UNIVERSITY OF LJUBLJANA

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MASTER’S THESIS

AD PERSONALIZATION AND THE PRIVACY PARADOX IN DATA-DRIVEN MARKETING COMMUNICATION STRATEGIES

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LIST OF ABBREVIATIONS

ASP – App service provider

CART – Classification and Regression Tree

CEO – Chief executive officer

CM – Cookie Matching

CMO – Chief marketing officer

CPC – Cost-per-click

CRM – Customer relationship management

CTR – Click-through rate

ERP – Enterprise resource planning

GDPR – General Data Protection Regulation

IMC – Integrated Marketing Communication

KPI – Key Performance Indicator

OBA – Online Behavioural Advertising

PII – Personally identifiable information

PR – Public Relations

ROI – Return on Investment

SAAS – Software as a service

SPSS – Statistical Package for the Social Sciences

UX – User Experience

INTRODUCTION

Since the beginning of the 21st century, the way marketers create and deliver their marketing communication strategies has both drastically changed and evolved. The emergence of new technologies is providing marketers with new tools and communication techniques, enabling them to interact with their target audience more efficiently (Jayaram, Manrai & Manrai, 2015). Furthermore, data is the oil of digital economy and it has transformed the marketing world by generating a myriad of opportunities for marketers to attain new audiences (Chakravorti, Bhalla & Chaturvedi, 2019). They are able to leverage consumer data, collected based on their online behaviour and activities (Shanahan, Tran & Taylor, 2019). The use of advanced technologies and big data have significantly impacted the decision-making process within data-driven companies when it comes to their marketing communication strategies (Saura, 2020).

The daily roadmap for companies that are using the internet to communicate coherent messages across all channels includes integration of their promotional tools and leading an integrated marketing communication strategy. **Integrated marketing communication (IMC)** is defined as a "process of designing and delivering marketing messages to customers while ensuring that they are relevant and consistent over time and channels" (Palmatier & Sridhar 2017, p.162). One of the benefits of using an IMC strategy is the possibility to leverage consumer data and deliver one-on-one marketing communications (Kim, Han & Shultz, 2004).

When developing their IMC, companies frequently adopt a "**touch point approach**" where they take into perspective all possible ways of communicating with their desired audience (Belch & Belch, 2018, p. 27). Any contact between a certain brand and a consumer, at any point in time, is considered a touch point (Malthouse & Li, 2017). Companies gather **consumer data** about and directly from their consumers with the intention to improve their marketing activities (CMA, 2015). Nevertheless, the true value of consumer data are actually the insights that can be derived from it by carrying out **data analysis**. Increased data analysis is widening the advantage gap between data-driven and traditional marketing (Malthouse & Li, 2017).

With the help of web data analysis, marketers are able to track the degree of effectiveness of their campaigns (Beasley, 2013, p. 2). Defining clear and quantifiable goals on metrics such as KPIs (Waisberg & Kaushik, 2009) is crucial for a company to get measurable results (Flores, 2014, p. 4). **Click-throughs** (a ratio between the number of times an ad has been shown to people to the number of times it has been clicked on) (Google Ads Help, n.d.), can be taken as a KPI. However, what is important is that all metrics that the company decides to use are aligned with their business performance and are measurable in an easy manner (Trammell, 2016). Moreover, choosing proper **web analytics tools** is as equally important since there is a great deal of available tools, both free and paid. The most common ones include Google Analytics, Yahoo Web Analytics, Facebook Insights, Twitalyzer, KissMetrics, Compete etc. (Dubois, 2020).

