perform the final stage operations. It applies anchor boxes on feature maps and renders the final output: classes, objectness scores, and the bounding boxes. YOLOv5 returns three outputs: the classes of the detected objects, their bounding boxes, and the objectness scores ope (2023).

The equations used to compute the different target coordinates for the bounding boxes is presented by *Zhang et al.* (2022) as detailed:

$$b_x = (2 * \sigma * (t_x) - 0.5) + c_x$$

$$b_y = (2 * \sigma * (t_y) - 0.5) + c_y$$

$$b_w = pw * (2 * \sigma(t_w))^2$$

$$b_h = ph * (2 * \sigma(t_h))^2$$

Up to the day of writing this thesis and reading the paper of: ope (2023), there were no research papers for YOLOv5 published. However, the paper of *Thuan* (2021) states that by dissecting its structure code, the YOLOv5 model can be summarized as.

- Backbone: Focus structure, CSP network
- Neck: SPP block, PANet
- Head: YOLOv3 head using GIoU-loss

3.2.2 Makesense

In order to be able to evaluate the object detection model, a ground truth table of the advertisement images was necessary. Makesense[3], which is a free online tool for labeling photos, was used to manually label the advertisement images. Thanks to the use of a browser it didn't require any complicated installation, and any operating system can run it. The documentation can be found at [4]. After the advertisement images were loaded into a working directory the annotation could start, where bounding boxes were drawn over the objects, as shown in Figure 3.3

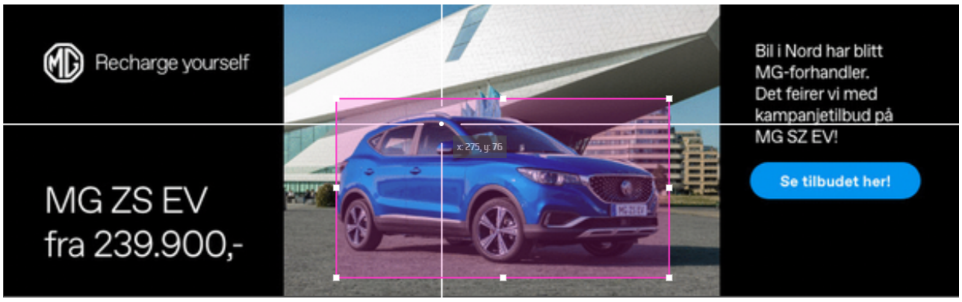


Figure 3.3: Manual labeling in Makesense

Makesense supports multiple annotations, such as bounding boxes, polygon, and point annotations. For the case of this thesis, the bounding boxes were the most relevant, as the output of the object detection provides bounding boxes as well.

Intersection over Union

In order to compare the ground truth table from the object detection model and the ground truth table from Makesense, Intersection over Union (IoU) was conducted. This is one of the most popular evaluation metrics used in object detection benchmarks. IoU is the most commonly used metric for comparing the similarity between two arbitrary shapes *Rezatofighi et al.* (2019). IoU encodes the shape properties of the objects under comparison by using the heights, widths, and locations of two bounding boxes. Intersection over Union for comparing the similarity between two shapes is attained by:

$$IoU = \frac{|A \cap B|}{|A \cup B|}$$

where A and B are sets of elements, and $|\cdot|$ denotes the cardinality of a set.

3.2.3 DeepFace

In order to be available to extract emotions from the images, libraries from DeepFace were utilized. Facial recognition has for the past decades been a hot topic. Different facial recognition libraries have been made available. Deepface has become popular and is used in numerous face recognition applications. Deepface is the most

[3] https://www.makesense.ai/
[4] https://skalskip.github.io/make-sense/

lightweight face recognition and facial attribute analysis library available for Python *Serengil* (2023). It is trained on a large data set of faces acquired from a population vastly different than the one used to construct the evaluation benchmarks *Taigman et al.* (2014). The library is published in the Python Package Index (PyPi) [5] The open-sourced library included leading-edge AI models for face recognition. It also handles procedures for facial recognition in the background. DeepFace requires only a few lines of code to run it, without any in-depth knowledge about all the processes behind it. Using face recognition with Deepface makes a set of features available, as detailed by *Serengil* (2023):

In order to detect the dominant emotion in each advertisement image related to the dataset, the DeepFace library 3.3.1 in Python was utilized. DeepFace provides a pre-trained Convolutional Neural Network (CNN) model for facial expression recognition. This model was conducted to further analyze the emotional state of each person that was detected in the images. Furthermore,

- **Face Verification**: The task of face verification refers to comparing a face with another to verify if it is a match or not. Hence, face verification is commonly used to compare a candidate's face to another. This can be used to confirm that a physical face matches the one in an ID document.

- **Face Recognition**: The task refers to finding a face in an image database. Performing face recognition requires running face verification many times.

- **Face Attribute Analysis**: The task of facial attribute analysis refers to describing the visual properties of face images. Accordingly, facial attributes analysis is used to extract attributes such as age, gender classification, emotion analysis, or race/ethnicity prediction.

- **Real-Time Face Analysis**: This feature includes testing face recognition and facial attribute analysis with the real-time video feed of your webcam.

The most relevant feature considering this thesis was the face attribute analysis, as the intention was to extract the most dominant emotion from the advertisement images together with the objects. The images were passed to the analyze() function of the DeepFace library with the 'emotion' action parameter to detect the dominant emotion in the image. Emotion Recognition, known as affective computing, is a rapidly growing branch of Artificial Intelligence that allows computers to analyze and understand human signs such as their facial expressions *Boesch* (2023). Emotion recognition is the task of machines analyzing, interpreting, and classifying human emotions through the analysis of facial features. An example of a facial attribute analysis for emotion recognition with DeepFace can be seen in figure 3.4, where the emotion with the highest accuracy is displayed as "dominant_emotion"

[5] https://pypi.org/project/deepface/

Figure 3.4: Facial attribute analysis Boesch (2023)


```
{
   "emotion":{
      "angry":7.603101671639384e-14,
      "disgust":2.7474185705216866e-21,
      "fear":1.688688161735822e-14,
      "happy":100.0,
      "sad":4.205067717644173e-10,
      "surprise":7.103817571484745e-13,
      "neutral":4.4851553027136504e-08
   },
   "dominant_emotion":"happy",
   "age":31,
   "gender":"Woman",
   "race":{
      "asian":0.9087088517844677,
      "indian":1.1444833129644394,
      "black":0.09399998234584928,
      "white":66.56872034072876,
      "middle eastern":16.655877232551575,
      "latino hispanic":14.628209173679352
   },
   "dominant_race":"white"
}
```


3.3 Predictive Model

This section presents the offline evaluation process, utilizing the dataset obtained after the feature extraction. To analyze the dataset and extract important features, a *random forest* model was employed, followed by a feature importance analysis. The performance of the random forest model was compared to a baseline decision tree model. The goal of the offline evaluation was to gain insights into user engagement and preferences across different advertising styles, providing a deeper understanding of user behavior in a controlled environment.

3.3.1 Random Forest

The predictive model built to analyze the dataset obtained from the object and emotion detection is a *Random Forest Regressor*. The library and implementation are sourced from scikit-learn [6]. The Random Forest algorithm was a suitable choice for the analysis due to its ability to handle imbalanced datasets and provide valuable insights for businesses in the advertising domain. After a random forest regressor was instantiated, the data were split into train and test-set, using n_click as the target variable. This variable represents the number of clicks, which is a crucial metric for media companies involved in advertising, and was, therefore, the choice of the target variable. To find the most suitable parameters for the regression model, *GridSearchCv* [7] was utilized. The grid search ran on various combinations of parameters. Such as the number of estimators, maximum features, maximum depth, and maximum samples. The GridSearchCV helped to identify the optimal parameter values that maximize the model's performance. Once the model was fitted to the training set, the target variable was predicted for the test set using rfc.predict(). Furthermore, the feature importances of the

[6] https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestRegressor.html

[7] https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

Random Forest model were computed using the feature_importances_attribute. This made it possible to rank the importance of each feature in predicting the target variable.

In order to evaluate the model performance, the following metrics for the loss by *Chicco et al.* are detailed under, where X_i is the predicted i^{th} value, and the Y_i element is the actual i^{th} value. The regression method predicts the X_i element for the corresponding Y_i element of the ground truth data set.

Coefficient of determination (known as r-squared or r2), can be interpreted as the proportion of the variance in the dependent variable that is predictable from the independent variables.
(worst value = $-\infty$; best value = $+1$)

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(\overline{Y} - Y_i)^2} \tag{3.3}$$

Mean square error (MSE) is useful if there are outliers that need to be detected. MSE is great for attributing larger weights to such points, thanks to the L2 norm: clearly, if the model eventually outputs a single very bad prediction, the squaring part of the function magnifies the error. Since $R^2 = 1 - \frac{MSE}{MST}$ and since MST is fixed for the data at hand, R^2 is monotonically related to MSE (a negative monotonic relationship), which implies that an ordering of regression models based on R^2 will be identical (although in reverse order) to an ordering of models based on MSE or $RMSE$.
(best value = 0; worst value = +∞)

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2 \tag{3.4}$$

Root mean square error (RMSE) The two quantities MSE and RMSE are monotonically related (through the square root). An ordering of regression models based on MSE will be identical to an ordering of models based on RMSE.
(best value = 0; worst value = +∞)

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(X_i - Y_i)^2} \tag{3.5}$$

Mean absolute error (MAE) MAE can be used if outliers represent corrupted parts of the data. In fact, MAE is not penalizing too much the training outliers (the L1 norm somehow smooths out all the errors of possible outliers), thus providing a generic and bounded performance measure for the model. On the other hand, if the test set also has many outliers, the model performance will be mediocre.
(best value = 0; worst value = +∞)

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|X_i - Y_i| \tag{3.6}$$

3.4 User Study

Section 2.1 illustrated how advertising has become a billion-dollar industry within media platforms, as confirmed by *Broder et al.* (2007). However, advertising is not just about the technical aspects that include high costs. Advertising involves the exchange of communication between media advertisements and consumers as well, as illustrated in the paper of *Kuksov et al.* (2013), where the importance of communication between advisers and consumers are presented. This is the reason why a user study was conducted as part of this master's thesis, in order to address biases and investigate user behavior within ads. This section presents the methods and platforms used to conduct the user study.

The user survey was designed and implemented using the web-based platform *Typeform* [8]. It is important to note that the project was registered with rette.app.uib, [9] which oversees the handling of personal information in research projects and student assignments at UiB (University of Bergen). Reaching out to consumers through the crowdsourcing platform *Prolific* [10] and asking them specific questions about their relationships with advertisements, was a simple but effective way to gain insights into user behavior towards advertisements. The majority of the questions consisted of multiple-choice and opinion scale options, including "other" options that allowed respondents to provide open-ended responses. Incorporating this option made it possible to gather additional insights as individuals could share their unique experiences and perspectives. The functionality of the Typeform platform allowed for the convenient download of survey results in the form of a CSV file. This made it possible to conduct in-depth data analysis and explore potential relationships within the user survey.

Two surveys were conducted, one with participants from Prolific and another with voluntary participants. Both surveys included identical questions. For the Prolific survey, participants were required to enter a unique ID to ensure completion, pass the *Instructional Manipulation Check* (IMU) check (see Figure 3.5), and receive payment. The questions of the user study can be found in Appendix A, while the results of the study can be found in Appendices B for prolific and B for the voluntaries. While the sample size is larger for the Prolific group, this section will present some figures from their results. However, all participant responses will be thoroughly analyzed and discussed throughout this section.

The user study involved 67 participants, whereas 13 were voluntary and 54 were engaged through the platform Prolific. The data were collected over a period of two months, from March to late April. The participants recruited through Prolific were monetarily compensated for their contribution to the study. Since the user study was implemented in English, a pre-screening was applied to the Prolific users, so that only users that can fluently speak English could participate. To ensure to obtain the data quality and prevent potential people who only attended for money, or "bots", one Instructional Manipulation Check *Oppenheimer et al.* (2009) was implemented in order to determine whether the participants were paying attention to the study (see figure 3.5). Users who failed the IMUs were discarded from the final data analysis, resulting

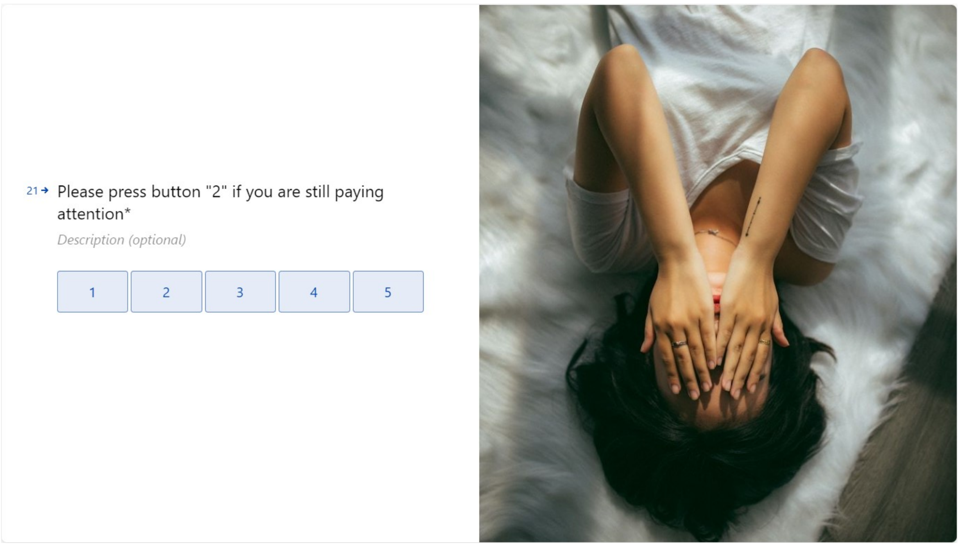
[8] https://www.typeform.com/

[9] https://rette.app.uib.no/

[10] https://app.prolific.co/

in a reduction of 4.55% from 66 to 63 users.

Figure 3.5: Screenshot of the Instructional Manipulation Check used to catch inattentive persons.



Data Collection Phases The user survey conducted in this study includes the following components:

- *Demographic information*: This includes gender, age, and any other relevant demographic data. This information was used in order to analyze how different demographics responded to the survey and their preferences.
- *Responses to open-ended questions*: Participants were asked to provide their opinions and feedback on ads shown on media platforms through open-ended questions. These responses were used to identify common themes or patterns in participants' attitudes toward ads and provide insight into the factors that influence user behavior toward advertisements.
- *Opinion scale questions*: Participants were asked to rate their feelings about advertisements on a quantitative scale. These responses retrieved data on how people feel about ads and analyze any differences between different demographic groups.
- *Multiple-choice questions*: Participants were presented with different ad options and asked to choose which one they would click on. They were also asked to provide reasons for their choice. The responses were used to analyze user preferences and behaviors toward different types of ads.

Previous studies have shown that demographic and personality factors can be linked to user preferences *Moghaddam and Elahi* (2019). For this reason, demographic data such as gender and age were collected in the user study. The data was used in order to analyze how different demographic groups would respond to the survey questions and their preferences. Additionally, personality traits such as extraversion and openness to experience may also influence user behavior toward advertisements. By including these factors in the survey, it enabled the possibility to identify whether they are influential to what people prefer in terms of advertisements in general.

Chapter 4

Evaluation and Results

In this chapter, the results of the analyses performed within this thesis have been described. First, a preliminary analysis of the data has been provided in section 4.1. This includes the data exploration and subsequent data cleaning of the Amedia data set. In section 4.2, feature extraction has been utilized, where objects and emotions are extracted from the images related to the advertisements. This is followed by an experiment where a predictive model is built accompanied by feature importance analysis. The last section 4.4 details the results obtained from the real user study.

4.1 Experiment A: Exploratory Data Analysis

In this section, a description of the initial exploratory analyses conducted on the data provided by Amedia is presented. The raw data, which serves as the foundation for this section, was presented in Section 3.1 and visualized in Figure 3.1.

Initially, unnecessary columns were dropped and data types were converted to their correct format. After removing the unnecessary observations, the dataset size decreased from approximately 650,000 observations (as mentioned in Section 3.1) to approximately 100,000 observations. The dataset from there on was further investigated to compute the click-through rate (CTR) for each age group, aiming to identify potential differences in ad-clicking behavior. To achieve this, additional data cleaning procedures were implemented, including verifying that advertisements were clicked on by checking if the "n_click" column had values greater than zero, and ensuring that the "n_impressions_measurable" column had a respectable audience reach, set to greater than 100 for improved numerical stability and statistical robustness in further analysis.

Figure 4.1 illustrates the number of observations in the dataset that had zero clicks, revealing that a large proportion of advertisements were not clicked at all. To be able to better understand the amount of reduction in terms of users this involved, the two Tables 4.1 and 4.2 clearly illustrate the reduction of users which from approximately 90 0000 to 700 by excluding advertisements that were not clicked.

Table 4.1: Users before excluding advertisements with no clicks

Age group	Users
75+	8918
70-74	9426
65-69	10382
60-64	10668
55-59	10848
50-54	11070
45-49	10163
40-44	8669
35-39	7763
30-34	6698
25-29	5549
18-24	3523

Table 4.2: Users after excluding advertisements with no clicks

Age group	Users
75+	221
70-74	220
65-69	222
60-64	209
55-59	164
50-54	146
45-49	115
40-44	60
35-39	56
30-34	36
25-29	35
18-24	19

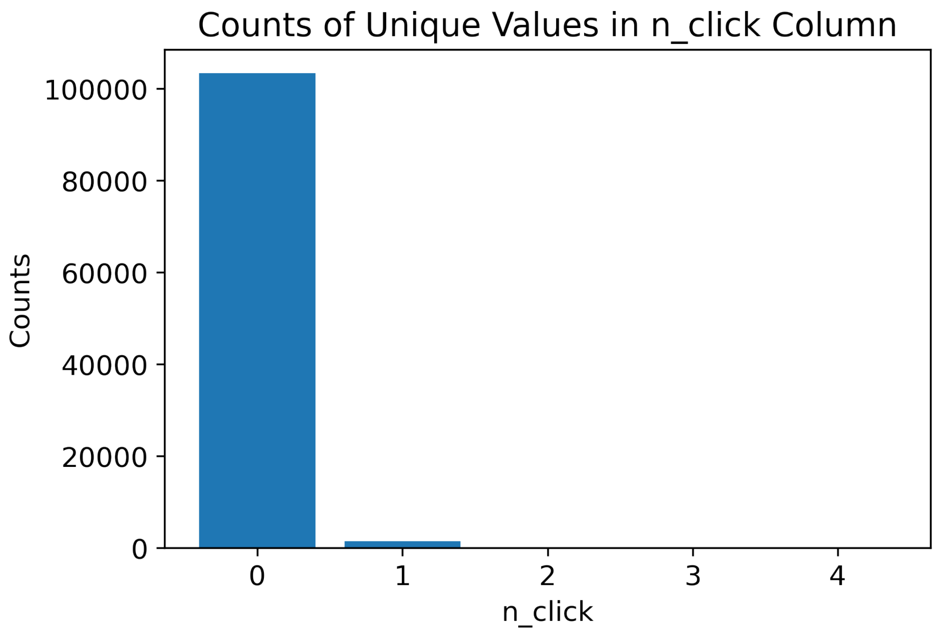


Figure 4.1: Total number of clicks

In addition to the previous figure, the clicking behavior of different age groups was analyzed. The two Tables 4.3 and 4.2 display this analysis shown with numbers, and the Figures 4.2 and 4.3 visualize the results shown in the figures. The figures detail the weighted average CTR values for all age groups computed from the data set, with the n_click as shown in the y-axis of the figure column adjusted to only include data where the ad was clicked on. The weighted average CTR for each age group can be found in Table 4.3. The CTR value for the 75+ age group was 0.006869, indicating that for every 1000 ad impressions, there were approximately 6.89 clicks from users above 75 years old. In contrast, the youngest age group (18-24) has the lowest CTR of 0.002126, meaning that for every 1000 ad impressions, there were approximately 2.1 clicks from people between 18-24 years old. The result of performing the weighted average of ctr values across all age groups may suggest the fact that elder people are more likely to click on advertisements than younger people.

Table 4.3: Age group and weighted CTR by age

Age group	CTR by age
18-24	0.002126
25-29	0.002911
30-34	0.001955
35-39	0.002050
40-44	0.003340
45-49	0.003376
50-54	0.003362
55-59	0.004936
60-64	0.006188
65-69	0.006683
70-74	0.006987
75+	0.006869

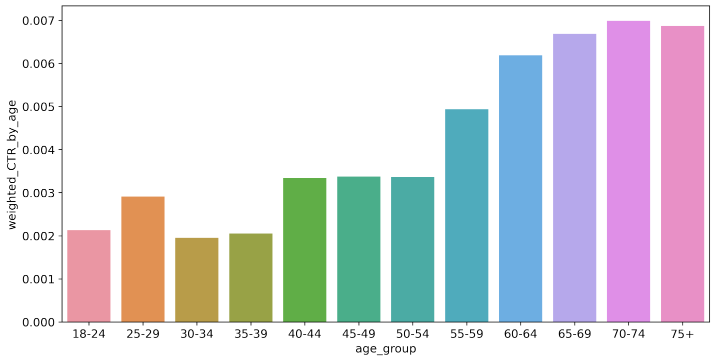


Figure 4.2: Weighted average ctr values for all age groups

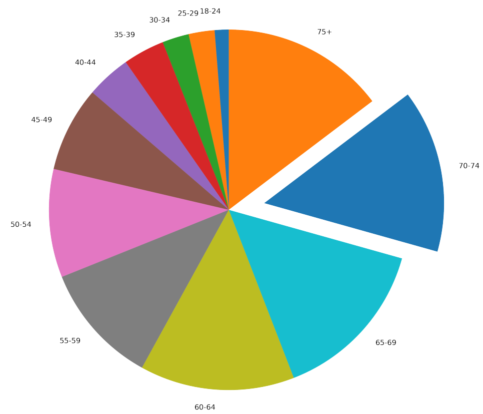


Figure 4.3: Users represented for each age-group

One possible explanation for this phenomenon is that older individuals may exhibit less critical judgment when confronted with content, or perhaps they tend to have more difficulty navigating digital interfaces accurately. However, previous research suggests that both young and elderly individuals encounter challenges in distinguishing between advertisements and news articles *NTB* (2021). This observation highlights the difficulty of navigating the vast digital landscape of information and sheds light on why the click-through rate (CTR) values for older individuals might be higher. The blurred line between ads and news articles contributes to the challenge of differentiating them.

Additionally, an examination of Table 4.2 provides insights into the distribution of individuals across different age groups, taking into account data cleaning and aggregation. Notably, the number of elder individuals outweighs the younger population, with

221 users aged 75+ compared to only 19 users in the 18-24 age group. This disparity further emphasizes the trend where younger individuals exhibit a lower propensity for clicking on advertisements, while the elder demographic shows a higher level of engagement.

The analysis of specific categories that interest different age groups may provide valuable insights by addressing the preferences of the users. To determine these preferences, Table 3.1 presents the cat20_maxlabel column, which defines the category of advertisements. Summing the CTR values for each age group and aggregating them with their respective categories for the actual advertisement, makes it possible to identify the top categories for each age group, as shown in Table 4.4. The findings from this table shed light on the most popular category in terms of advertisements for each of the age groups. It is important to note that these preferences may vary and could have a random component, but they still provide indications of the categories that resonate with each age group. Notably, the table reveals that the category "Kriminalitet og rettvesen" ranks highest in terms of CTR for younger users, suggesting their inclination towards this category. On the other hand, the category "Ulykker og naturkatastrofer" emerges as a preferred choice for elder users.

An intriguing result from the analysis is the identification of "Økonomi og næringsliv" as the most popular category among individuals aged 45-49. This finding highlights their particular interest in this category when engaging with advertisements. Such insights into age-specific category preferences can be valuable for advertisers and marketers seeking to tailor their campaigns effectively. Overall, the table 4.4 provides a comprehensive overview of the top categories for each age group, showcasing the diverse interests and preferences within different categories. By understanding these patterns, media companies cam use such information to strategically target their campaigns to resonate with specific age groups and enhance the effectiveness of their marketing efforts. The data set which started with a total of 685553 observations is now reduced to 635 observations for further analysis shown in the next section.

Table 4.4: Most Popular Category for Each Age Group (CTR)

Age Group	Category	CTR
18-24	Kriminalitet og rettsvesen	0.026901
25-29	Kriminalitet og rettsvesen	0.034223
30-34	Kriminalitet og rettsvesen	0.053122
35-39	Ulykker og naturkatastrofer	0.082453
40-44	Ulykker og naturkatastrofer	0.035858
45-49	Økonomi og næringsliv	0.056067
50-54	Kriminalitet og rettsvesen	0.074141
55-59	Ulykker og naturkatastrofer	0.089934
60-64	Kriminalitet og rettsvesen	0.106361
65-69	Kriminalitet og rettsvesen	0.133932
70-74	Ulykker og naturkatastrofer	0.099463
75+	Kriminalitet og rettsvesen	0.094301

4.2 Experiment B: Feature Extraction - Objects and Emotions

Following the exploratory data analysis, objects and emotions were extracted from the advertisement images to explore their potential influence on ad click behavior. This section will therefore describe how these features were extracted, together with the results. In addition, the quality of the object detection is presented, by performing an Intersection over Union.