A marketing communication strategy which enables companies to leverage data analysis and whose main aim is to acquire and increase traffic as well as to deliver targeted messages to the appropriate audience is **online advertising** (Techopedia, 2018). In fact, the existing model of online advertising consists of diverse intermediary stakeholders and technologies whose primary goal is to deliver one-on-one messages, also known as personalized advertisements (Jimenez, Arnau, Hoyos & Forne, 2017, p.38). **Ad personalization** focuses on the consumer as an individual, by tailoring ads according to his or her preferences (Bleier & Eisenbeiss, 2015a; Keyzer, Dens & Pelzmacher, 2015). Such ads take the form of promotional electronic newsletters, product recommendations (Awad & Krishnan, 2006), social media advertisements (Keyzer, Dens & Pelzmacher, 2015), banner advertisements or mobile advertisements (Bang & Wojdynski, 2016). When it comes to personalized advertising, **ad relevance** plays an important factor, as it measures how related consumers feel towards a certain product or service and how much it responds to their needs (Jung, 2017). This response is based on the self-referencing theory, which explains the link between ad relevance and consumer's positive reaction.

However, as **personal information** is the pillar of personalized marketing communications, marketers need to be aware that personalization can bring simultaneously positive and negative effects to the company, if not used and implemented properly (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015). From loyalty programs to mobile applications and websites, personal information combined with behavioural data is widely requested from users in order to receive appropriate benefits for some (if not all) of their online purchases (Norberg & Horne, 2014). This creates a "trade-off between the informativeness of advertising and the degree of privacy intrusion" (Tucker, 2012, p. 326). Research has shown that **trust** initiates willingness among consumers to share personal information to companies in different contexts (e.g., Hoffman, Novak & Peralta, 1999; McKnight, Choudhury & Kacmar, 2002; Schoenbachler & Gordon, 2002; Anderson & Agarwal, 2011; Bleier, Goldfarb & Tucker, 2020 p. 8). It is notable that the feelings of trust towards companies have to be present in almost every situation for the consumers to disclose personal information (Schoenbachler & Gordon, 2002, p.3). If retailers are perceived as trustworthy, their click-through rates are consequently improved, and personalization becomes economically beneficial (Bleier & Eisenbeiss, 2015a).

Moreover, trust can diminish **privacy concerns** that trigger feelings of vulnerability simultaneously, whenever companies gather and use consumers' personal data (Martin, Borah & Palmatier, 2017). Vulnerability indicates exposure towards wrongdoing or harm (Smith & Cooper-Martin, 1997) and when we speak of consumer data vulnerability, we are referring to the consumer's privacy and their level of tolerance when breaching that privacy with harmful data practices (Martin, Borah & Palmatier, 2017). The main triggers for consumer privacy threats and **perceptions of privacy violation** are tied with the capabilities and infrastructure of ad platforms (Jimenez, Arnau, Hoyos & Forne, 2017). Almost every personalized ad indicates that companies are voluntarily inclined towards leveraging consumers' information knowledge, gathered by tracking their browsing activities (Anand & Shachar, 2009; Bleier & Eisenbeiss, 2015a).

Overall, people are prompted to control the level of personal information disclosure (Altman, 1975; Wright & Xie, 2019). To keep the feeling of control, consumers might also adopt certain courses of actions such as falsifying and/or excluding data (Lwin & Williams, 2003; Lwin et al., 2007; Norberg & Horne, 2014). Both falsifying and excluding data can have substantial negative effects over companies whose operations are data-driven and primarily depend on consumer data (Norberg & Horne, 2014). By using **transparent practices** i.e., keeping the consumers informed on which and how the information is being collected, as well as the ways it can be deleted, companies can avoid receiving false data (Karwatzki, Dytynko, Trenz & Veit, 2017). This way, transparency would not only positively affect privacy concerns, but also it would benefit consumers' trust (Treiblmaier & Pollach, 2007; Karwatzki, Dytynko, Trenz & Veit, 2017) and the **feeling of privacy control** (Karwatzki, Dytynko, Trenz & Veit, 2017).