The utilization of these techniques can be exemplified through an advertisement showcased in Figure 4.4. In this example, object detection successfully identified a person within the advertisement with a high probability of 93.75%. By incorporating these techniques into the analysis, two new features were introduced to the dataset derived from the exploratory data analysis discussed in Section 4.1. Consequently, the dataset now encompasses the following features: "age_group," "gender," "Adviser," "industry," "page_type," "format," "n_click," "n_impressions_measurable," "ctr," and the two new features, "object" and "dominant_emotion." Detailed descriptions of these features are listed in Section 3.1. Additionally, the "cat20_maxlabel" feature has been renamed as "Category" to prevent confusion within the dataset. Following the feature extraction process, the dataset contains 635 observations with a total of 13 features, as illustrated in Figure 4.5.

Figure 4.4: Advertisement example with object detection

Among the 635 observations, a total of 236 persons were detected. Remarkably, the most frequently detected dominant emotion was "fear", occurring 96 times, followed by occurrences of "happiness", "sadness", "anger", and "surprise". These findings are depicted in Figure 4.6. On the other hand, apart from persons, the most frequently

Figure 4.5: Dataframe example after adding the new features

age_group	gender	Adviser	industry	Category	page_type	format	n_click	n_impressions_measurable	ctr	object	dominant_emotion
over40	M	S - L Nord / Coop Extra	Øvrige	Kriminalitet og rettsvesen	contentpage	netboard	1	246	0.004065	bus	not_person
over40	M	S - L Nord / Coop Extra	Øvrige	Vær	contentpage	toppbanner	1	121	0.008264	no object	not_person
over40	F	S - L Nord / Coop Extra	Øvrige	Bolig og eiendom	contentpage	midtbanner	2	283	0.007067	person	fear
over40	F	S - L Nord / Coop Extra	Øvrige	Kriminalitet og rettsvesen	contentpage	midtbanner	2	1401	0.001428	person	happy
over40	F	S - L Nord / Coop Extra	Øvrige	Medisin og helse	contentpage	midtbanner	1	141	0.007092	Car	not_person

detected object was actually a "tie," observed 25 times. Notably, other objects such as "bus," "car," "boat," "bowl," "stop sign," "frisbee," "banana," "book," "orange," and "sandwich" were almost equally distributed. Intriguingly, Figure 4.7 highlights that there were 285 instances where no object was detected, potentially due to blank white images or images without discernible objects. The prevalence of ties as the most detected object raises questions regarding the object detection model's accuracy in predicting objects within advertisements, potentially leading to mispredictions.

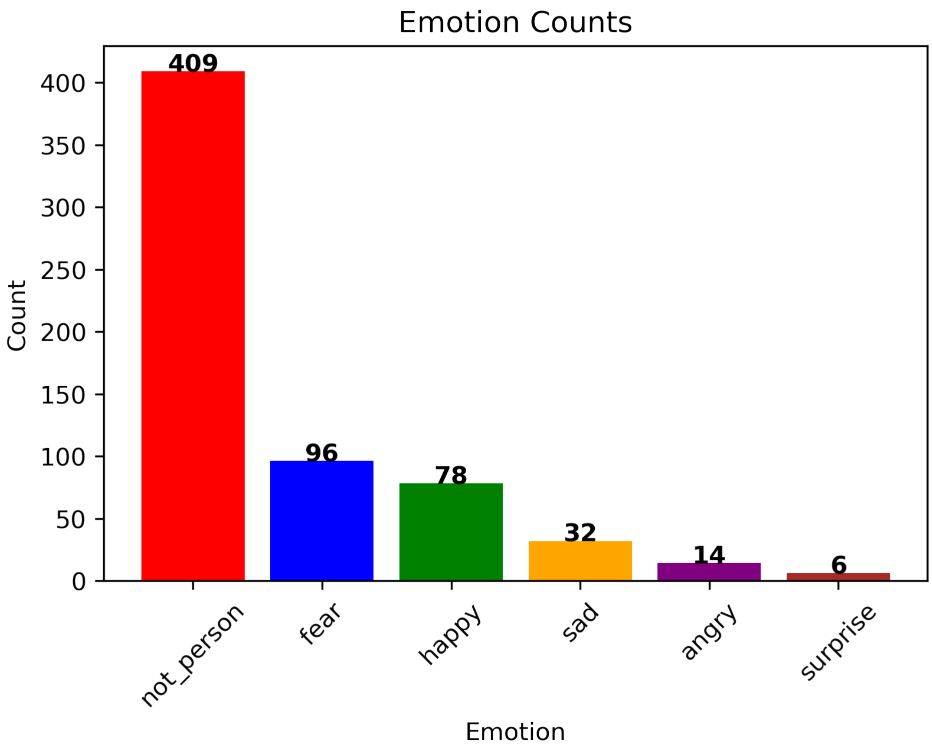


Figure 4.6: Emotions detected from the dataset

These findings could offer valuable implications for advertisers seeking to maximize the effectiveness of their campaigns. The prevalence of fear as the dominant emotion, as seen in Table 4.7, suggests that incorporating fear-inducing elements, may capture viewers' attention and evoke stronger emotional responses. On the other hand, the prominence of "happy" emotions indicates that advertisements portraying positive and

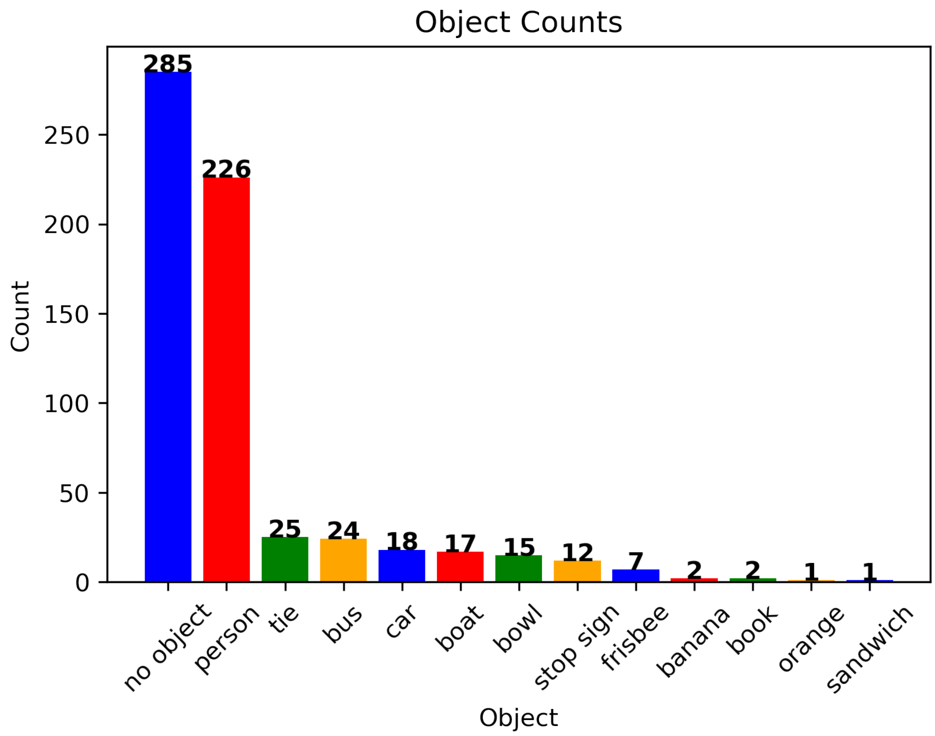


Figure 4.7: Objects detected from the dataset

uplifting scenarios can also be highly engaging. Media companies can leverage these insights, as highlighted in Table 4.6, to potentially connect with their target audience.

The finding, as presented in Table 4.6, illustrated that advertisements featuring a person, particularly when portrayed as happy, yield the highest mean CTR underscores the persuasive power of human faces in advertising. It suggests that viewers are more inclined to click on ads that feature relatable and joyful individuals, potentially due to the positive associations they evoke. This insight opens opportunities for advertisers to emphasize the emotional appeal of their products or services by incorporating happy individuals in their campaigns.

Similarly, the presence of fear as the dominant emotion for a person in an advertisement, as indicated in Table 4.7, maybe a strategic choice to elicit a heightened emotional response from viewers. Although it remains speculative, this finding suggests that fear-inducing ads might attract more clicks due to the attention-grabbing nature of such emotional stimuli. Media companies could explore creative ways to incorporate controlled elements of fear or suspense to enhance the impact and engagement of their campaigns.

Additionally, the observation, as presented in Table 4.6, showcases that the second and third most popular objects in terms of CTR are bananas and sandwiches providing interesting insights into user behavior. It suggests that users who clicked on these ads may have been attracted by the idea of food, particularly grocery-related items. This highlights the importance of personalization and visually appealing representations of products in advertisements. Media companies can leverage these insights by emphasizing food-related content, showcasing appetizing visuals, and creating a connection between the product and the viewers' needs or desires.

Table 4.5: Top 5 Objects and Emotions with their CTR (Computed using the Mean)

Table 4.6: Top 5 Objects (CTR: Mean)

Object	CTR
person	0.010300
banana	0.009437
sandwich	0.008850
book	0.007969
stop sign	0.007793

Table 4.7: Top 5 Emotions (CTR: Mean)

Emotion	CTR
happy	0.013322
fear	0.009393
sad	0.007576
surprise	0.007375
angry	0.007166

4.2.1 Feature Extraction Quality

In order to assess the performance of the object detection process, the Intersection over Union (IoU) metric was employed. IoU measures the overlap between the detected objects and the ground truth annotations, providing an indication of the accuracy and precision of the detection algorithm.

Table 4.8 presents the results of the IoU analysis for various object labels. The obtained IoU values provide insights into the effectiveness of the object detection model in accurately localizing and identifying specific objects.

The results reveal varying levels of accuracy across different object categories. The label "meat" achieved the highest IoU value of 7.107601, indicating a strong alignment between the detected objects and the ground truth annotations for this category. On the other hand, "banana," "duck," and "bottle" demonstrated moderate IoU values of 0.846279, 0.215183, and 0.560074 respectively, suggesting a relatively lower precision in detecting and localizing these objects.

Label Name	IoU
meat	7.107601
banana	0.846279
duck	0.215183
bottle	0.560074
person	0.464778
burger	0.129327
box	0.124361
not_person	0.118790
phone	0.114619
bus	0.088931

Table 4.8: IoU per Label Name

However, it is important to note that certain object labels, including "burger," "box," and "not_ person," demonstrated relatively lower IoU values of 0.129327, 0.124361, and 0.118790, respectively. These lower IoU values suggest a significant disparity between the detected objects and the ground truth annotations for these specific categories. It is crucial to conduct further investigation to identify the potential factors contributing to these discrepancies, which may include challenges in object recognition.

Moreover, the IoU analysis revealed relatively lower accuracies for objects such as "phone" and "bus," as indicated by their IoU values of 0.114619 and 0.088931 respectively. These results suggest that the detection model might encounter challenges in accurately identifying and localizing these particular object categories.

The IoU analysis provided insights into the performance of the object detection process. The presence of lower IoU values indicates room for improvement in the object recognition model. Further refinement of the detection algorithm, considering factors such as data augmentation, model architecture, and training techniques, could enhance the accuracy and precision of the object detection in this thesis.

4.2.2 Predictive Model

In this section, the offline evaluation of the data set received from section 4.1 and 4.2 is presented. Two different models are built, using the random forest as the main model, and the decision tree as a baseline. The model performances are evaluated using mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and R2 as evaluation metrics. As a follow-up experiment, the importance of different features is computed.

In order to evaluate the performance of the random forest model, it is compared with a decision tree as a baseline. The results are shown in table 4.9. The metrics used are MSE, MAE, RMSE, and R2 scores. Applying these metrics provided different perspectives of the model's predictive accuracy as well as capturing the variance in the target variable. The target variable chosen from the data set(recall 4.5 was the n_click feature. The reason behind choosing n_click as the target variable to predict was natural, as advertisements on media platforms are strategically placed with the intent of attracting clicks. This provided a better understanding of the factors that influence the click count.

Examining table 4.9, it showcases the performance of both the random forest and decision tree (baseline) models. The random forest model achieved a lower value of 0.12 compared to the decision tree of 0.17. This indicates a slightly better predictive performance of the RF model. The MAE of the RF model scored 0.18 compared to the baseline's MAE of 0.15. The difference is small, but it may suggest that the random forest has a higher bias in predicting the click count. The RF model achieved a lower RMSE of 0.34 compared to the decision tree baseline of 0.41. This showcases the improved predictive performance of the random forest model compared to the baseline. The last evaluation metric R2 score measures the proportion of variance in the target variable. It varies from 0 to 1. The higher value, the better fit of the model to the data. The random forest model scored 0.93 compared to the baseline's 0.91. This again indicates that the RF model has a slightly better indication of capturing a larger proportion of the variance in the number of clicks. The outcome of the model's performance was expected, as the random forest model had improved parameters by running a grid search to find optimal parameters.

As a follow-up experiment, the importance of different features is computed from the random forest model. This was computed in order to indicate the relative contribution of the features to the overall predicting power. Among all of the features presented in Table 4.10, the "ctr" (click-through-rate) feature demonstrates the high-

Table 4.9: Comparison of Random Forest and Decision Tree Regressors

Comparison of Models				
Model	**MSE**	**RMSE**	**MAE**	**R2 Score**
Random Forest	0.12	0.34	0.18	0.93
Decision Tree (baseline)	0.17	0.41	0.15	0.91

est importance in terms of predicting the number of clicks (n_click) with a score of 0.495008. As expected, the CTR feature has a substantial influence on the number of clicks. The next feature with the second highest feature importance score is the n_impressions_measurable, with a score of 0.432059. This clearly illustrates that the number of measurable impressions has a strong correlation with the click count. This illustrates the importance of maximizing the visibility of the advertisements to increase the chances of generating clicks. On the other hand, some features exhibit relatively lower importance in predicting the target variable, such as the two feature extracting features, "object" and "dominant_emotion" with scores of 0.007995 and 0.003519 respectively. These scores from this particular data set may indicate that the object and emotions didn't participate to gain more clicks from the users. However, it is worth mentioning that the scores could be different with another dataset with more images including more persons could lead to higher performance in terms of predicting the number of clicks. Recall the results from section 4.1 illustrates that observations, where a person was included, received the highest mean ctr-value.

However, it makes sense that the more exposed the advertisements are to the users, the higher amount of clicks the advertisements receive, as shown in this experiment. It¨s worth noting that the evaluation metrics only provide an overall assessment of the model's performance, but may not capture all nuances. It may be essential to strike a balance between the accuracy of the model and practical considerations, as a machine-learning model may not always be the most effective choice in real-world advertising scenarios.

Table 4.10: Feature Importance

Feature	Importance
ctr	0.495008
n_impressions_measurable	0.432059
Adviser	0.031267
Category	0.022900
object	0.007995
gender	0.004340
dominant_emotion	0.003519
format	0.001899
industry	0.000687
age_group	0.000327
page_type	0.000000

4.3 Experiment C: Real User Study

In this section, the results observed from the user study are presented and discussed. The data collection of the survey first and foremost started by doing research on the participants, such as collecting their gender: (see Figure B.2), their age: (see Figure B.3), and their current city of residence: (see Figure 4.8). Retrieving this information aimed to provide a basis for comparison and reflection with the observations presented in table 3.1, presented in section 3.1. Obtaining this valuable information made it possible to investigate potential variations in opinions based on gender, age, and the participants' current city of residence. The distribution of respondents across different cities can be seen in Figure 4.8, demonstrating a wide geographic spread throughout Norway, with Oslo and Bergen, the two largest cities, being the most dominant. Having participants from various locations across the country contributes to uncovering potential regional differences in opinions.

Phase 1: Demographic information:

In this phase of the user study, the participants were asked to provide their current city of residence, as well as their gender. The results showed that the user study has an approximately equal distribution of men and women, with a slightly larger population of men than women. Specifically, there were 35 men and 20 women, see Figure B.2 in the appendix. A similar distribution was observed in the other user survey for the voluntaries, where there were a total of 8 men and 6 women see Figure B.2 in the appendix. The participants in the user survey were predominantly young, with the most dominant age group being between 18-25 (see Figure B.3).

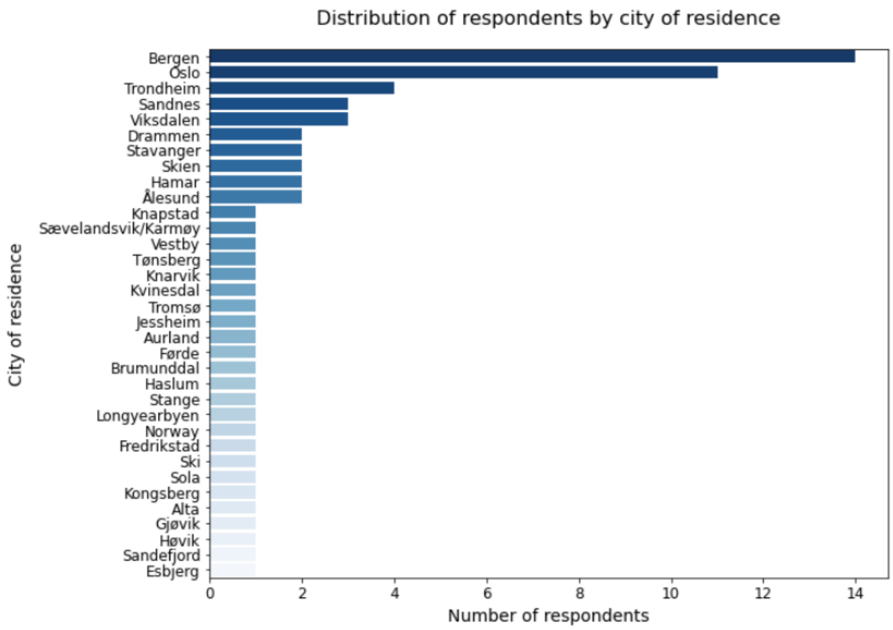


Figure 4.8: City distribution

In Figure 4.9, the two biggest cities in Norway, Oslo, and Bergen, were the cities where most of the participants were located, as shown in figure 4.8. In order to investigate if there could be different opinions across these two cities, some data analysis was performed. Figure 4.10 illustrates that Kiwi and Spar were the most popular shops for Bergen and Oslo, respectively. However, further research on smaller cities like Aurland, the results showed that Spar was the only shop of interest for the participants. The reason why Spar was only of interest to the participants from Aurland, maybe because Spar is actually the only shop which is located in Aurland, and therefore, the participants may only be interested in clicking on advertisements related to Spar.

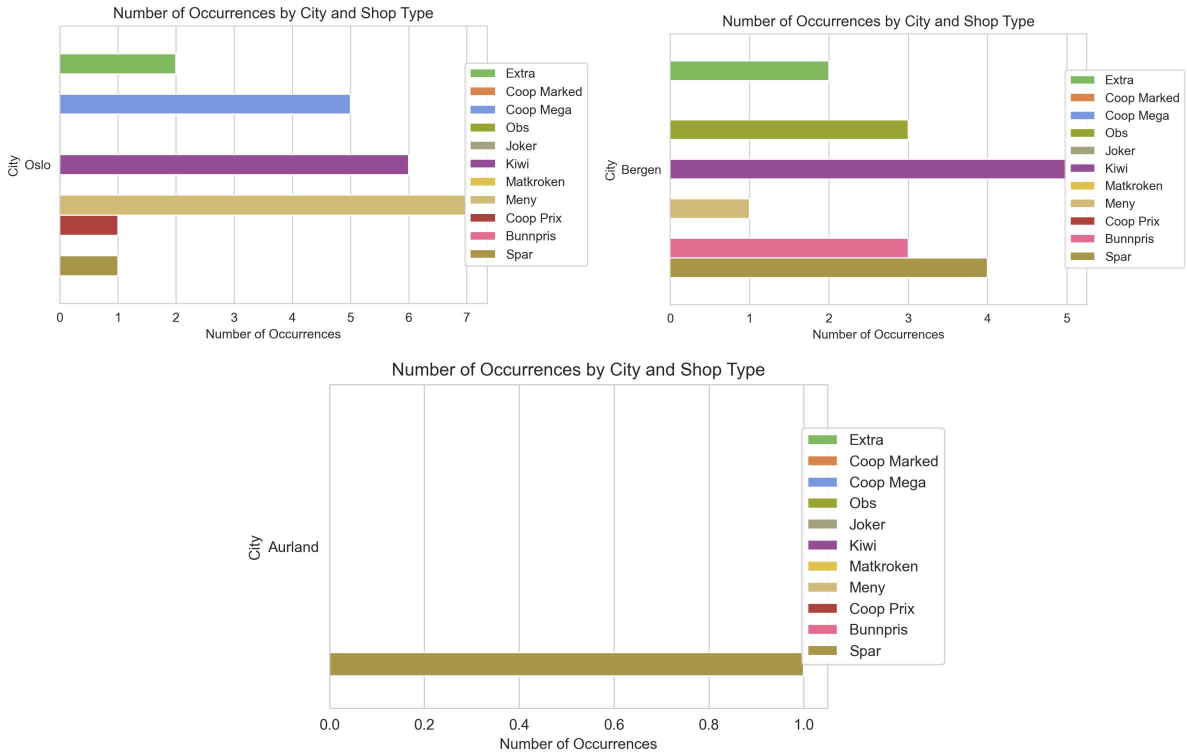


Figure 4.9: Most popular shop in terms of advertisement

Moving on to Figure 4.9, the most popular advertisement content in Bergen, Oslo, and Viksdalen are examined. While Oslo and Bergen are larger cities, Viksdalen, a small village, is included due to its significant number of survey participants. It is somehow expected to note that participants from both Oslo and Bergen showed a preference for shopping content in advertisements. However, the second most popular content differed between the two cities, with sport being favored in Bergen and travel/nutrition in Oslo. In contrast, participants from Viksdalen, with fewer shopping opportunities compared to Oslo and Bergen, displayed a stronger inclination towards sports-related ads. This may suggest that the local context and available amenities may influence the content preferences of individuals, leading to a higher interest in outdoor activities and sports-related promotions. It is important to consider that individual preferences can vary, and these observations provide valuable insights but do not constitute definitive conclusions.

In my opinion, the differences in advertisement preferences among cities can be attributed to various factors, such as cultural differences, economic factors, and lifestyle choices. For instance, as mentioned earlier, Viksdalen may have a greater focus on outdoor activities due to its location and smaller population, which may be reflected in its advertisement preferences. Additionally, the results from Oslo and Bergen, being the two biggest cities in Norway, could also be due to the fact that people in these cities have access to more shopping opportunities. As a result, they may be more inclined to prefer shopping-related advertisements compared to people from smaller villages or towns.

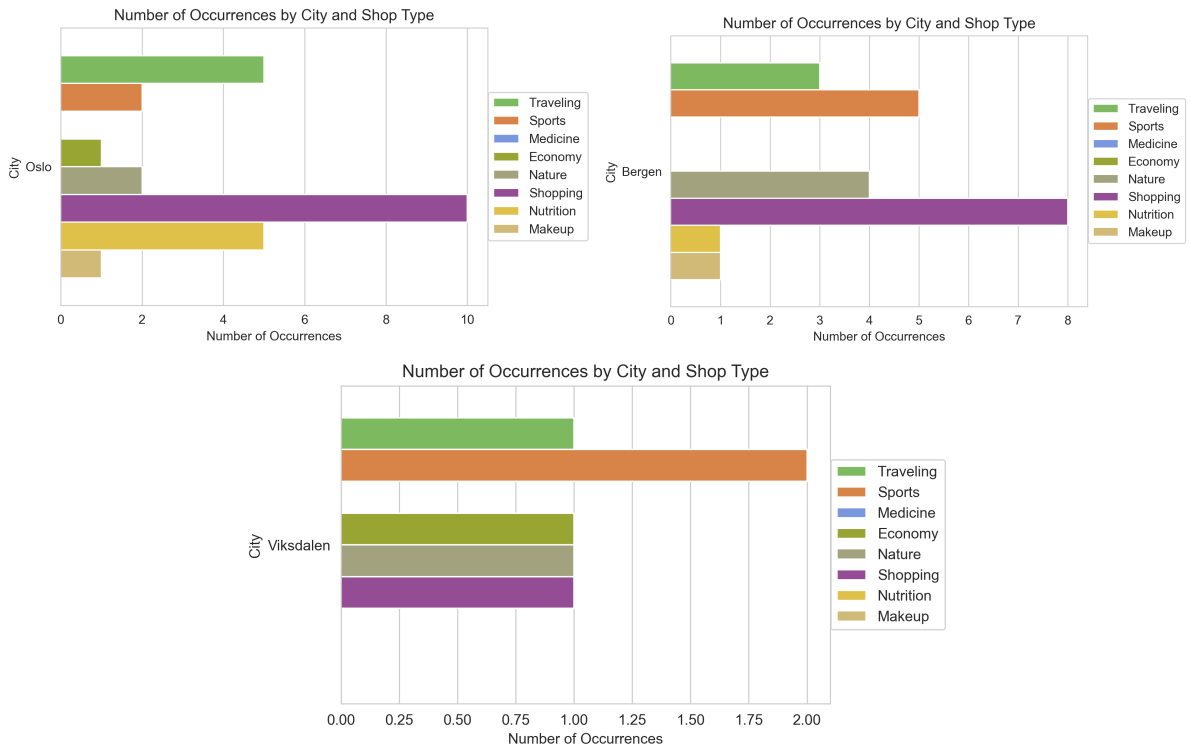


Figure 4.10: Most popular content in terms of advertisement

Phase 2: Opinion scale questions:

During this phase of the user study, participants were requested to share their opinions regarding the impact of various factors on the likelihood of users clicking on advertisements. These factors included placement/size, color/contrast, relevance to the year, and emotional appeal. This is illustrated in questions A.25, A.26, A.27 and A.28, The results of these questions are shown in Figures B.27, B.28, B.29 and B.30. The scoring scale ranges from 1 to 5, where a rating of 1 signifies "Strongly disagree" and a rating of 5 indicates "Strongly agree".

The participants were prompted to respond to the following statements:

1. Do you think that the placement/size of the advertisement matters whether people click or not? shown in B.27
2. Do you think that color/contrast in advertisements plays a role in whether people click or not? shown in B.28
3. Do you think that emotions in the advertisement play a role in whether people click on advertisement? shown in B.29
4. Do you think that people in general are more likely to click on an advertisement if the advertisement is related to the time of the year? B.30

The average score for the first question was 3.6, indicating that most participants believe that the placement and size of advertisements on media platforms play a significant role in whether people click on them or not. Similarly, the average score for the second question was 3.7, indicating that most participants also believe that colors and contrasts in advertisements play a role in their click-through rates.

With regard to the bullet point considering emotions, which reflects section 4.2, where object and emotion detection were performed on different advertisement images, the survey results show an average score of 3.8. This indicates that people believe that advertisements with appealing emotions, such as happiness or sadness, are more likely to be clicked on by users.

The last bullet point had an average of 4, which indicates that most of the participants seem to agree that they are more likely to click on advertisements if they are related to the time of the year. This highlights the importance of contextualized advertisements in media platforms.

In my opinion, the results of these questions are not surprising. The placement, size, color, emotion, and relevance to the year in advertisements can all contribute to their effectiveness in catching the attention of viewers and encouraging them to click on them. For example, an advertisement with bright colors and high contrast is likely to stand out more and catch the viewer's attention, while an advertisement that evokes strong emotions can create a memorable impression and motivate the viewer to take action.

The participants were also prompted to respond to the following statements:

1. "I sometimes choose not to click on an advertisement since it is either not relevant for me or it is disturbing" (Figure A.11)

2. "I sometimes click on advertisements since I find them relevant for me, and they are contextualized" (Figure A.12)

The first statement received an average rating of 4.7, indicating that over 78% of the participants strongly agreed that they sometimes choose not to click due to the fact that they find ads irrelevant or disturbing (see Figure B.12). This suggests that a majority of users refrain from clicking on advertisements due to the perception that they can be disturbing or irrelevant. In contrast, the second statement had an average rating of 3.3 (see Figure B.13), indicating that more than half of the participants actually found the ads shown to them contextualized and relevant. These results highlight a mixed sentiment among the participants regarding the relevance of advertisements. Interestingly, the outcome for the second statement contradicts the expectation, as most participants seemed to agree that the ads were not relevant.

Phase 3: Multiple-choice and open-ended questions:

In this phase of the user study, the participants were asked to provide answers to address their general relationship to advertisements. Examining the results where the participants were asked how they feel about advertisements shown in media platforms, see figure A.4, the user study clearly illustrates the participants felt that there exist biases in the advertising industry. Over 75% of the participants reported that they feel advertisements shown to them were often irrelevant and disturbing (see Figure 4.11).

However, over 45% of the participants still felt that advertisements were relevant and necessary. This suggests that despite the negative perception of advertising, it remains an important aspect of media platforms.

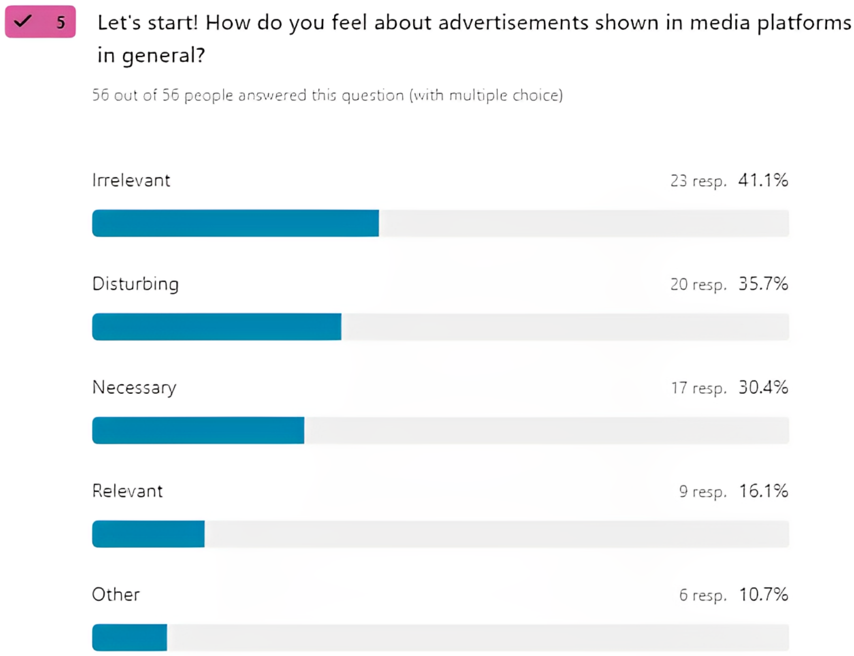


Figure 4.11: How the participants feel about advertisements shown in media platforms

Furthermore, the survey participants were asked whether they used Adblock (see Figure A.6), a tool to prevent requests from different types of third-party domains *Wills and Uzunoglu* (2016). Approximately 65% of the participants reported using Adblock (see Figure B.6). In follow-up questions (Figures B.7 and B.8), most of the people who used Adblock reported that they did so because advertisements are either disturbing or not relevant. Some interesting open-ended answers were expressed under the "other" option, such as "no trust left," and one respondent reported being a gambling addict and needing to use Adblock because the advertisements shown promoted gambling. This again highlights the issue of making contextualized advertisements, which can both contribute to relevant and personalized content, but at the same time provide content that is not appropriate in terms of actual life situations.

For those who didn't use Adblock, most people reported not using it because they felt bad for blocking ads or because they found ads relevant. Another interesting response was that Adblock affected some of the web applications the respondents used. Questions 10 (Figure A.9) and 12 (Figure A.11) reflect on the points mentioned in the Problem Statement Section 1.2, where factors that make people not click on advertisements are biased such as irrelevance or disturbance. This is confirmed by the results in Figure B.9, where most of the participants felt that the present context is the reason why people don't click ads, followed up by the fact that they are disturbing. In third place, the topics also matter, which illustrates that some feel that advertisements are not personalized for them. An open-ended question added to this was "Lack of trust: Young people have developed a sort of intuitive filter to ignore the traditional ads." This is a statement from a person who claims that younger people have developed a filter to avoid ads. This shows that younger people might tend to avoid ads, where they actually don't pay attention to them. As mentioned earlier in this section, advertisements are about communication, but they are also about attention, and here is an example of a person who has developed a filter to avoid them. The follow-up question in Figure B.11 shows that most people seem to agree that people tend to click on ads if the ad matches the actual content and if the topics of the ad are relevant.

The results from the user study further lead to the next set of questions about people's preferences for different types of advertisement content, as shown in Figure A.5. This inquiry was conducted to determine whether there were any differences in preferences across different age groups. The data shows that the most popular advertisement content categories were shopping, traveling, and sports (see Figure B.5). However, some data analysis was done to filter and examine the results for each city, gender, and age group.

Table 4.11 details the most popular shops and advertisement content for each age group. Among the younger participants, Kiwi was the most popular shop, while Extra was the most popular for the elder population. Furthermore, shopping was the most popular type of advertisement content for the younger age groups, while people between 25-29 preferred sports-related ads. For the older generation, shopping and traveling were both popular. The popularity of travel-related ads among elderly individuals may be attributed to factors such as their financial stability and increased availability of leisure time for exploring new destinations.

Table 4.11: Most Popular Shop and Interest for Each Age Group

Age Group	Most Popular Shop	Most Popular Content
18-24	Kiwi	Shopping
25-29	Kiwi	Sports
30-34	Meny	Shopping
35-39	Kiwi	Shopping
40-44	Extra	Shopping
45-49	Spar	Traveling
50-54	Meny	Shopping
55-59	Extra	Traveling
60-64	Extra	Shopping
70-74	Extra	Traveling

Table 4.12: Most popular shop and interest by gender

	Most Popular Shop	Most Popular Content	Second Most Popular Interest
Female	Kiwi	Shopping	Nature
Male	Kiwi	Sports	Economy

Table 4.12 shows the distribution between men and women in terms of the most popular shop and advertisement content. Both genders preferred Kiwi as the most popular shop. For men, sports and economy-related content were the most popular, while for women, shopping was the most popular, followed by nature-related content. These

findings are consistent with common gender stereotypes, as women are usually associated with shopping, and men with sports. These two tables shown can help media companies gain insight into how they might target their audience based on personalization. Overall, these results might provide valuable information about people's preferences for different types of advertisement content across different age groups, genders, and locations. The differences observed between different age groups and genders could be explained by factors such as their current economic status and gender stereotypes.

The user study involved an experiment where participants were shown four different examples, each containing two different articles presented with the same advertisement option next to it. The first example is detailed in figure 4.12. The participants were asked which option they would rather click on, in order to investigate whether contextualization or personalization of the advertisements played a role in whether people chose to click or not.

The first question (see Figure A.14) asked the user to choose between an advertisement promoting fast food from McDonald's, and another option promoting charity and poverty. The context of the article was a sick person lying in bed, with text describing how students have been poisoned lately, as shown in Figure 4.12.

Figure 4.12: First example

The results for those who chose to click option 1 in Figure B.15, showed that more than 75% would have clicked on this option, as it was relevant for them. For those who clicked option 2 (see Figure B.16), almost 50% of the participants would have clicked on this option, as it was relevant to the context of the article. These results were surprising, as it was expected that most people would click on option 2, as option 1 was intended to be disturbing. However, while reading the open-ended answers in Figure B.15, people wrote that the reason they would click option 1 was that they were hungry while doing the survey. Some also mentioned that since they are students they cannot afford to pay to charity. The results illustrated that sometimes context does not actually play a role in what types of advertisements people choose to click, but rather how they feel at the moment, such as being hungry. However, over 60% of the participants felt that option 1 was not relevant or was disturbing. In this study, the results were expected to favor option 2, but the fact was that 70% of the participants would have clicked on option 1.

In the survey's second question (see Figure A.17), participants were shown two different ads alongside a football article. Option 1 featured an advertisement promoting a football subscription, while option 2 promoted buying a new car from Volvo in Figure 4.13. The primary objective of this example was to examine the correlation between content and context, specifically showcasing football ads next to a football article making the example contextualized.

The results showed that the answers for both options were equally distributed, which was expected. Those who chose option 1 did so because the context of the article

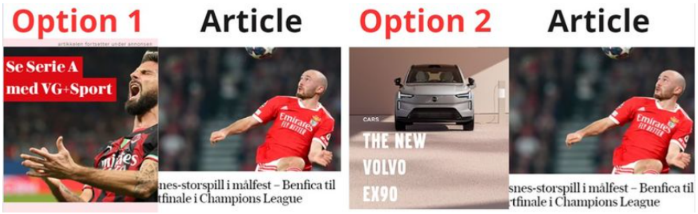


Figure 4.13: Second example

was the primary factor that drew them in. However, 70% of those who chose option 2 clicked the ad because it was relevant to them. Interestingly, further investigation showed that about 80% of the participants who selected option 2 because of relevance were men 4.14.

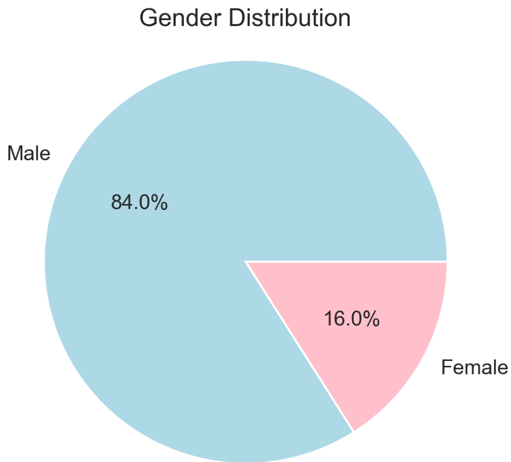


Figure 4.14: Gender distribution for relevance - Option 2

This result highlights the importance of personalization, as discussed in section 2.3. The participants did not pay attention to the actual context of the article, but rather their personal interests and relevance to the displayed car ad. This suggests that targeting a male audience with more "masculine" items such as cars may be an effective strategy for the media industry. However, this is only an assumption. It may demonstrate that personalized advertisement may be a more effective approach to target specific consumers than displaying contextualized advertisements alongside news articles.

In the next question (see Figure A.20), the aim was to investigate how participants would react to uncontextualized or potentially disturbing ads. To achieve this, a form of disturbance was added to the context, in the hopes of highlighting any discomfort or disturbance it may cause. Figure 4.15 displays an article showing a person standing on a weighing scale, with accompanying text instructing readers on how to get rid of fat. Two different advertisements were placed next to the article. Option 1 was a promotion for McDonald's fast-food, while option 2 was an advertisement for a gym subscription. The purpose of placing option 1 next to the article was to see how participants would react to a fat-related food advertisement next to an article that promotes fat reduction. The results (see figure B.21) showed that more than 50% of the participants would have clicked on option 1. The majority felt that this option was more relevant to them. A

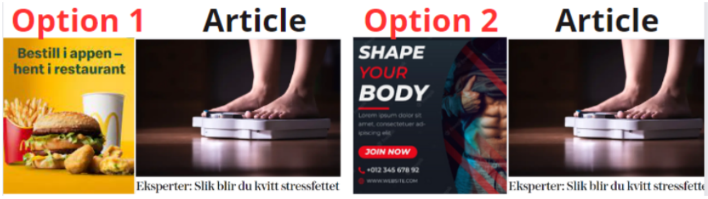


Figure 4.15: Third example

vast population of participants cited their hunger as a reason for selecting option 1. Others mentioned that option 2 played on insecurities or sex appeal. This suggests that some participants found option 2 more disturbing, and therefore option 1 was a more appealing choice.

In contrast, the results for option 2 in Figure B.23 showed that most people would have clicked on the ad since it was relevant in terms of context. Only 8% of the participants who clicked on option 2 thought that option 1 was disturbing considering the context. This was surprising, as the intention of placing option 1 next to the article was to elicit discomfort. However, this was not the case, and it appears that relevance was a more important factor in determining participants' choices.

It might have been better to present a more "neutral" option, such as a gym subscription ad that did not focus on the body in the picture to generate more clicks. The results suggest that contextualized advertisement is not always the main reason why people click on ads, and that relevance/personalized ads often plays a more significant role.

In the final example of the user survey, depicted in Figure A.23, the objective was not to contextualize the advertisement within the context of the article but rather to investigate whether there was a difference in the participants' preference for a makeup advertisement option 1 or a male perfume advertisement option 2, see Figure 4.16. The

Figure 4.16: Fourth example

results in Figure B.24 show that 60% of the participants would have clicked on option 1, while the remaining 40% would have clicked on option 2. Further analysis revealed that 13 women and 2 men would have clicked on option 1, while 25 men and 4 women would have clicked on option 2. These results were consistent with expectations, as option 1 can be viewed as a more women-focused advertisement, while option 2 is more geared towards men.

The results for option 1, shown in Figures B.25 and B.26, indicate that participants would have clicked on the ad based on its relevance. However, there may be circumstances where a man is seeking makeup (for example for his girlfriend's birthday) and therefore chooses to click on the ad, making it contextualized for him. For male participants who would have clicked on option 1, this may have been the case.

Upon analyzing the results for option 1, it became apparent that some participants expressed their reluctance to click on option 2 due to personal concerns related to the person featured in the advertisement, Johnny Depp. This indicates that individual biases and personal issues may play a major role in users' decision-making process when engaging with ads. In the context of option 2, some participants mentioned that they did not find makeup or perfume for women relevant to their interests, making option 2 more appealing to them. These observations highlight the diverse array of factors that influence users' choices when deciding whether to click on ads, including content relevance and individual preferences. It demonstrates that personal factors and individual context can greatly impact users' engagement with advertisements, underscoring the complexity involved in designing effective ad campaigns.

4.4 Discussion

In section 4.1, the investigation and data analysis of real-time data pertaining to online advertising provided valuable insights into user behavior within the media industry. It is important to note that a larger data sample with a higher number of clicks could have yielded even more intriguing findings. Nevertheless, the results obtained from the exploratory data analysis provided fascinating insights, particularly regarding the varying preferences among different age groups. The feature extraction process described in section 4.2 proved to be a valuable learning experience, although the results were not optimal. However, it is worth emphasizing that a larger participant sample would have contributed to a more diverse range of opinions, thereby enriching the overall results. Additionally, including a larger variety of advertisement images featuring individuals could have enhanced the investigation of whether objects or emotions correlate with higher click rates.

Furthermore, the implementation of the random forest model, along with the examination of feature importance, shed light on the significance of ensuring that advertisements are visually appealing and noticeable to consumers, ultimately increasing the likelihood of them being clicked on. This underscores the importance of optimizing visibility and engagement factors in ad design and placement strategies. The utilization of Amedia's Big Data capabilities is suggested to capitalize on the effects proposed in this thesis. Furthermore, the findings indicate that a reexamination of the exploratory study on a larger dataset is recommended.

The user study conducted in section 4.3 aimed to investigate the effect of contextualized and personalized advertisements on user behavior. The results from the user study showed that contextualized advertising does not always guarantee that users will click on ads and produce a higher click-through rate. In some cases, the relevance of the ad to the user's interests or needs is more important than whether or not the ad is contextualized. For example, in the first example shown in the survey, participants were more likely to click on an ad for fast food, even when it was placed next to an article about weight loss. This suggests that users may be more motivated by their immediate needs, such as hunger, than by the context of the content they are viewing.

In the second example shown in the survey, two different ads promoting different products were placed next to a football article. The results showed that users were more likely to click on the ad that they found most relevant, rather than the one that was more contextually aligned with the article. This suggests that user preference plays a significant role in determining whether an ad is effective or not.

The third example demonstrated how the placement of an advertisement next to an article that contradicts its message can influence user behavior. In this case, an ad promoting fast food was placed next to an article about weight loss, while an ad promoting a gym subscription was placed next to the same article. Surprisingly, the majority of participants clicked on the fast food ad, even though it contradicted the article's message. This indicates that personalization and preference may override contextual alignment and ethical considerations when it comes to user behavior.

The fourth example showed the effect of gender targeting in advertisements. Two ads, one for makeup and one for male perfume, were shown to participants. The results indicated that the majority of female participants clicked on the makeup ad, while the majority of male participants clicked on the perfume ad. However, some male participants did click on the makeup ad, which suggests that contextualization is not always black and white and depends on user preference. It is worth noting that some participants did not express concern about the ethical implications of the ads they were shown, but rather focused on their personal preferences and needs. This suggests that advertisers may need to balance ethical concerns with user preferences and needs when designing advertising campaigns.

Overall, the results of this user survey indicate that while contextualized advertising can be effective, it is not always the most important factor in determining whether or not users will click on an ad. Advertisers may need to consider other factors, such as user interests and needs, as well as gender and other demographic information, when designing advertising campaigns that are effective and relevant to their target audience. The findings of this study shed light on situations where individuals prioritize their personal needs and interests over ethical considerations when it comes to advertisements. It is important to recognize that these results are based on relatively small sample size, and caution should be exercised in generalizing them to the broader population. However, they do provide valuable insights into the complex interplay between personal motivations and ethical concerns in the realm of advertising.

It is worth emphasizing, as discussed in section 2.5, that the outcomes of this study could have been markedly different if it had been conducted in a different cultural context with divergent ethical approaches. Cultural norms, values, and attitudes play a significant role in shaping individuals' perceptions and responses to advertisements. What may be considered acceptable or ethical in one culture might be viewed differently in another.

Chapter 5

Conclusion

5.1 Summary

The present study investigates user behavior towards advertisements shown on media platforms, utilizing a combination of real-world data analysis and a real user survey. The study aims to shed light on how different visual features impact user engagement with advertisements, as well as explore the factors that influence user behavior towards ads in media platforms.

To achieve this, the study first develops a novel analysis method of real-world data. The method enables the investigation of the relationship between visual features and audience behavioral data in a real-world dataset provided by a major media company in Norway, Amedia. By applying this method, the study gains insights into the impact of different visual features on user engagement with advertisements.

Next, the study creates a novel dataset of visual features extracted from multiple advertisement campaigns, along with their corresponding click-through rates. This made it possible to explore the impact of visual features on user engagement. Furthermore, the study performs a comprehensive offline evaluation of its visual feature extraction method building a predictive model to assess its effectiveness in capturing relevant features to the dataset obtained. This evaluation provides insights into the strengths and limitations of the approach and can guide future work in this area.

Finally, the study conducts a real user survey to collect both qualitative and quantitative data on how users feel about ads shown on media platforms. This survey made it possible to explore the factors that influence user behavior toward advertisements, including demographic and personality factors. The results of this user study can provide insights into how to design more effective advertising campaigns that better meet user needs and preferences for media companies, benefitting both advertisers and users.

5.2 Main Contributions

The present study aims to investigate user behavior towards advertisements shown on media platforms through a combination of real-world data analysis and a real user survey. The main contributions of this work are outlined below:

- *Novel analysis method of real-world data*: A novel analysis method was developed to investigate the relationship between visual features and audience behavioral data in a real-world data set provided by a major media company in Norway, Amedia. This approach provided insights into how different visual features can impact user engagement with advertisements in this thesis.

- *Novel data set of visual features*: A creation of a novel data set of visual features extracted from multiple advertisement campaigns, along with their corresponding click-through rates. This dataset can be used to further explore the impact of visual features on user engagement, and it can also serve as a benchmark for future research in this field.

- *Comprehensive offline evaluation of visual feature extraction*: A comprehensive offline evaluation of the visual feature extraction method to assess its effectiveness in capturing relevant information from the advertisements. This evaluation provides insights into the strengths and limitations of our approach and can guide future work in this area.

- *Real user study with qualitative and quantitative data*: A user survey was conducted to collect both qualitative and quantitative data on how users feel about ads shown on media platforms. The investigation fo the user study made it possible to explore the factors that influence user behavior toward advertisements, including demographic and personality factors. The results of this survey can provide insights into how to design more effective advertising campaigns that better meet user needs and preferences.

5.3 Conclusion

In addressing research question 1 (see section 1.3), the study explored the experience of users with contextual advertisements through a user study. The findings revealed that when the context of the user aligned well with the advertisement, they were more likely to click on the ad. For instance, in some instances, users exhibited a tendency to click on ads driven by factors such as hunger or emotional appeal, irrespective of the ad's contextual relevance. This provides insights into improving the relevance of contextualized advertisements and enhancing personalization (RQ1). The study highlights that users' immediate needs and personal preferences can significantly influence their response to ads, emphasizing the importance of understanding and catering to user motivations beyond contextual alignment.

Regarding research question 2 (see section 1.3), this thesis involved a comprehensive analysis of a real dataset provided by Amedia, with a specific focus on evaluating online advertising. The analysis revealed interesting patterns, including insights into the behavior of elderly individuals, as observed from the dataset. Additionally, a feature extraction process was conducted on the advertisement images, extracting objects and emotions. Surprisingly, the results of the predictive model indicated that the presence of objects did not significantly contribute to the likelihood of user clicks, whereas the number of impressions played a more influential role. However, it is important to note that these findings may vary with other image datasets, as well as a larger and more diverse sample size, as discussed in the previous section. the findings from the user study complemented the data set analysis, providing additional insights into user preferences and behaviors. Integrating these various sources of information provided a deeper understanding of the potential application of machine learning approaches to improve advertisement personalization on media platforms.