While people are expressing their privacy concerns and fear of information disclosure, the question of whether they indeed care about their privacy remains unanswered (Kokolakis, 2017). Unfortunately, consumers are torn between receiving better services and products, in exchange for providing and disclosing their personal information (Norberg, Horne & Horne, 2007). On one hand they state that they are very concerned about the privacy of their personal information (Kokolakis, 2017), but on the other they act in a contradictory way, when it comes to sharing that information in exchange for benefits (Norberg, Horne & Horne, 2007). This term is known as "**privacy paradox**" and is used as a referral to the disconnect between the consumer's privacy preferences and the actual information disclosure behaviour (Martin & Murphy, 2016; Barth & Jong, 2017). It seems like there are various drivers, which push the users off the edge, when they decide whether they care more about their privacy and information disclosure or receiving certain benefits.

In our thesis, we will explore how perceptions of trust, privacy control, privacy violations and ad relevance appear as a consequence of the consumer's attitude towards personalized advertisements and influence their likelihood to click-through. These drivers were selected, as they were most often referred to as most relevant in previous research, when it comes to personalized advertising. While across literature we can find studies, which tackle these drives in a more "paired manner" such as trust in retailers and personalized advertisements or privacy concerns and perceived benefits from personalized advertisements, there seems to be no existing research which measures all of these drivers combined at once. For example, Bleier and Eisenbeiss (2015a) find that if retailers are found as trustworthy, they can benefit from personalized ads and consequently improve their click-through rates. Lack of trust on the other hand, can create a negative effect and evoke privacy concerns (Bleier & Eisenbeiss, 2015b). Jung (2017) studied the interconnection between ad relevance and ad effectiveness. The results show that if an ad is perceived as relevant, it can influence the attention of the viewer and consequently decrease the chance to avoid the ad. Furthermore, Xu, Teo, Tan and Agarwal (2012) observe the perceptions of privacy control and privacy violations and find that the latter can be in fact reduced through the perception of the former. They suggest that perceived privacy control is the focal mechanism through which course of actions such as government regulations, industry self-regulation and self-protection, influence the level of perceived privacy violation.

The **main purpose** of this research is to develop knowledge about data-driven marketing communication strategies within companies and to identify the attitudes of consumers towards personalized advertisements as well as the reactions that consequently appear, i.e., perceptions of ad relevance, privacy violation, privacy control and trust as crucial drivers that influence their click-through intentions. Therefore, **the goals** of this research are as follows:

(1) To learn whether companies use and how they use consumer data for marketing activities; In particular, is online personalized advertising one of the implemented data-driven strategies when it comes to their marketing communications.

(2) To examine the relationship between ad personalization and the likelihood of a click-through.

(3) To understand the process that leads consumers to click-throughs; precisely how the process is influenced by the perceived ad relevance and privacy violation.

(4) To explore if increased perception of privacy control affects the relationship between personalization and the perception of privacy violation.

(5) To understand how trustworthiness affects the perception of privacy violation and the likelihood of a click-through.

(6) To identify the prevailing drivers that lead an individual to click-through.

Consequently, the **main research question,** which will be addressed through our thesis, is: *What is the relationship between personalization and the likelihood of a click-through and is this relationship mediated by perceived ad relevance and privacy violation, while moderated by privacy control and trust?*

While the **supporting research questions** of our thesis are: *Do increased perceptions of privacy control negatively impact the relationship between personalization and perceived privacy violation?* further, *Can trust in the retailer positively impact the relationship between perceptions of privacy violation and the likelihood of a click-through*? and *Among levels of personalization, ad relevance, trust, brand attitude, perceived privacy violation and control which are the prevailing drivers that lead an individual to click-through?*

To establish a viable methodological framework for our thesis, we rely on primary and secondary data sources. In particular, the pillars of the theoretical framework are composed by looking at existing academic literature within the field, both abroad and domestic. Based on this literature, key concepts are defined, and relevant studies are summarized. Furthermore, the empirical part is built on the basis of primary research and involves qualitative and quantitative data: in-dept interviews and a survey-questionnaire. We conducted interviews with companies from different industries that helped us gain insights on their data-collection practices as a base of personalized marketing communications. Finally, due to the unavailability of studies that would answer our research questions at once, we were incentivized to carry out an empirical study on our own in the form of a survey questionnaire.