In conclusion, the study of this master thesis has addressed both research questions and provided valuable insights into the improvement of contextualized advertisements with better personalization (RQ1) and the potential of machine learning approaches in enhancing advertisement personalization on media platforms (RQ2). I have discovered that users' immediate needs and personal preferences can play a significant role in determining their response to ads, highlighting the importance of considering these factors alongside contextual relevance. Moreover, the analysis of a real dataset and user study findings have contributed to a more comprehensive understanding of user behavior and preferences. An important finding from the user study is that a portion of participants demonstrated a lack of concern for ethical issues in advertising. This highlights a significant aspect of user behavior where personal needs and interests take precedence over ethical considerations. While it is crucial to note that this observation only applies to a subset of users and may not be representative of everyone, it is still noteworthy to observe such a mindset. The findings presented throughout this thesis hold the potential for advertisers in media companies to enhance their advertising campaigns by creating personalized content that resonates with their target audience. By leveraging the insights gained from this research, advertisers can use these results to engage and connect with potential users on media platforms.

5.4 Limitations and Future Work

The field of this master's thesis offers numerous opportunities for further exploration and development. However, it is important to acknowledge the limitations encountered during the research process. One of the limitations is the relatively small size of the aggregated dataset, which restricted the number of observations available for further analysis. Despite this limitation, the analysis still yielded interesting and valuable results.

There is also another limitation to the dataset of images used. Having a larger and more diverse collection of advertisement images would have provided a richer training set for the object detection model, being more representative. By incorporating higher-quality images featuring individuals, it is possible that the results could have been more nuanced and insightful. Furthermore, while the previous section discussed factors such as user preferences, needs, and contextual relevance, it is important to note that the text accompanying the advertisement also plays a significant role. In future work, conducting sentiment analysis on the text within the images could provide valuable insights into the potential correlation between the textual content and click-through rates (CTR). This analysis could explore how text conveying elements of danger or excitement may impact user engagement with advertisements.

Additionally, a potential avenue for future research involves the development of a prototype that predicts appropriate advertisements for media companies. This could be achieved through the implementation of a recommender system. Such a system could leverage the content of various media platforms to recommend suitable and personalized advertisements to consumers. By employing this approach, advertisers would be able to promote advertisements that align more effectively with specific content, thus optimizing their reach and impact.

While this thesis has provided insights into personalized advertising and the application of machine-learning approaches, there are several limitations that should be addressed in future work. Expanding the dataset size, incorporating a wider range of advertisement images, performing sentiment analysis on textual content, and developing recommender systems are all promising avenues for further exploration. These suggestions are just one of the many approaches that can be applied to enhance the understanding of user behavior and contribute to the development of more effective and personalized advertising strategies in the media industry.

Appendix A

Appendix A: User Study Questions

The different questions from the user study are included in this appendix.

Figure A.1: Question 2

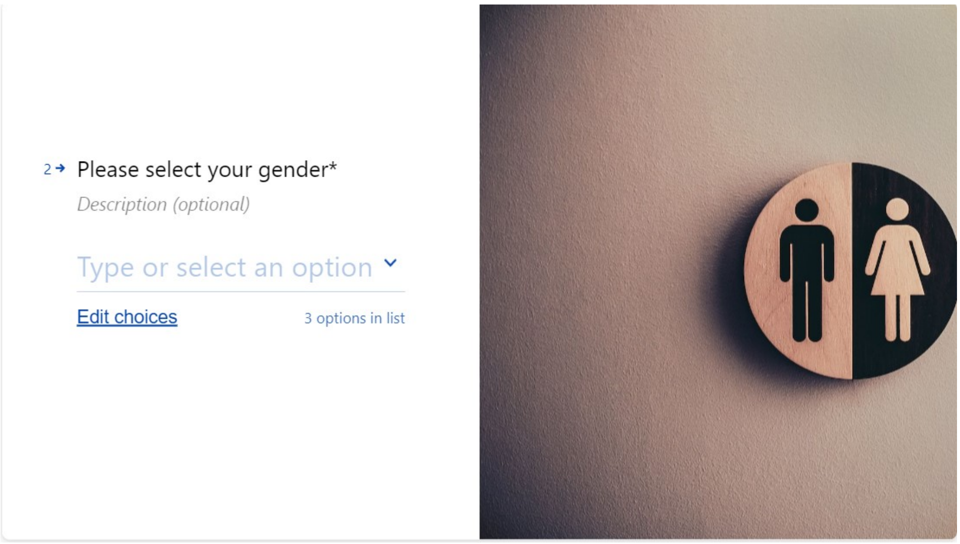


Figure A.2: Question 3

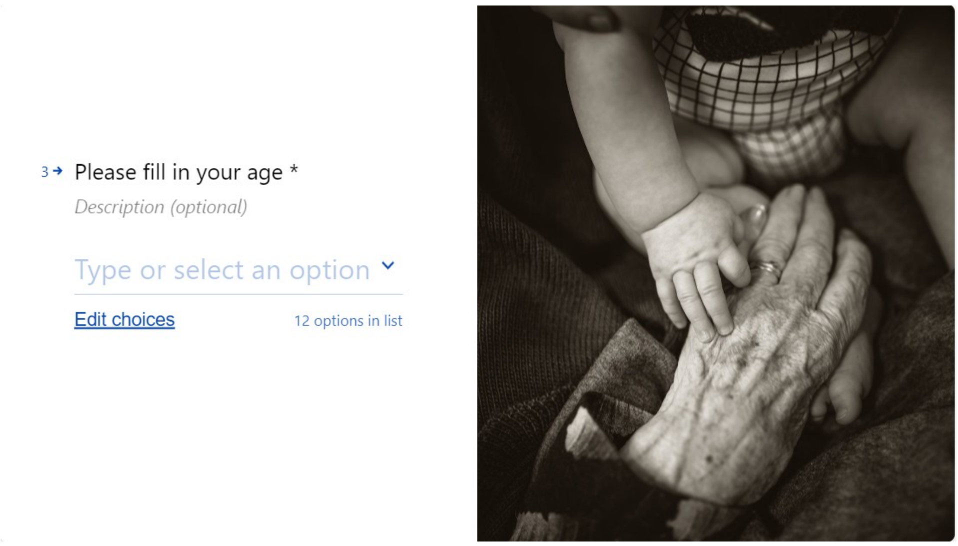


Figure A.3: Question 4

4→ What is your city of residence?

Please write city or town, not country

Type your answer here...

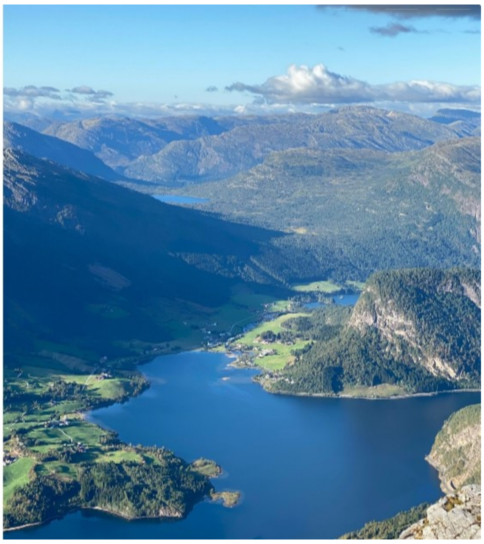


Figure A.4: Question 5

5→ Let's start! How do you feel about advertisements shown in media platforms in general?*

Media platforms such as Facebook or VG

Choose as many as you like

- A Relevant
- B Irrelevant
- C Necessary
- D Disturbing
- E Other

Add choice

Figure A.5: Question 6

6→ What kind of advertisements do you prefer in terms of content?*

Examples:
Sports companies advertising sport related stuff
Shopping companies advertising clothing
Travel companies adavertising holidays

Choose as many as you like

- A Traveling
- B Sports
- C Medicine
- D Economy
- E Nature
- F Shopping
- G Nutrition
- H Makeup
- I No preference
- J Other

Add choice

Figure A.6: Question 7

Figure A.7: Question 8

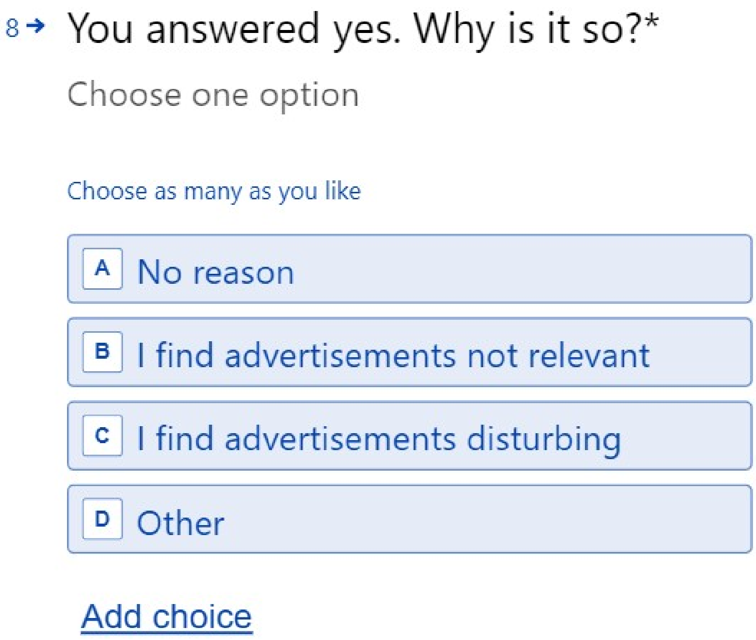


Figure A.8: Question 9

Figure A.9: Question 10

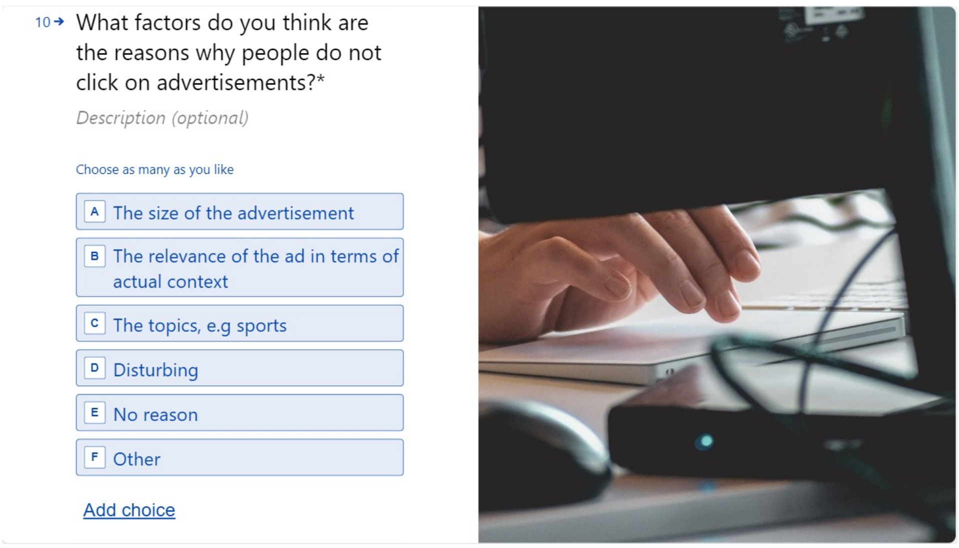


Figure A.10: Question 11

11→ Are there any specific colors that make you click on an ad?*

Description (optional)

Choose as many as you like

- A Red
- B Orange
- C Yellow
- D Green
- E Blue
- F No preference

Add choice

Figure A.11: Question 12

12→ What factors do you think are the reasons why people click on advertisements?*

Description (optional)

Choose as many as you like

- A The colours in the advertisement
- B The size of the advertisement
- C The relevance of the ad in terms of actual context
- D The topics, e.g sports
- E No reason
- F Other

Add choice

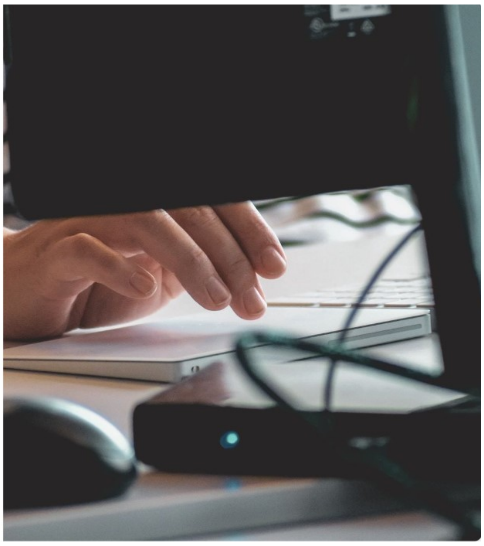


Figure A.12: Question 13

13→ To what extent do you agree or disagree with the following statement:
"I sometimes choose not to click on an advertisement since it is either not relvant for me, or it is disturbing".*

5 - Strongly agree
4 - Agree
3 - Either agree nor disagree
2 - Disagree
1 - Strongly disagree

1	2	3	4	5

Figure A.13: Question 14

14→ To what extent do you agree or disagree with the following statement:
"I sometimes click on advertisements since i find them relevant for me, and they are contextualized"*

5 - Strongly agree
4 - Agree
3 - Either agree nor disagree
2 - Disagree
1 - Strongly disagree

1	2	3	4	5

Figure A.14: Question 15

15→ Which one of these advertisements would you rather click?*

The options shown are the advertisements

A Option 1

B Option 2

Add choice

Figure A.15: Question 16

16→ You choosed option 1. Why is that so? *

Description (optional)

Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.16: Question 17

17 → You choosed option 2. Why is that so? *

Description (optional)

Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.17: Question 17

18 → Which one of these advertisements would you rather click?*

The options shown are the advertisements

- A Option 1
- B Option 2

Add choice

Figure A.18: Question 19

19→ You choosed option 1. Why is that so? *

Description (optional)

Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.19: Question 20

20 → You choosed option 2. Why is that so? *

Description (optional)

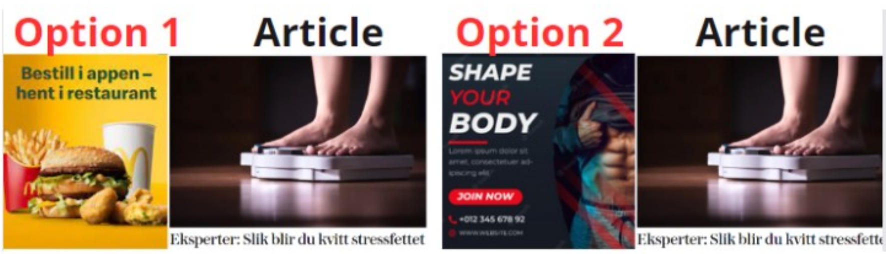
Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.20: Question 22

22 → Which one of these advertisements would you rather click?*

The options shown are the advertisements



- A Option 1
- B Option 2

Figure A.21: Question 23

23 → You choosed option 1. Why is that so? *

Description (optional)

Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.22: Question 24

24 → You choosed option 2. Why is that so? *

Description (optional)

Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.23: Question 25

25 → Which one of these advertisements would you rather click?*

The options shown are the advertisements

- A Option 1
- B Option 2

Figure A.24: Question 26

26 → You choosed option 1. Why is that so? *

Description (optional)

Choose as many as you like

- A The other option was not relevant
- B I found this option more relevant for me
- C The other option was disturbing
- D I found this option relevant for the context of the article
- E No reason
- F Other

Figure A.25: Question 28

28 → Do you think that the placement/size of the advertisement matters whether people click or not?*

5 - Strongly agree
4 - Agree
3 - Either agree nor disagree
2 - Disagree
1 - Strongly disagree

1	2	3	4	5

Figure A.26: Question 29

29 → Do you think that colour/contrast in advertisements play a role in whether people click or not?*

5 - Strongly agree
4 - Agree
3 - Either agree nor disagree
2 - Disagree
1 - Strongly disagree

1	2	3	4	5

Figure A.27: Question 30

30 → Do you think that emotions in the advertisement play a role in whether people click on advertisement?*

5 - Strongly agree
4 - Agree
3 - Either agree nor disagree
2 - Disagree
1 - Strongly disagree

1	2	3	4	5

Figure A.28: Question 31

31→ Do you think that people in general are more likely to click on an advertisement if the advertisement is related to the time of the year?*

Advertisement example illustrated in the picture down below:
Easter-related advertisement since Easter is approaching

5 - Strongly agree
4 - Agree
3 - Either agree nor disagree
2 - Disagree
1 - Strongly disagree

1	2	3	4	5

Figure A.29: Question 32

32 → When a store runs an advertisement, are there any brands/stores you prefer to click over others?*

There can also be other businesses, such as sports and perfumery businesses. Fill them in by clicking the button "other".

Choose as many as you like

- A Extra
- B Coop Marked
- C Coop Mega
- D Obs
- E Joker
- F Kiwi
- G Matkroken
- H Meny
- I Coop Prix
- J Brunnpris
- K Spar
- L Other

Figure A.30: Question 33

33 → Anything else you want to add when it comes to preferences or other things when it comes to advertising?

Description (optional)

Type your answer here...

Appendix B

Appenidx B: User Study Results - Voluntaries

These are the results from the voluntaries

Figure B.1: Question 1

Figure B.2: Question 2

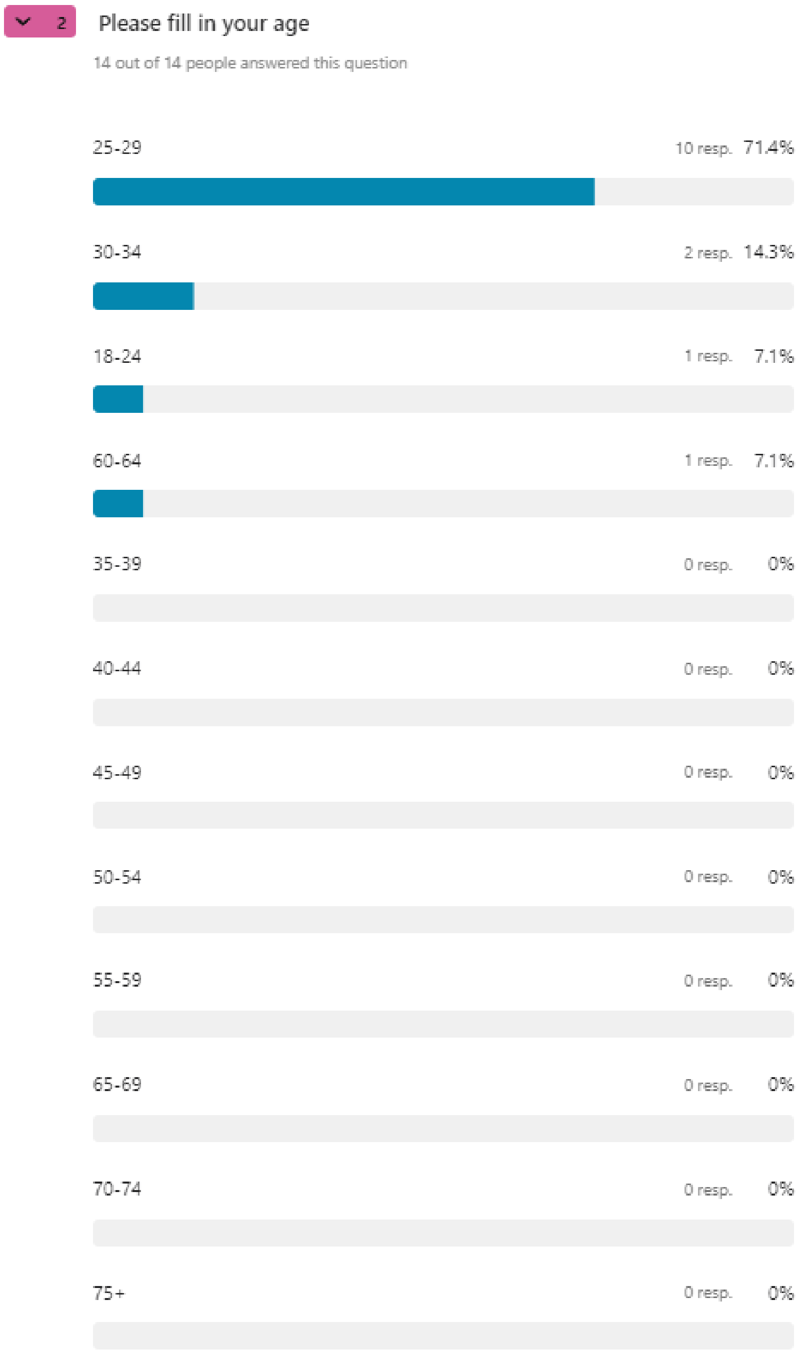
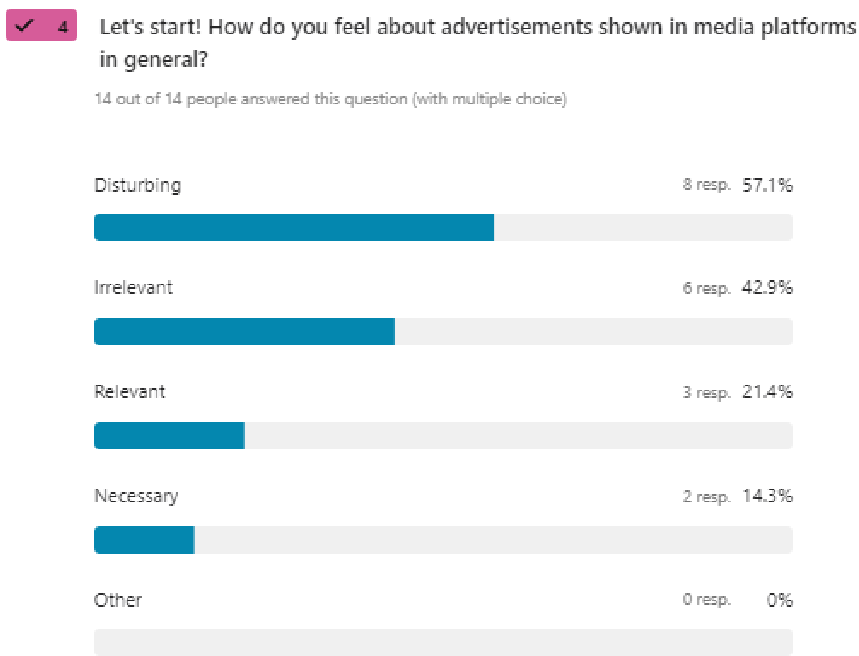


Figure B.3: Question 4



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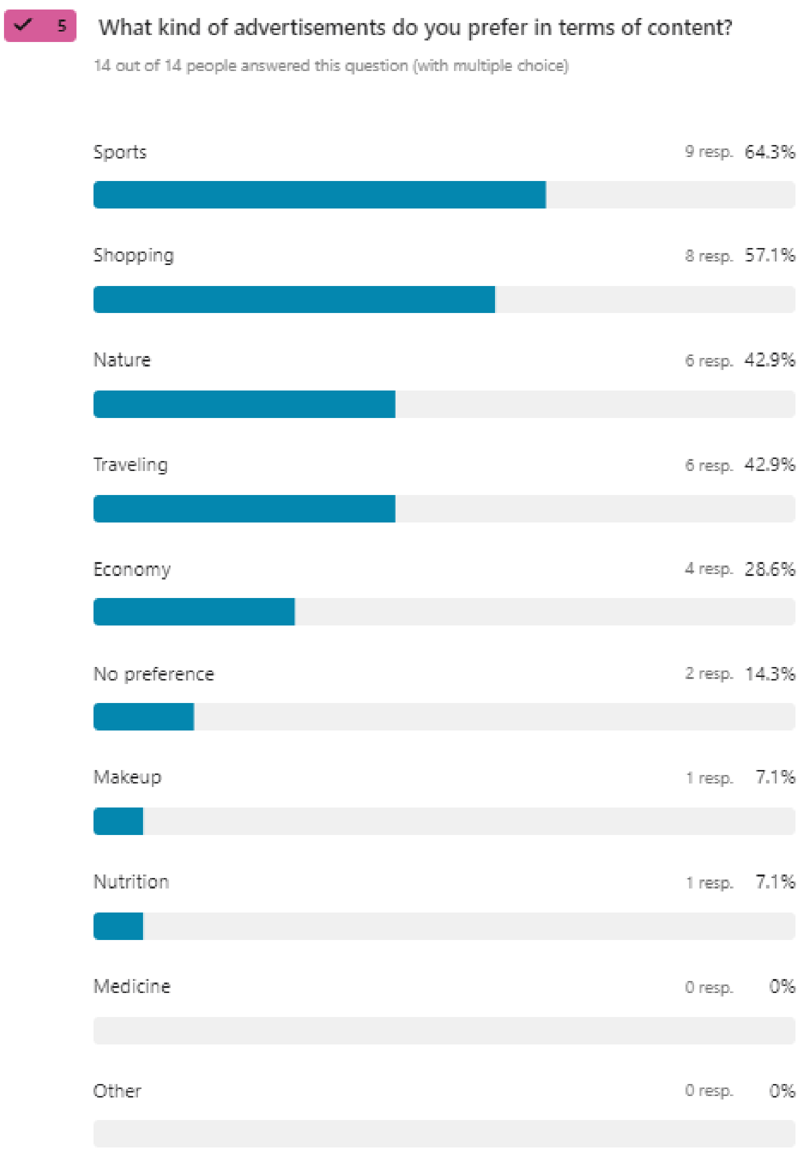
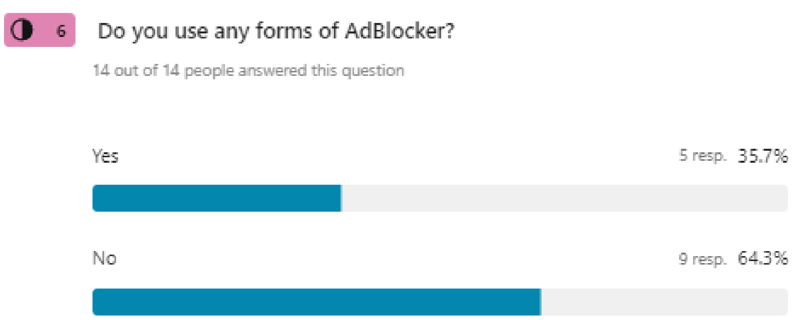


Figure B.5: Question 6



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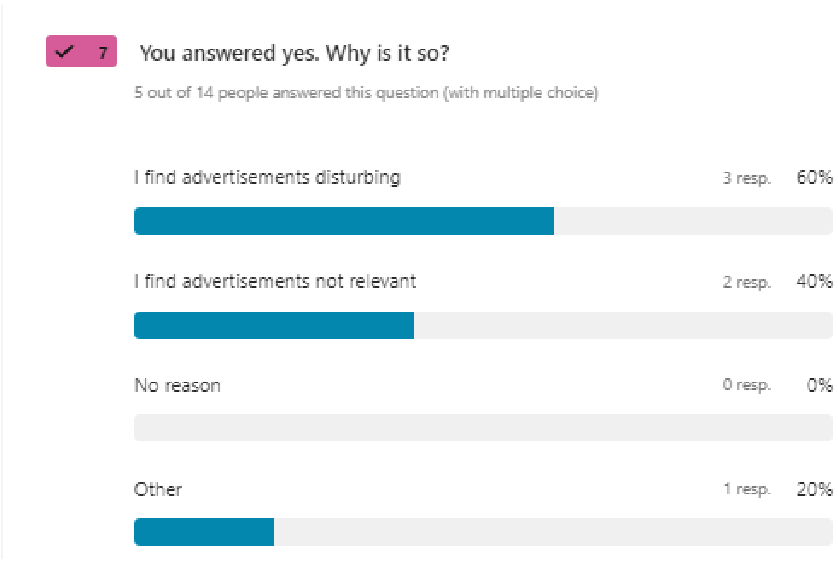


Figure B.7: Question 8

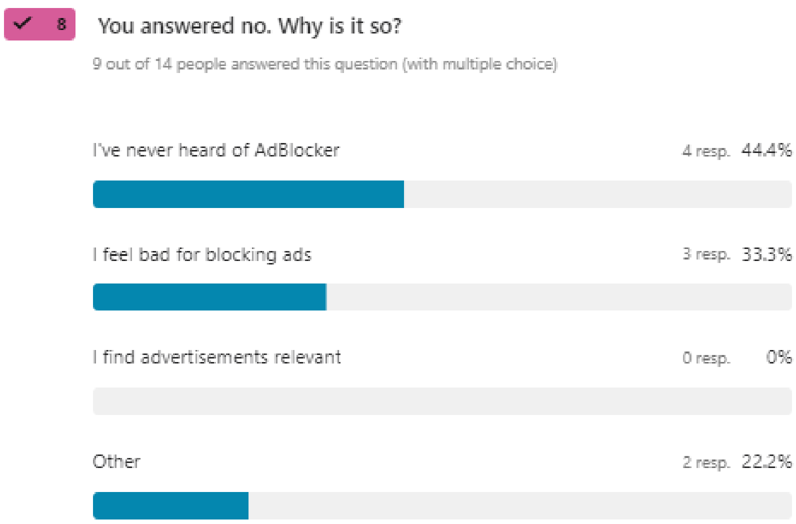


Figure B.8: Question 9

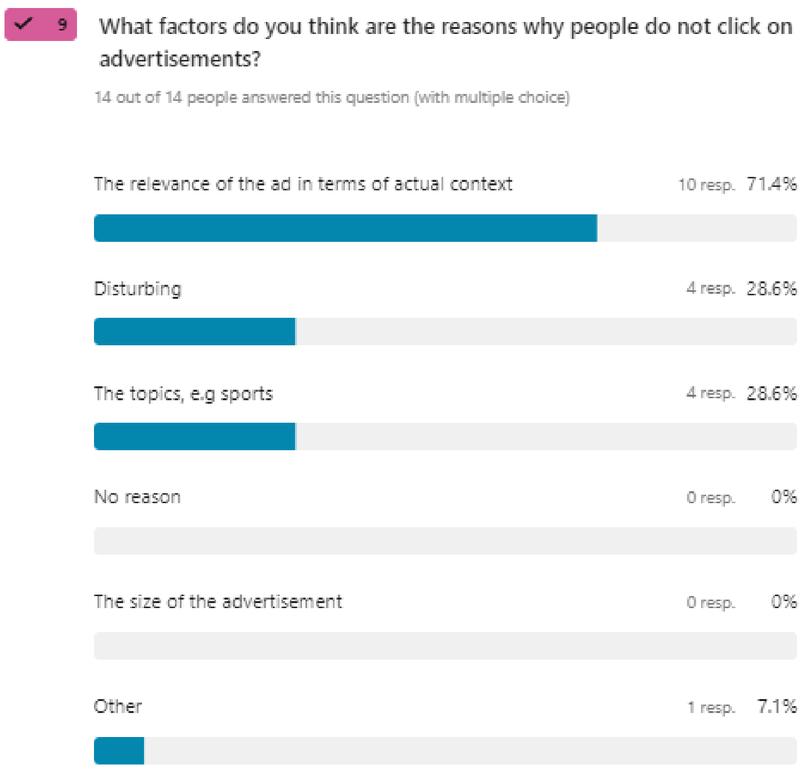


Figure B.9: Question 10

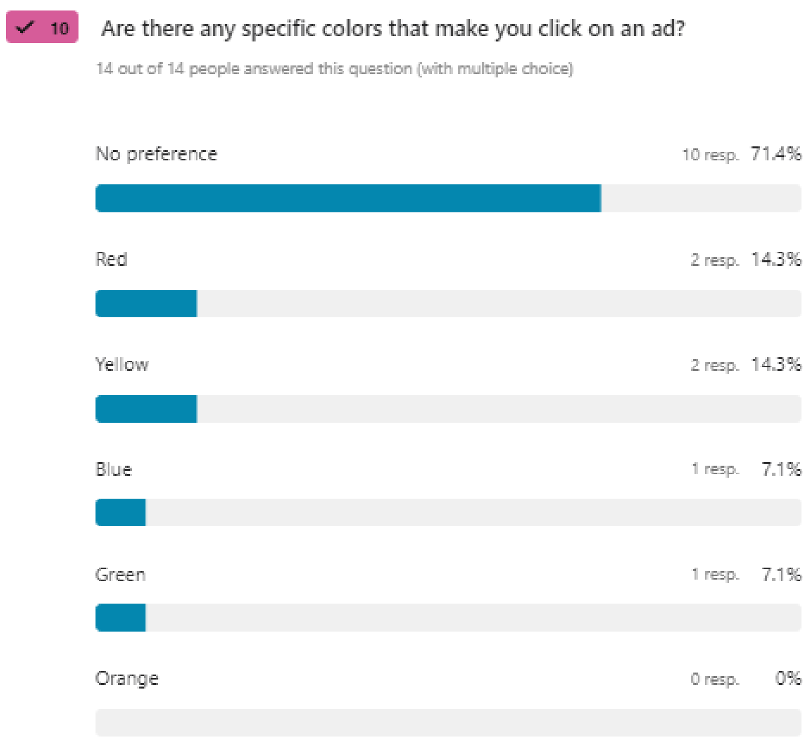


Figure B.10: Question 11

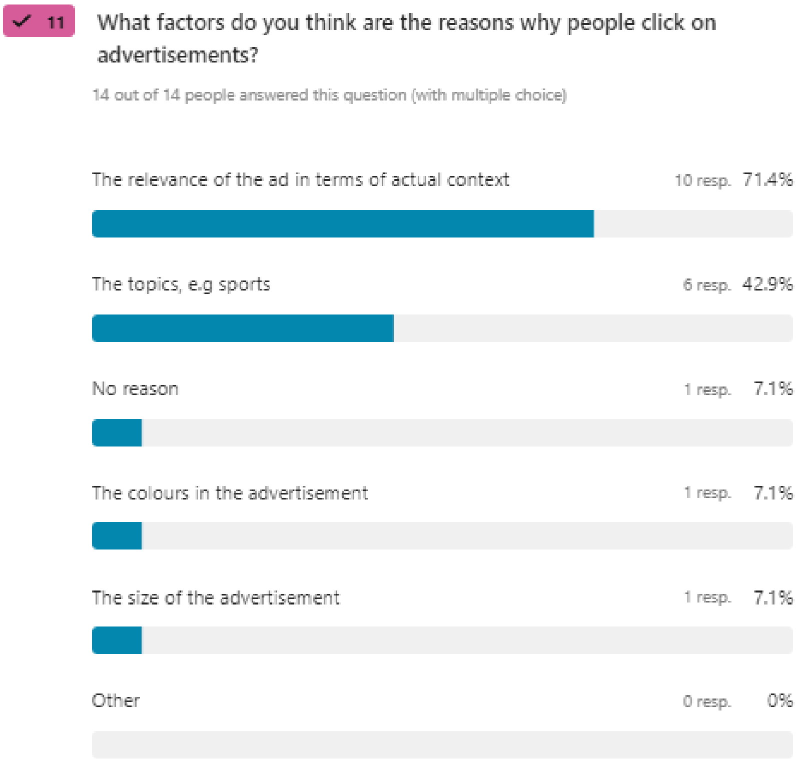
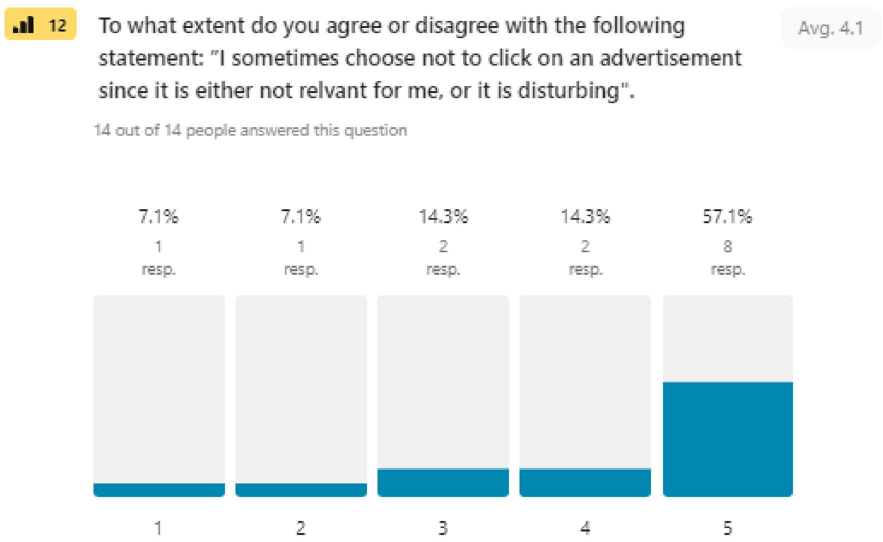


Figure B.11: Question 12



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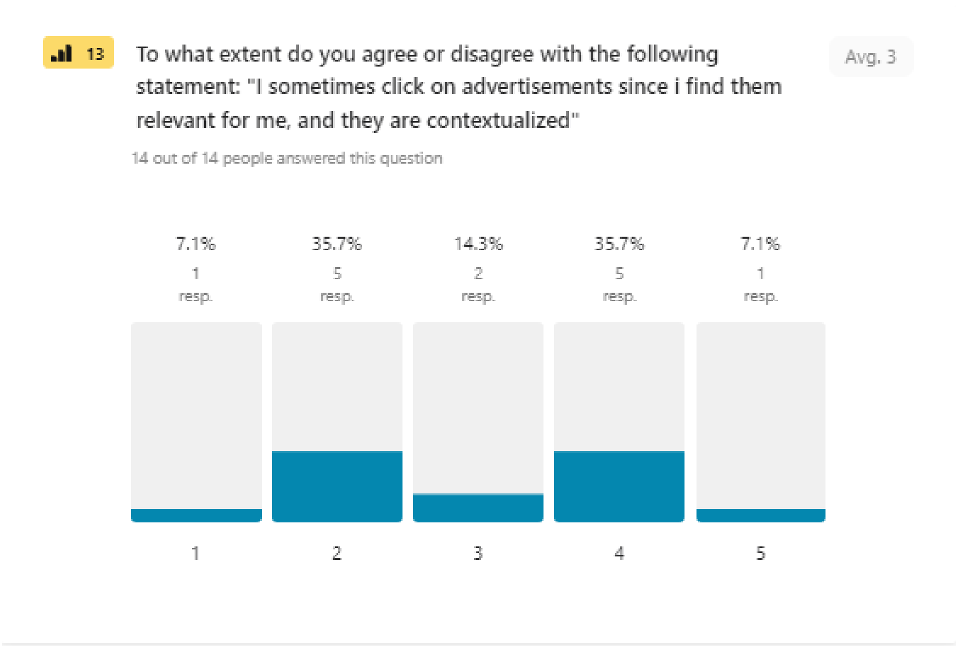

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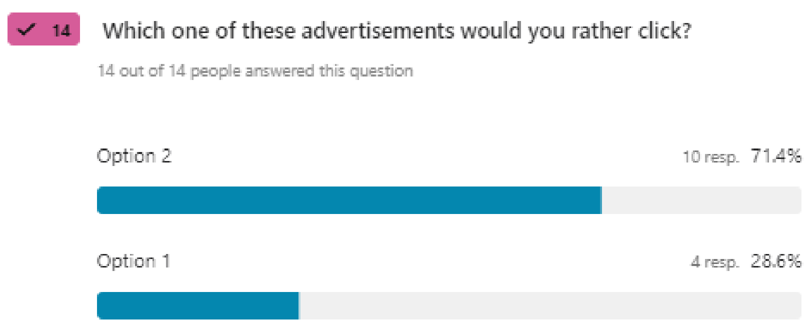

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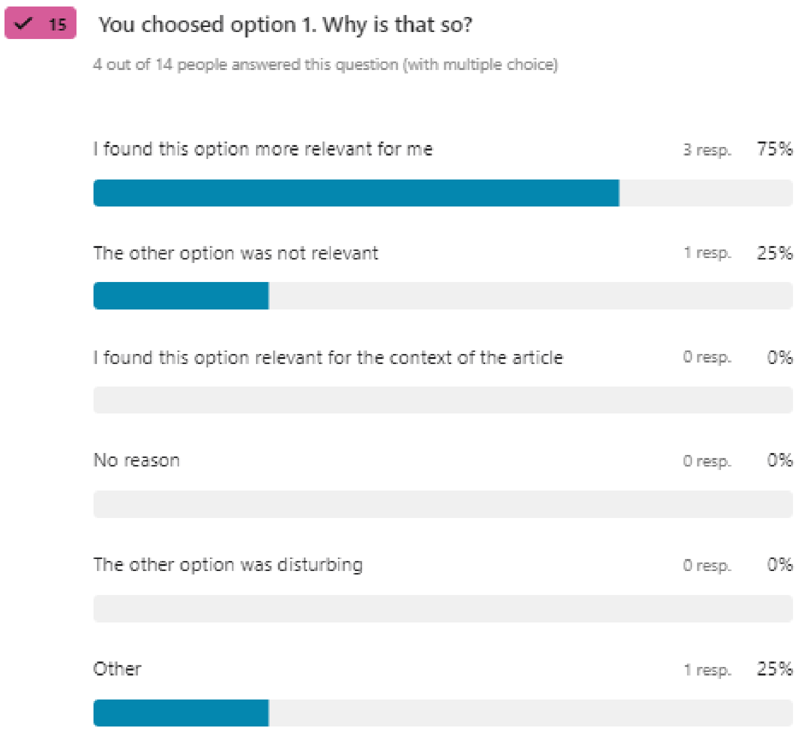

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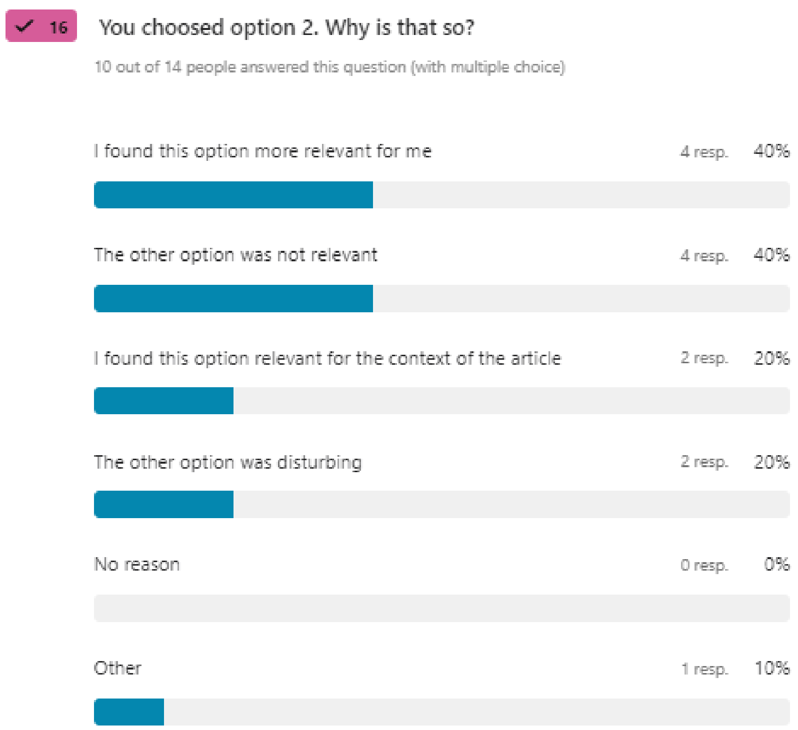

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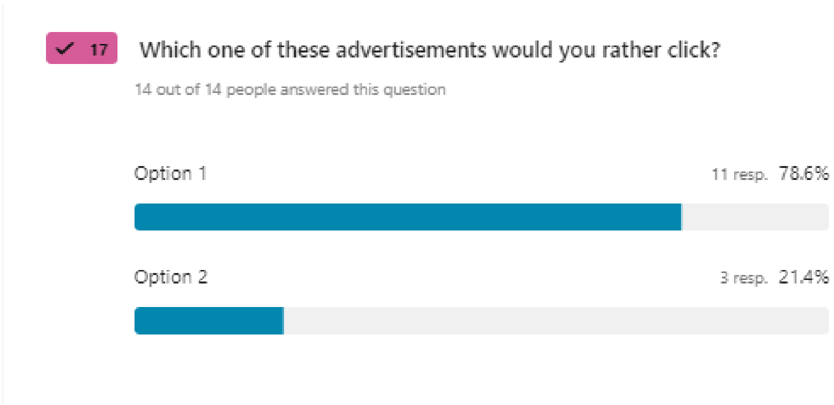


Figure B.17: Question 18

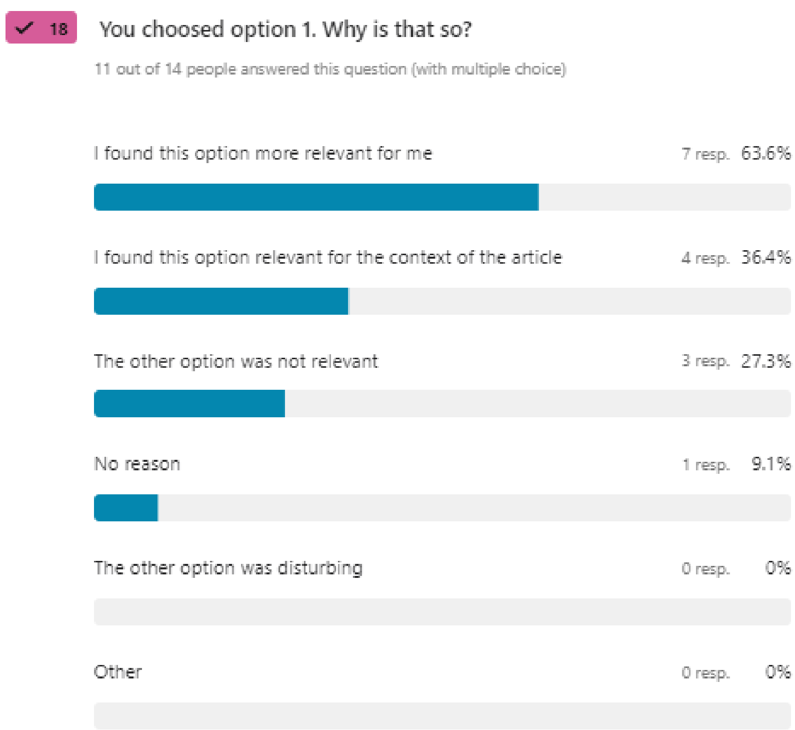
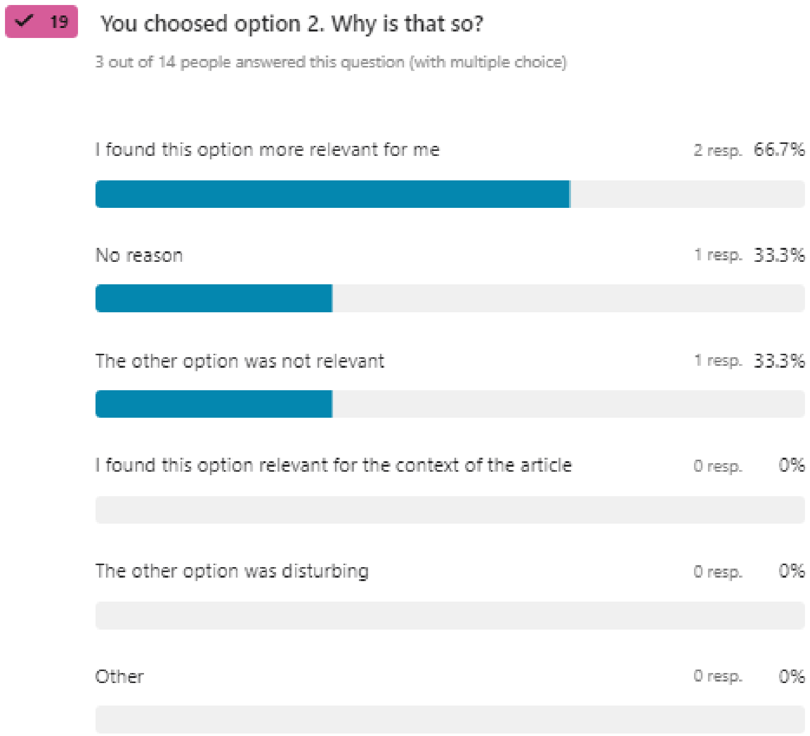


Figure B.18: Question 19



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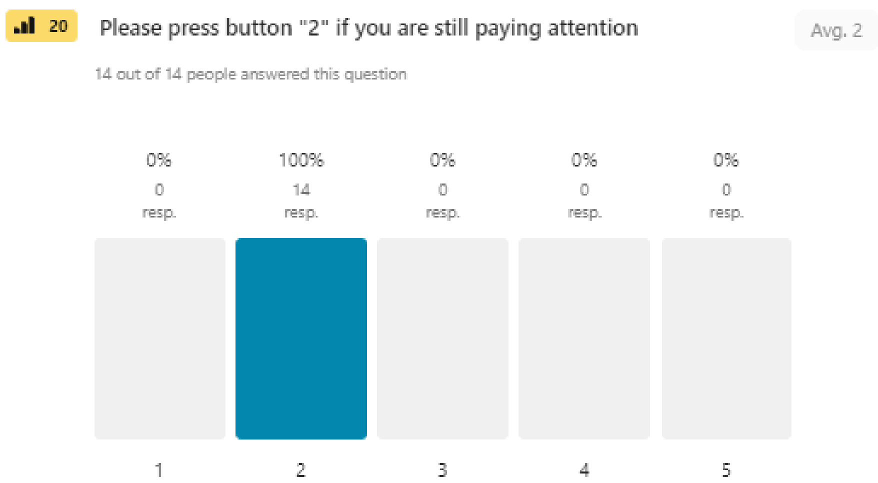