With the **findings** from this master thesis, we hope to shed light on personalized advertising, including all prevailing positive as well as negative drivers that might influence the ad effectiveness, in particular the click-through intention. Moreover, we expect that these insights will help marketers to be more effective when structuring their marketing communication strategies.

1 DATA-DRIVEN MARKETING COMMUNICATIONS

1.1 Integrated Marketing Communications

As marketing communications are considered to be the dynamic part of the marketing world, focusing on the return of investments and setting clear objectives (Colley, 1961, p. 76) are not the only things which need to be considered when planning the marketing communication activities. Simultaneously, new media is introducing new technological ways for companies to reach their consumers, companies on the market are implementing these ways to achieve a better cost efficiency and consumers are changing their overall perception on the current marketing communications (Belch & Belch, 2018). This causes marketing communications to go through drastic changes, therefore, companies need to adapt their communications strategy and create synergy throughout the planning process (Peltier, Schibrowsky & Schultz, 2003). In order to do so and consequently achieve a better performance, companies started using integrated marketing communications.

Integrated marketing communication (IMC) is defined as a "process of designing and delivering marketing messages to customers while ensuring that they are relevant and consistent over time and channels" (Palmatier & Sridhar 2017, p.162). Furthermore, due to the availability of consumer data, the IMC focuses on the consumer itself by delivering one-on-one marketing communications (Kim, Han & Shultz, 2004). The traditional IMC mix includes advertising, sales promotion, public relations, direct marketing and personal selling (Phelps & Johnson, 1996). These elements were using mainly physical materials and a non-personal communication approach, however, with digitalization it is important to include new elements such as social media or digital marketing (Kushwaha, Singh, Varghese and Singh, 2020).

Including new elements from the online world allows companies to deliver one-on-one marketing communication more efficiently by having an audience contact, or also named as a touch point perspective (Belch & Belch, 2018, p. 27). Any contact between a certain brand and a consumer, at any point in time, is considered a touch point (Malthouse & Li, 2017). Although categorizations of consumer touch points may vary, one that is very common is the one of paid, owned and earned media as seen in Figure 1 (Belch & Belch, 2018, p. 27).

Owned media touch points include channels that are in fact the owned assets that the company has full control over, such as websites, blogs, e-mails, social media accounts and mobile applications (Kotler, Kartajaya & Hooi 2019, p. 131). Ryan (2014, p. 35) defines the website as the main online real estate of the company and a hub where the company communicates with its consumers. Websites are considered as an important component of a company's digital marketing strategy, since they influence consumers' purchase intentions (Ryan, 2014, p. 35). Similarly, companies can use blogs as a channel to improve consumer's perception of the overall brand within the industry (Ryan, 2014, p. 35-36). Further, e-mails are another channel through which companies are able to maintain the relationships with their consumers by sending frequent newsletters (Ryan, 2014, p. 35-36).