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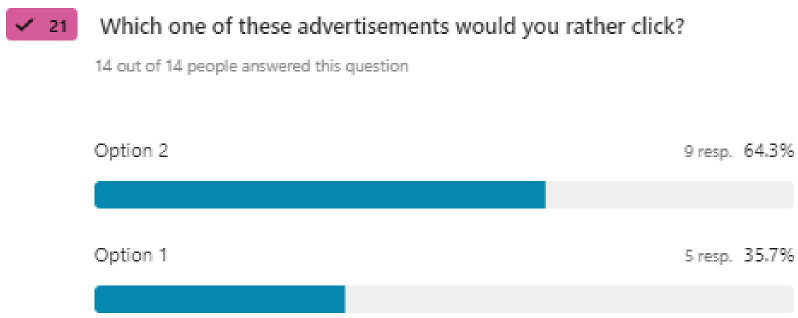
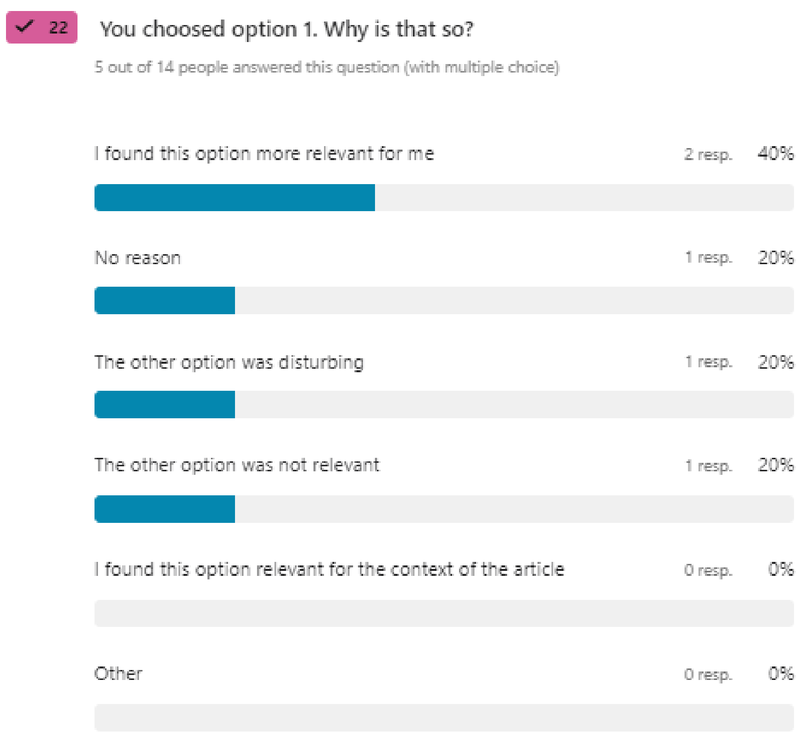


Figure B.21: Question 22



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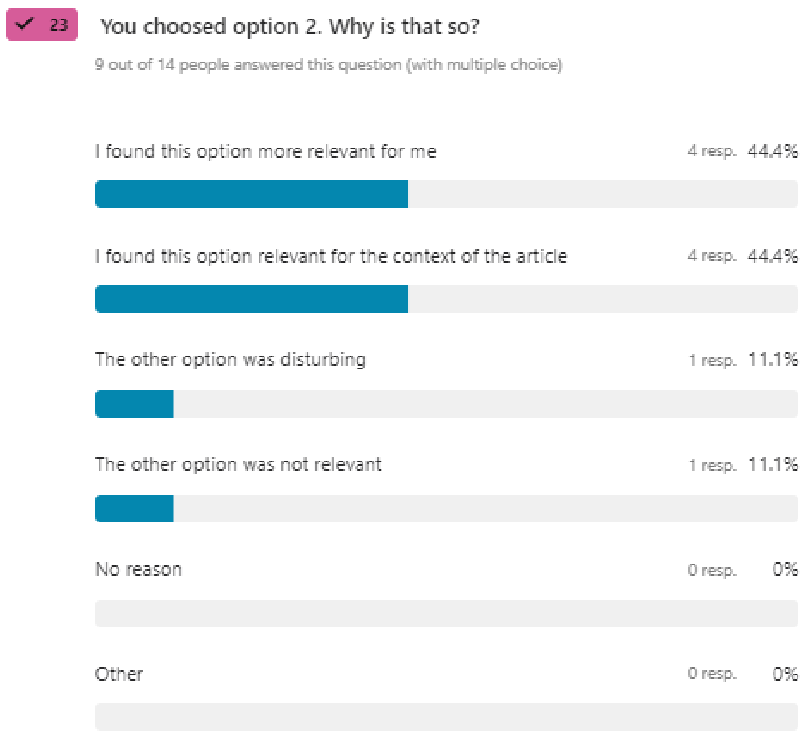
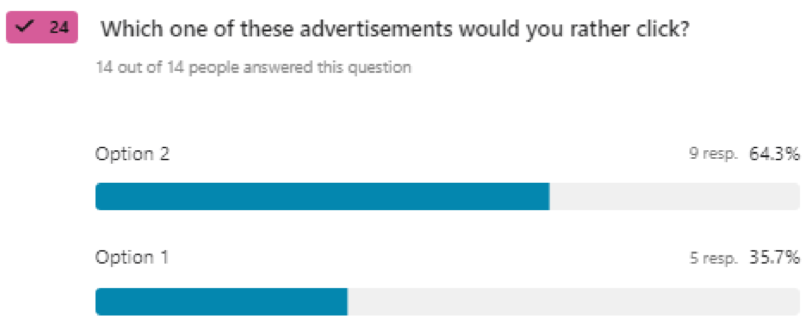


Figure B.23: Question 24



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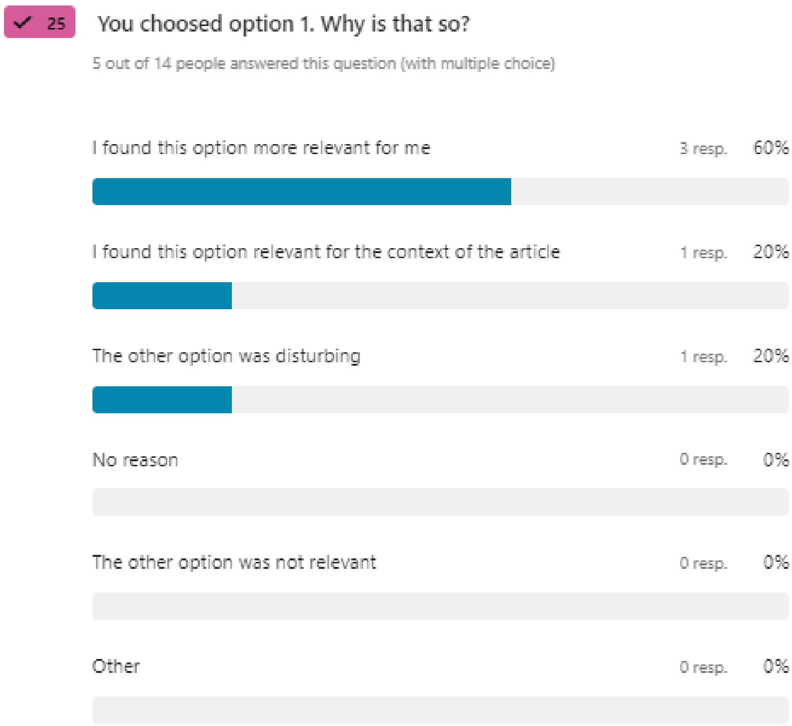

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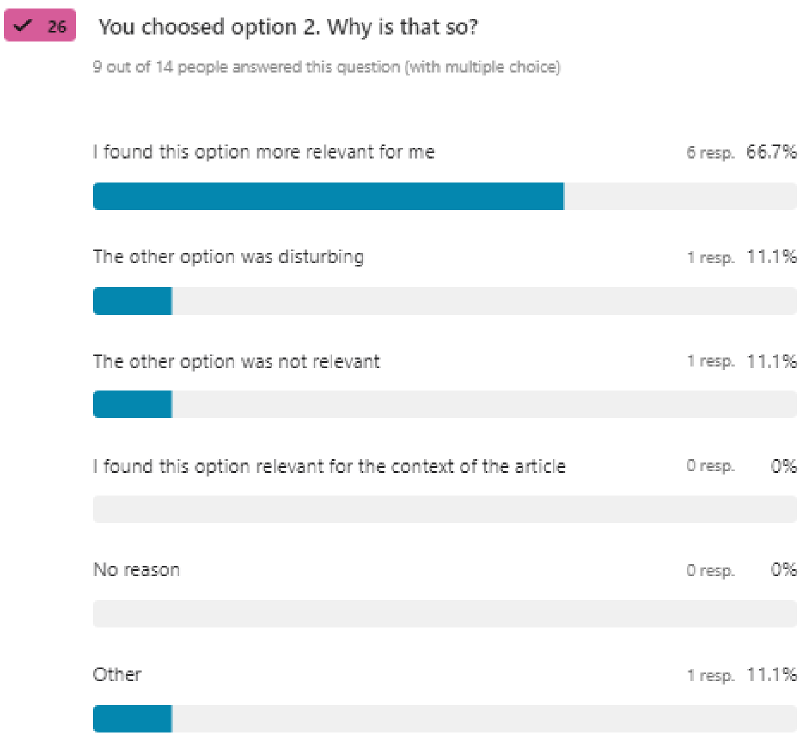

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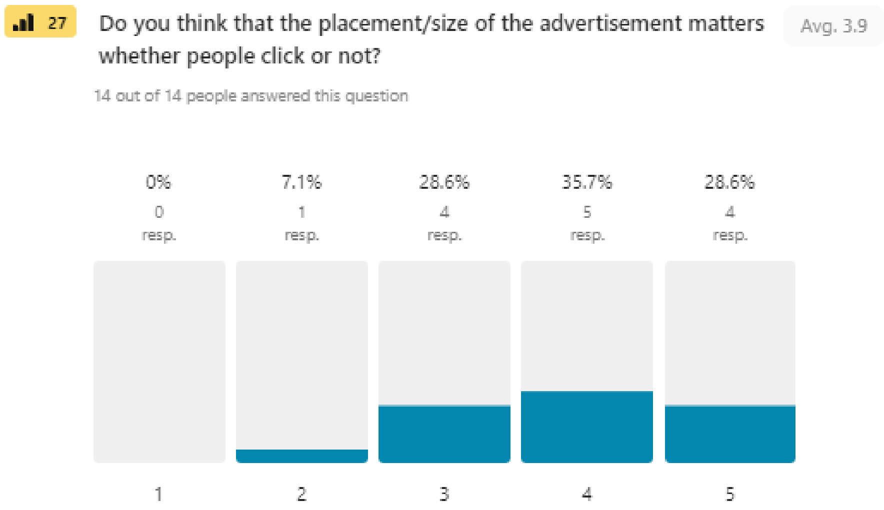

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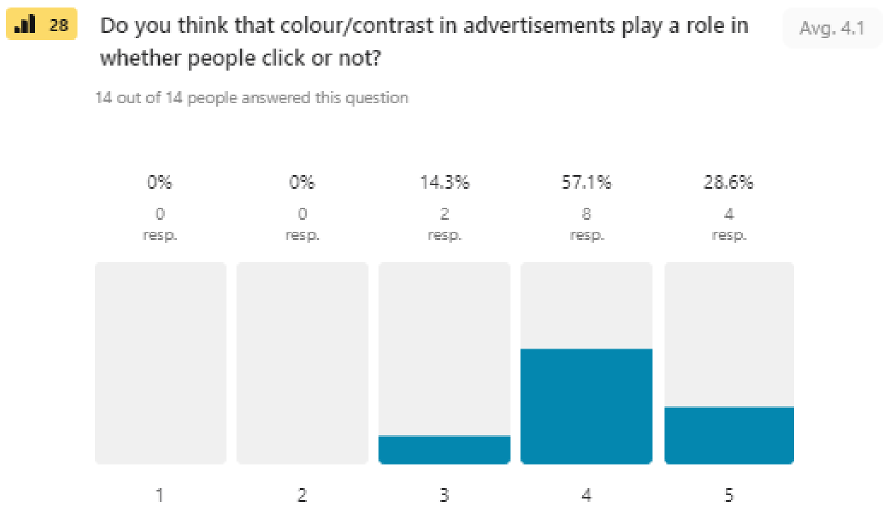

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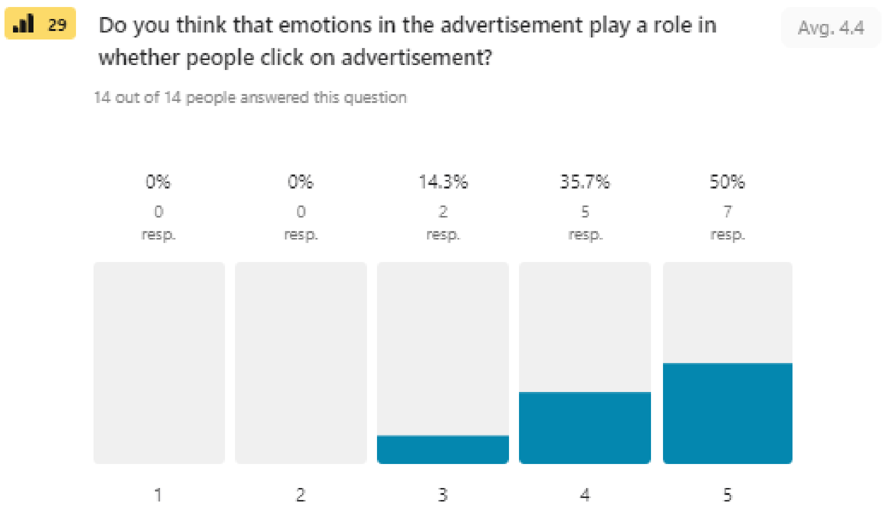

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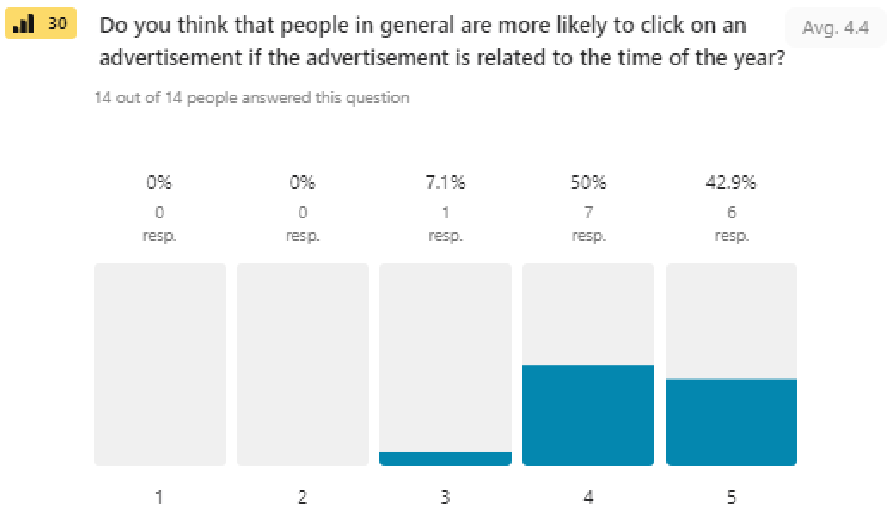


Figure B.30: Question 31

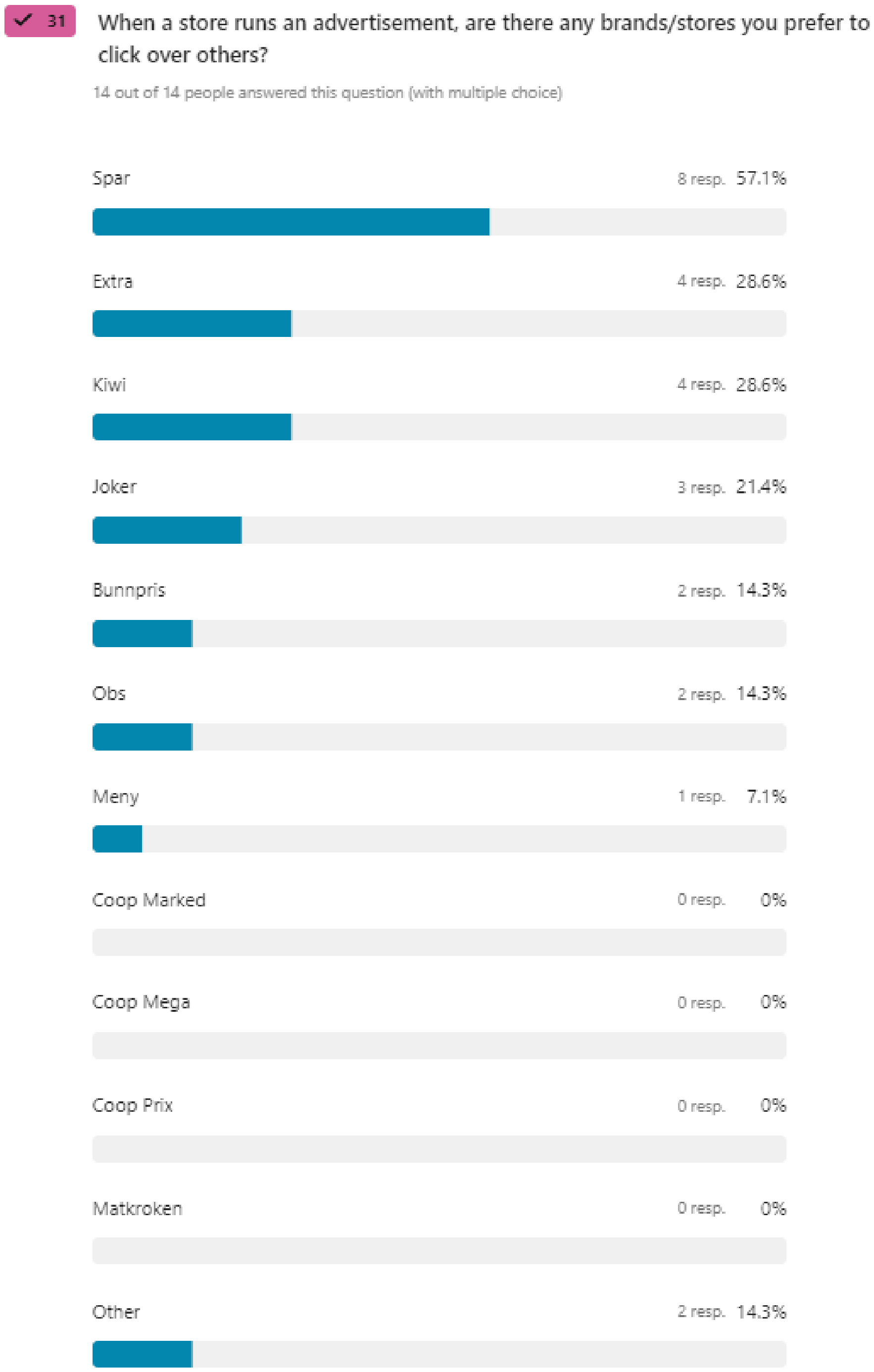
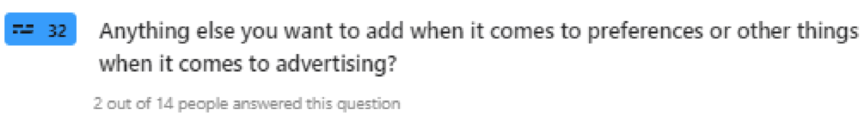


Figure B.31: Question 32



Appendix B

Appenix B: User Study Results - Prolific

These are the results from the participants from Prolific

Figure B.1: Question 1

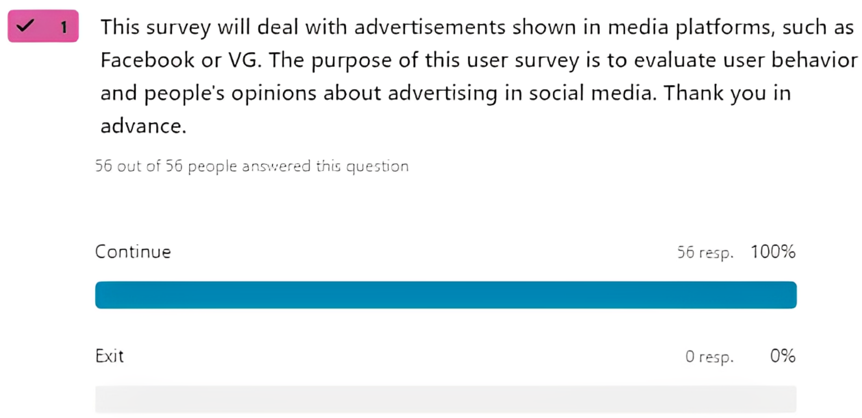


Figure B.2: Question 2

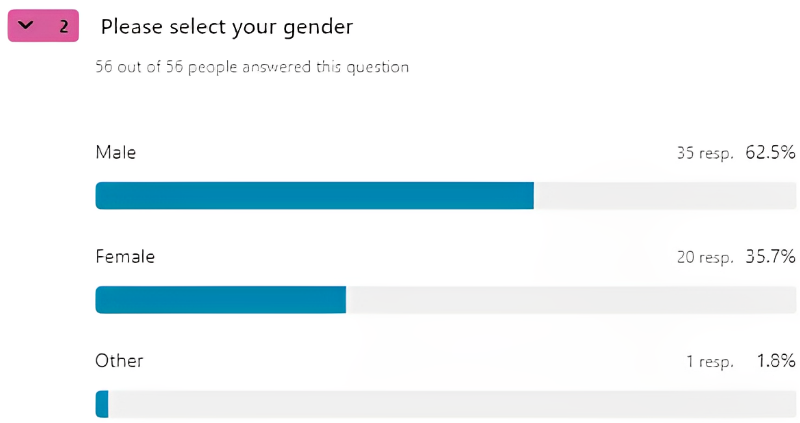
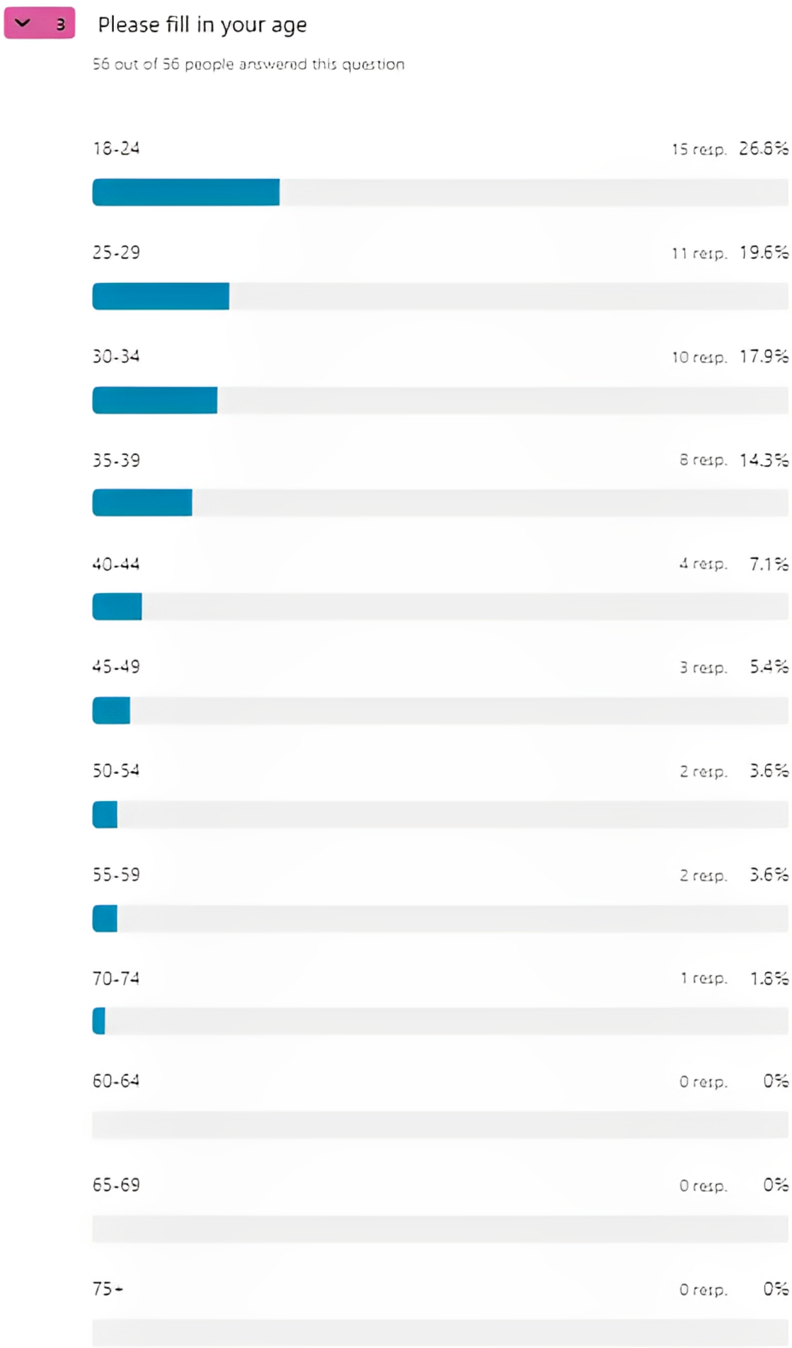


Figure B.3: Question 3



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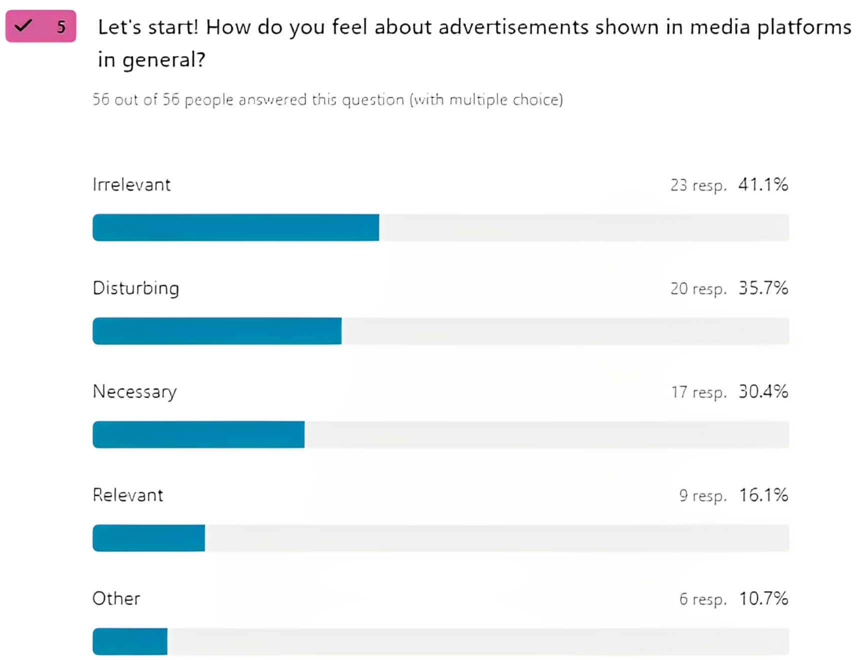

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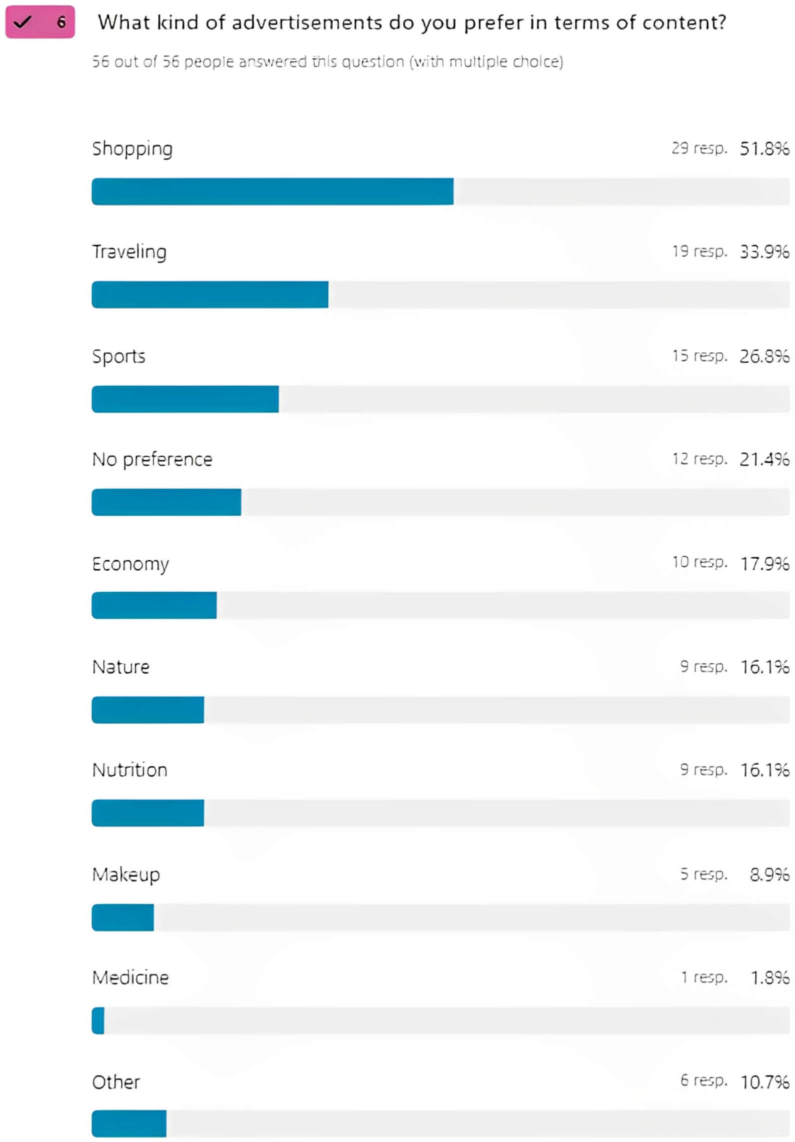
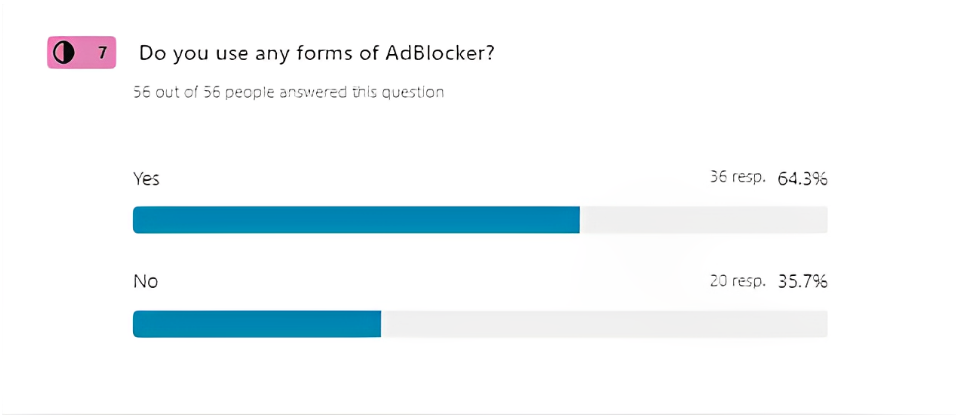


Figure B.6: Question 7



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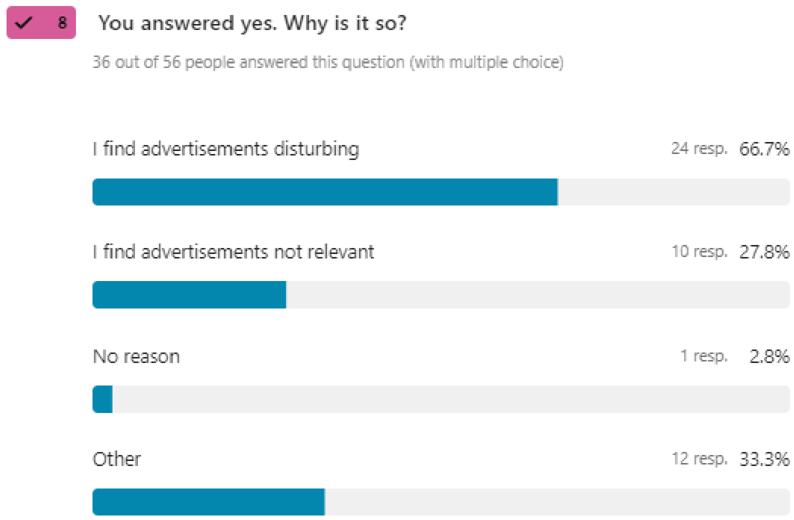

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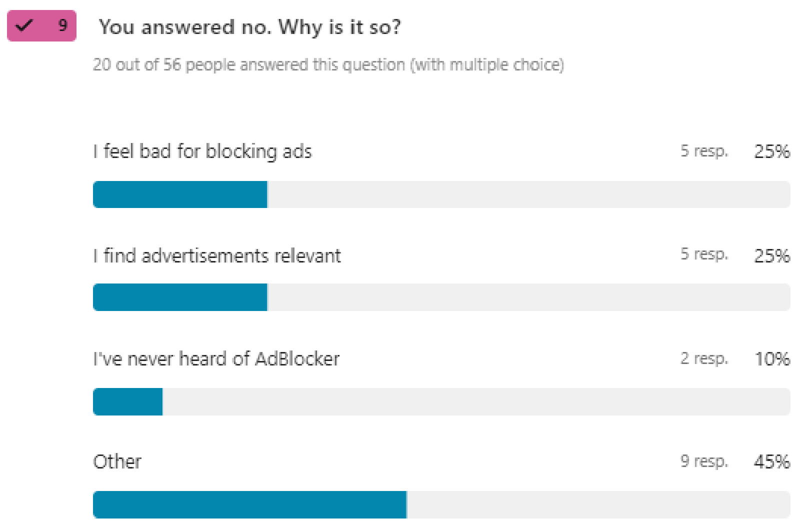


Figure B.9: Question 10

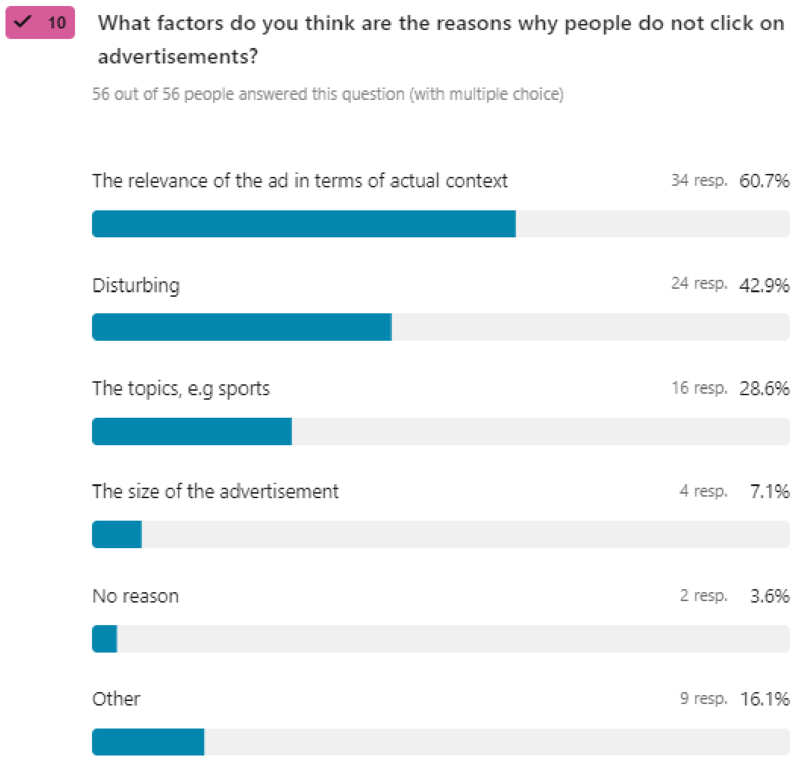


Figure B.10: Question 11

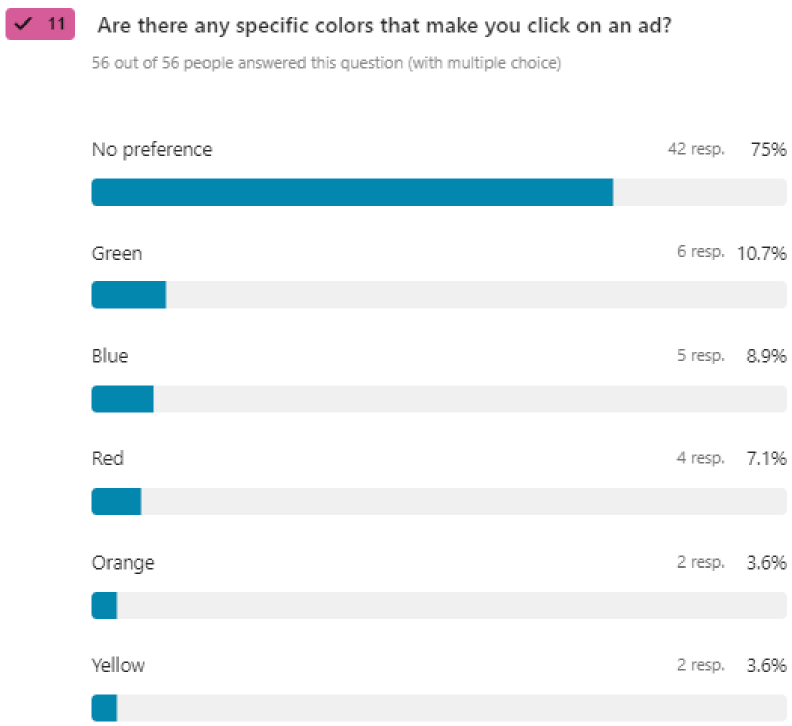
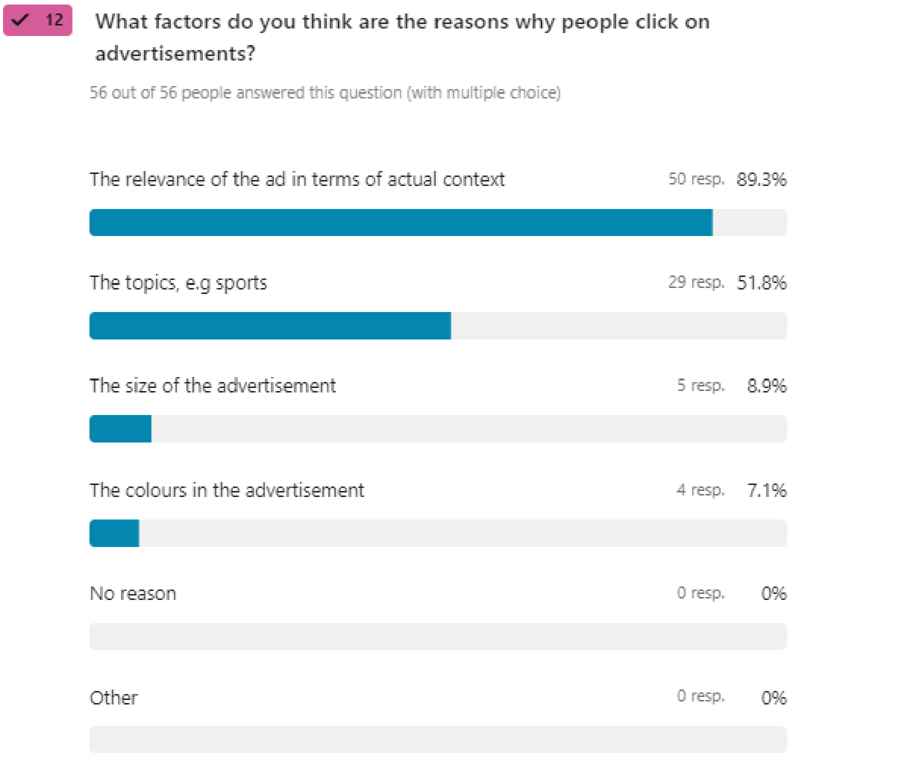


Figure B.11: Question 12



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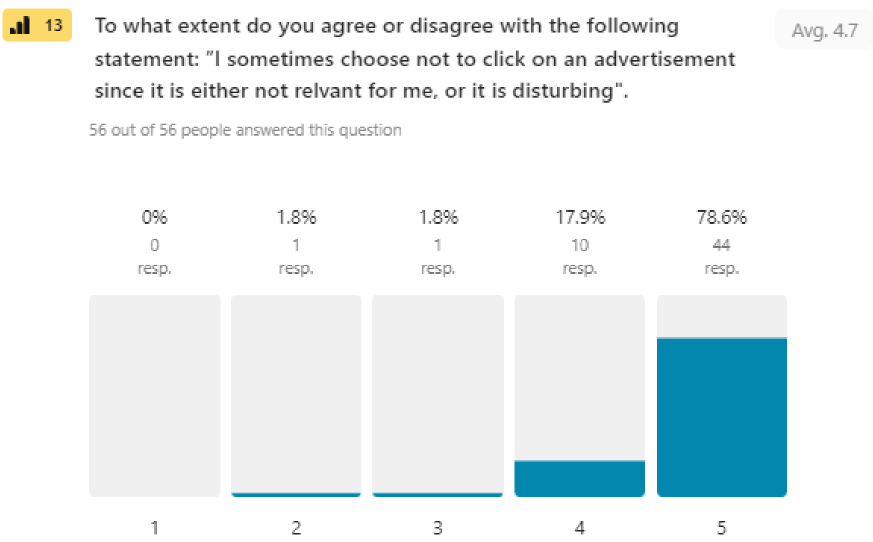

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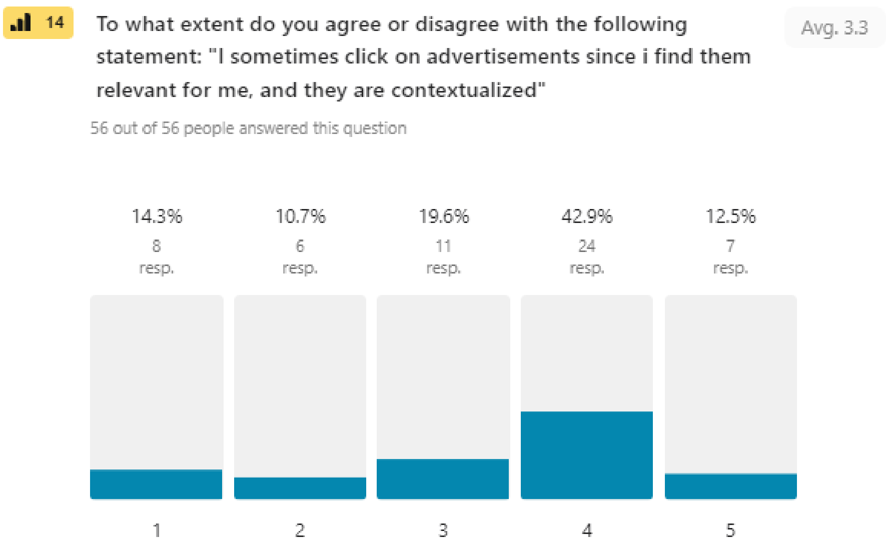
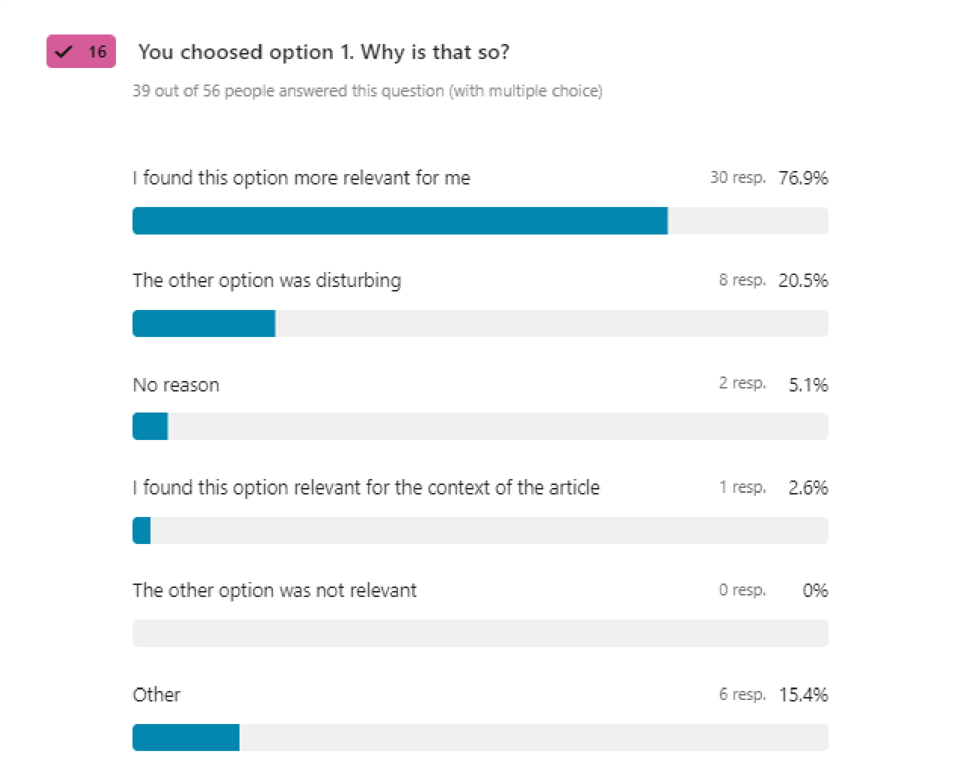


Figure B.14: Question 15

Figure B.15: Question 16



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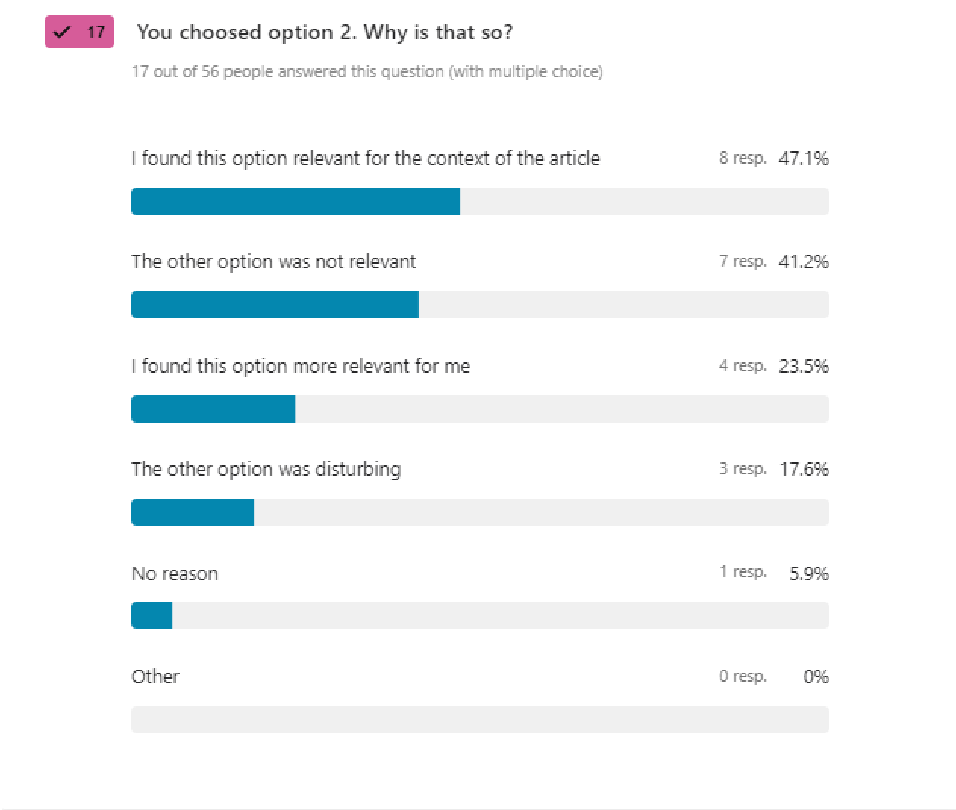

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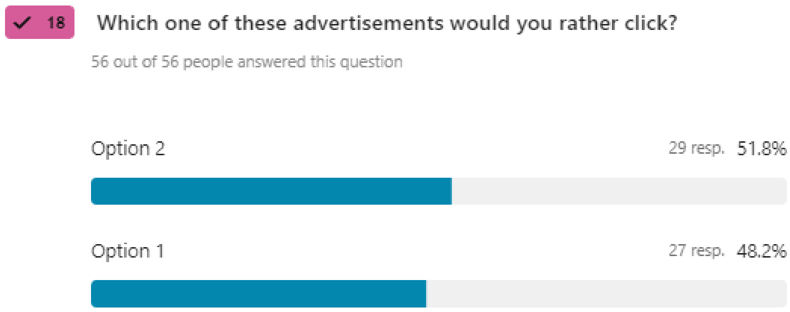

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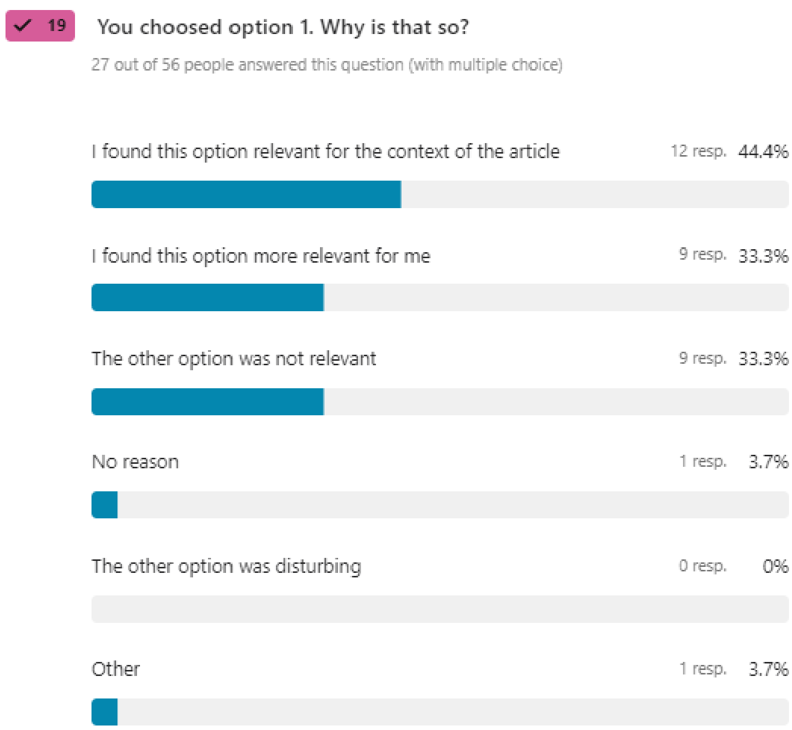

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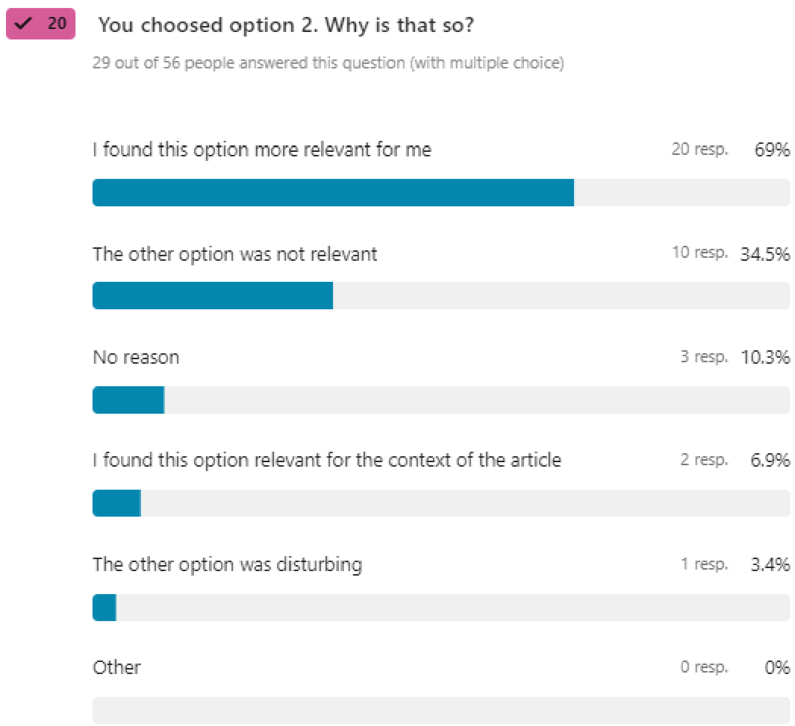


Figure B.20: Question 21

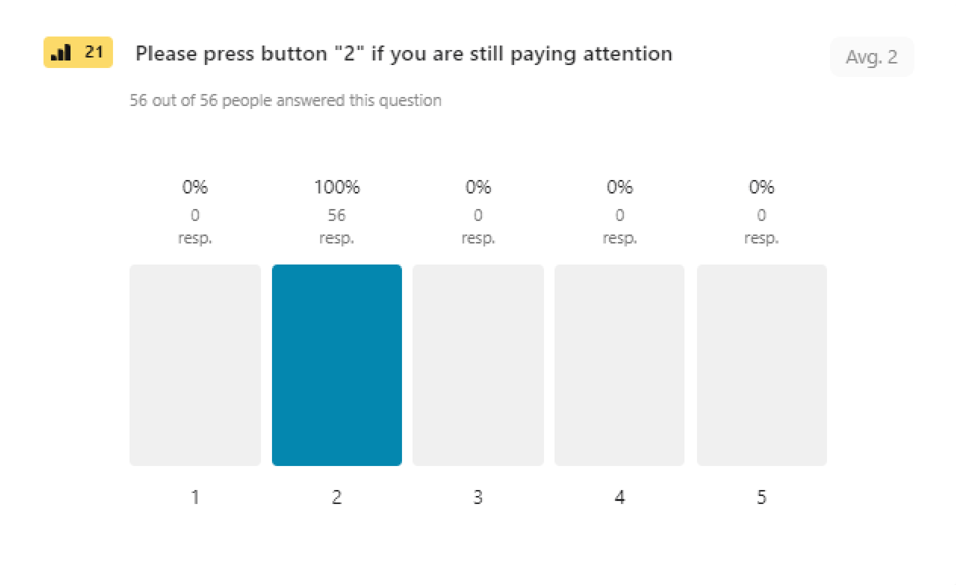


Figure B.21: Question 22

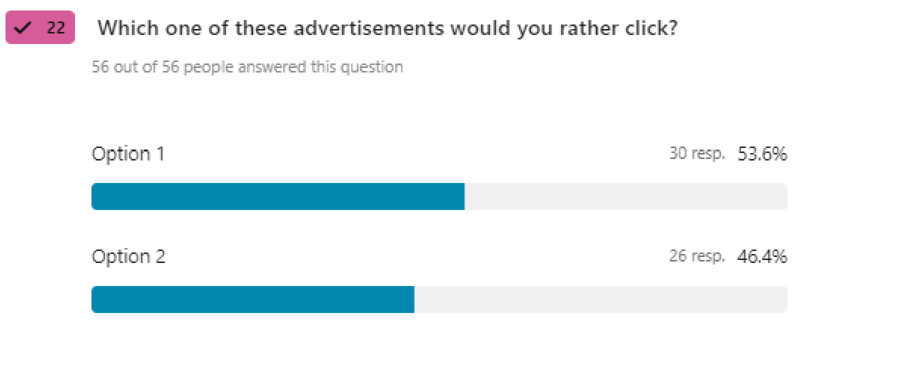
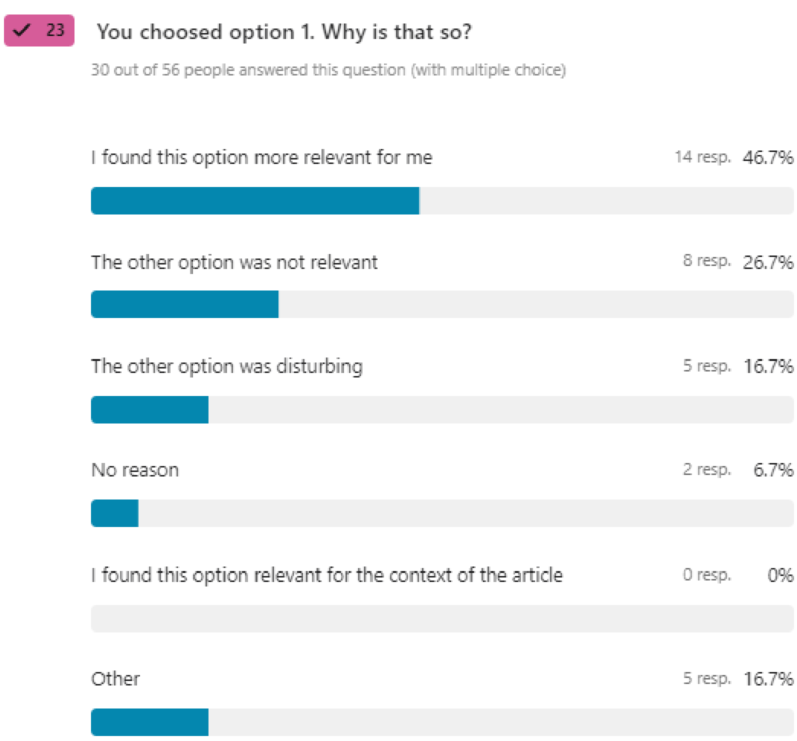


Figure B.22: Question 23



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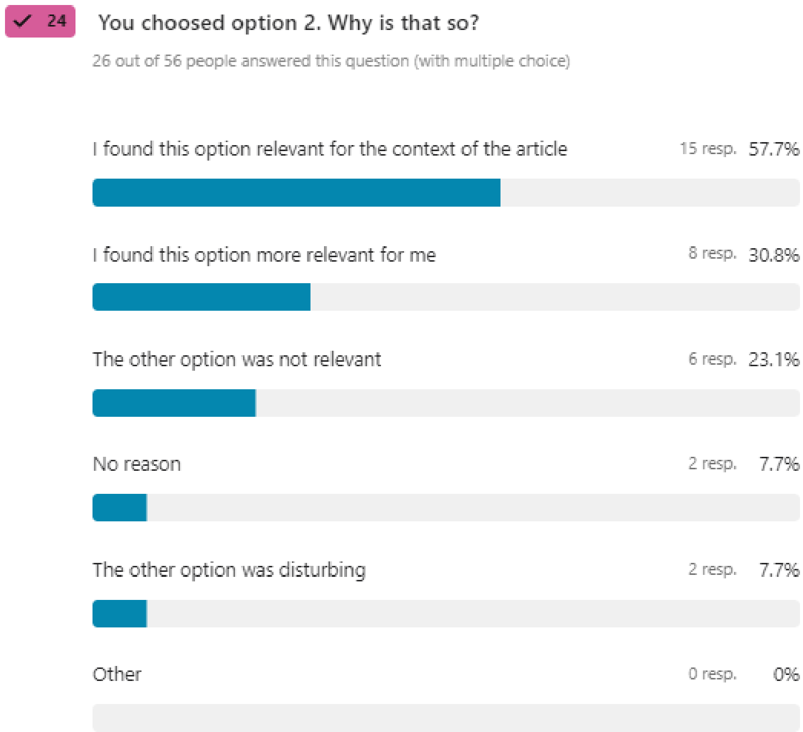


Figure B.24: Question 25

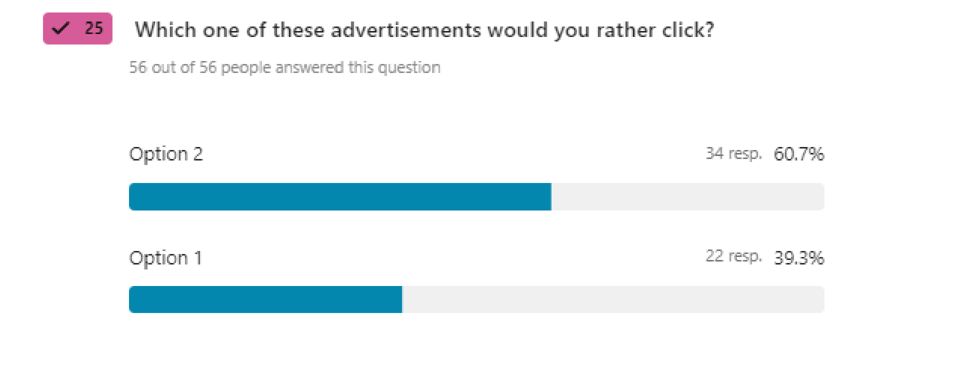


Figure B.25: Question 26

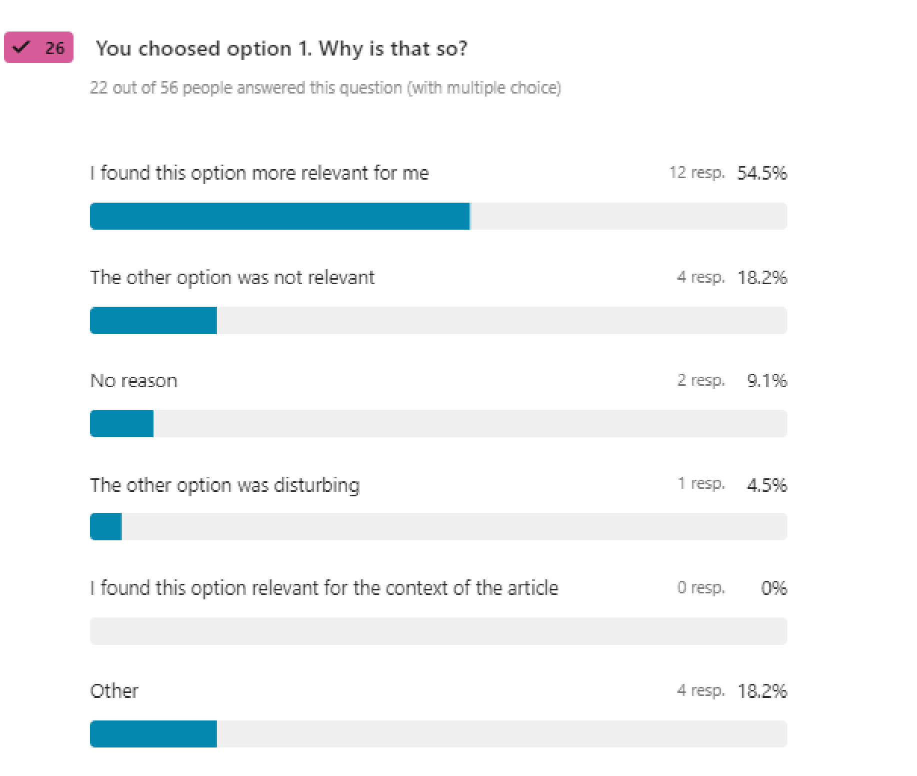
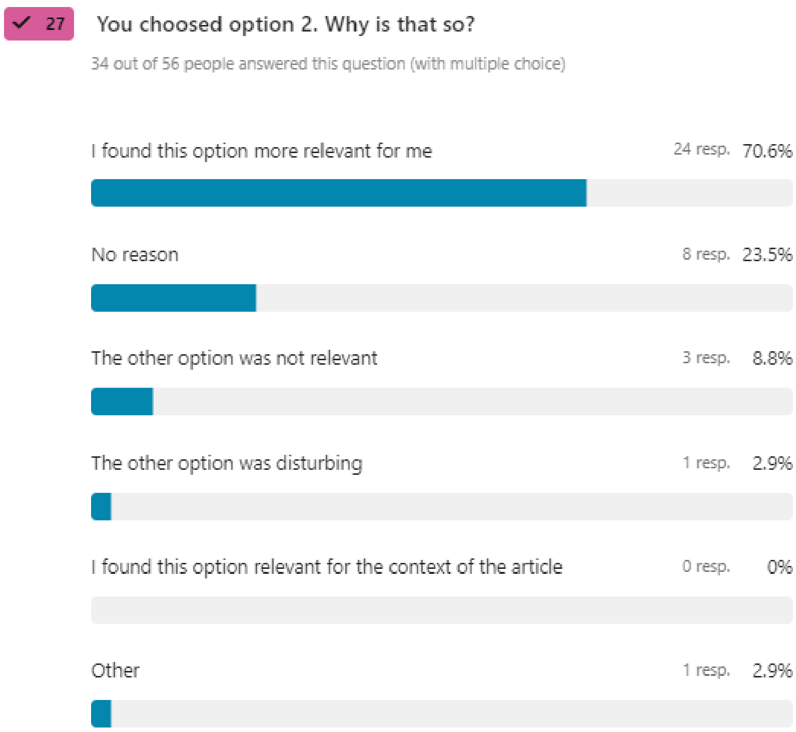


Figure B.26: Question 27



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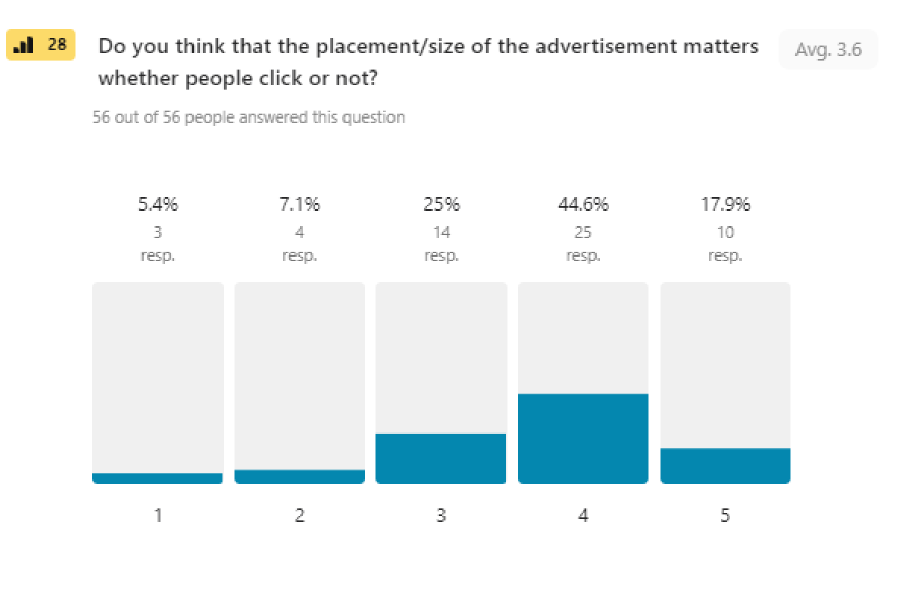

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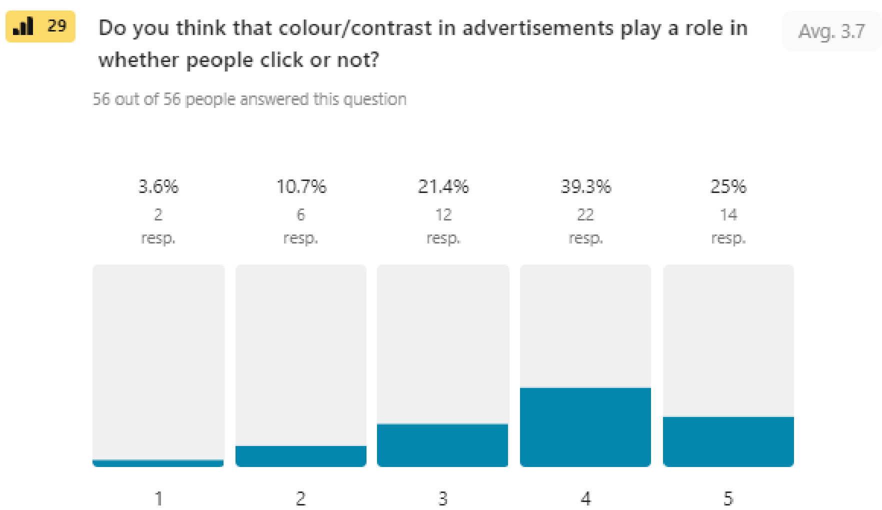

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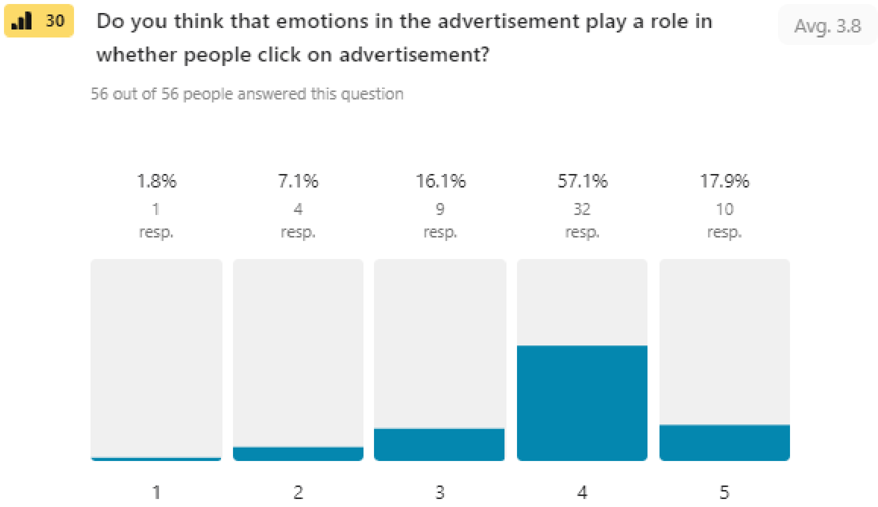

Figure B.30: Question 31

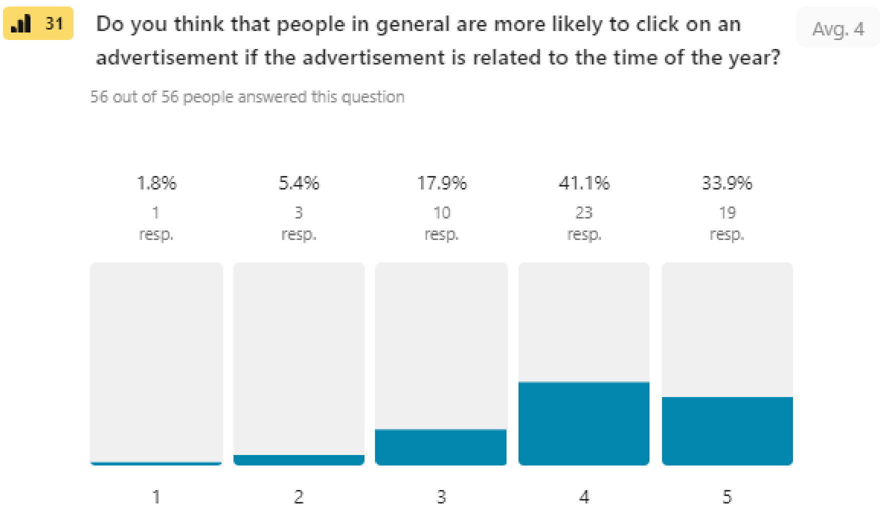

Figure B.31: Question 32

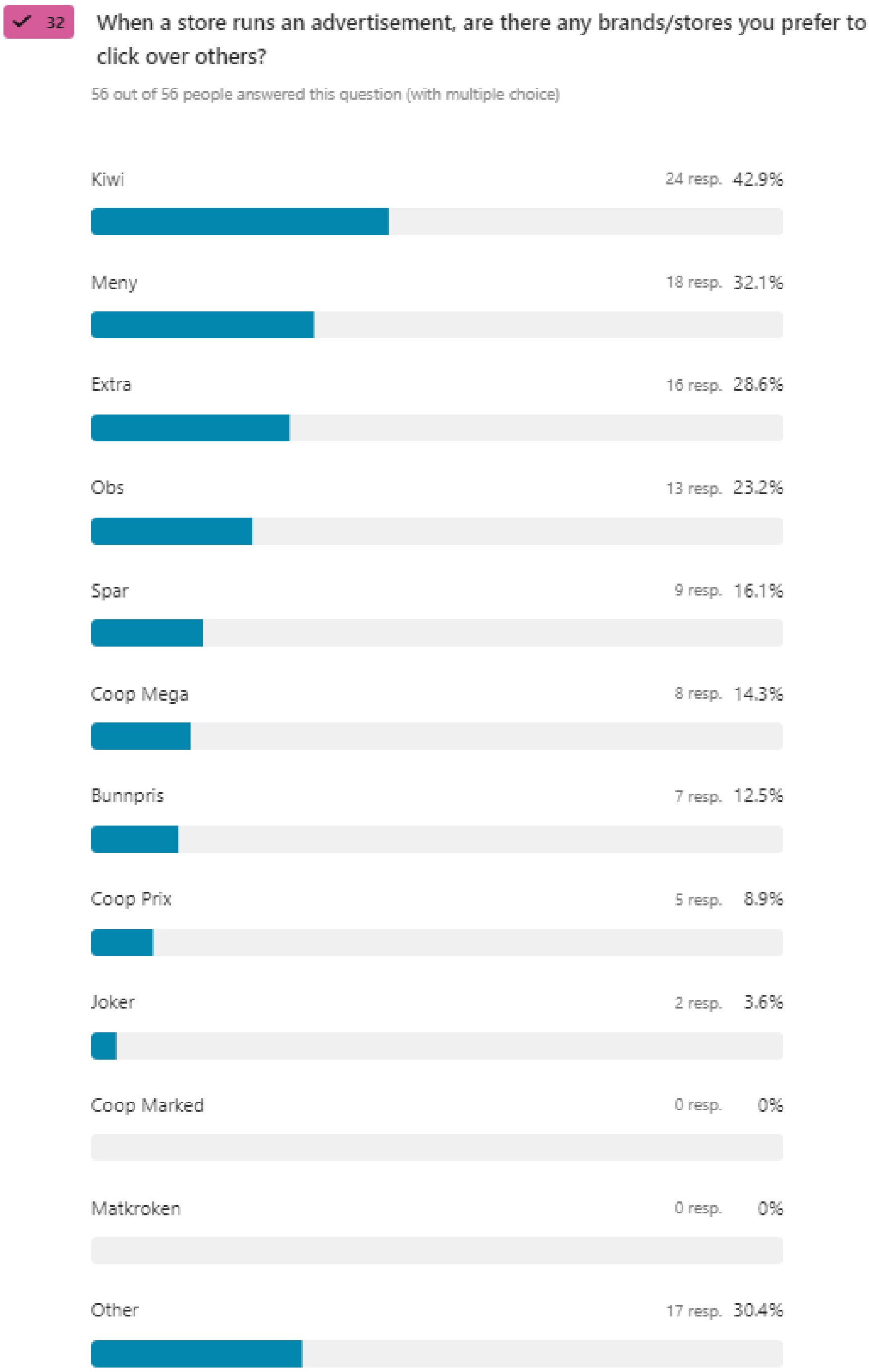

Figure B.32: Question 33

33 Anything else you want to add when it comes to preferences or other things when it comes to advertising?

21 out of 56 people answered this question

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