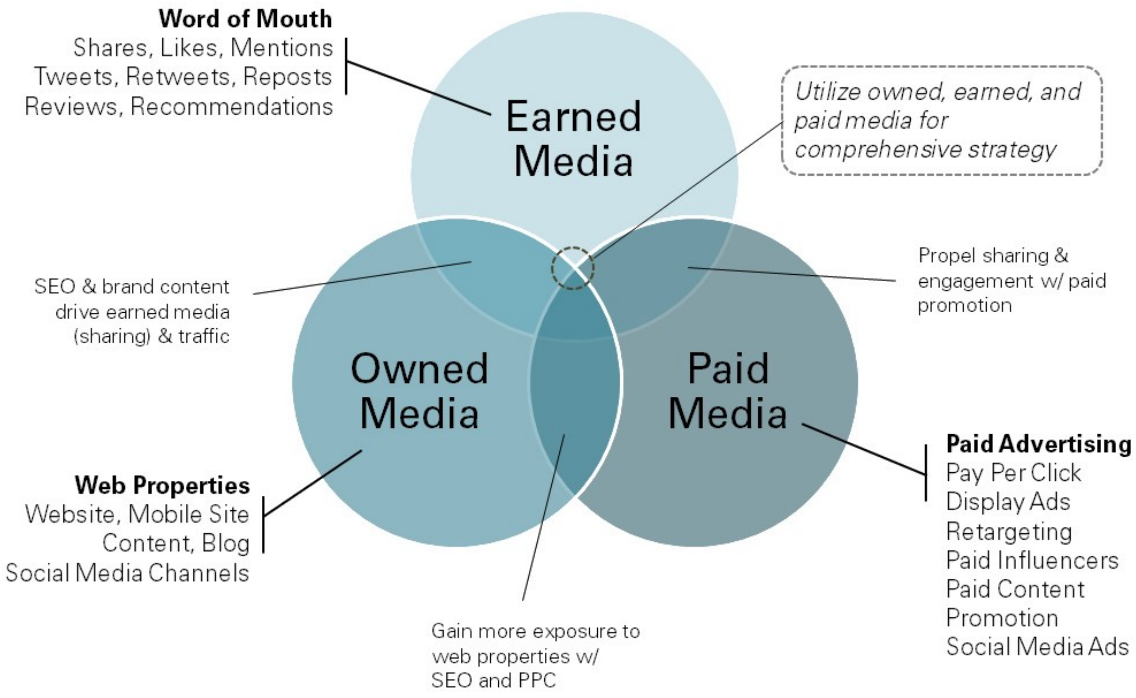
Over the past decade, social media channels have provided the best results in terms of growth for companies (Ryan, 2014, p. 35-36). Social media is defined as a group of websites and applications that "enable users to create and share content or to participate in social networking" (Lexico, n.d). One of the most popular social media channels nowadays are Facebook, Instagram, Twitter or Pinterest (Ryan, 2014, p. 35-36). Mobile applications are a software program that runs on a mobile phone (Cambridge Dictionary, n.d.) and are a channel through which companies can achieve a better consumer experience as they provide a more accessible and usable interface (Ryan, 2014, p. 35-36).

While with owned media touch points companies can reach and communicate only with their existing audience, with paid media touch points they can reach and acquire new consumers (Kotler, Kartajaya & Hooi, 2019, p. 131). In addition, through the channels included in paid media they are able to drive their consumers towards the owned media touch points. These channels include search engine listings, paid social media and mobile advertising media (Kotler, Kartajaya & Hooi, 2019, p. 131). Companies are tracking and quantifying the efficiency of their paid marketing communication through the click-through rate - the times customers clicked on an ad and the number of impressions - the times an ad has been shown (Kotler, Kartajaya & Hooi, 2019, p. 131).

By paying an advertisement in a specific search engine, the company's advert is positioned on the top or the top right spot of the search engine listing (Kotler, Kartajaya & Hooi, 2019, p. 131). On social media, paid advertisements allow the company to target specific social media users more precisely (Kotler, Kartajaya & Hooi, 2019, p. 131). Mobile advertising is defined as a "form of advertising that transmits advertisement messages to users via mobile phones, personal digital assistants (PDAs), or other wireless communication devices" (Chen & Hsieh, 2012, p. 545). It is a great channel to reach new users, due to its increasing popularity (Ryan, 2014, p. 35-36).

Earned media touch points are highly valued as they are more difficult to "earn" compared to the owned and paid ones. An example of an earned media touch point is the "word-of-mouth" channel (Kotler, Kartajaya & Hooi, 2019). According to Richins (1984, p. 697), word-of-mouth can be defined as an interpersonal communication between consumers who are expressing their personal thoughts after encountering a company's product and/or service. Earned media is normally "earned" through strong public and media relations, accompanied by paid and owned media as support channels (Kotler, Kartajaya, and Hooi 2019, p. 131).

Figure 1: Types of media



Source: OneUpWeb (2020).

While the offline traditional touch points, such as print ads, are difficult to observe and keep track of, the ones that take place in the digital environment enable continuous monitoring and data storage for a substantial number of consumers (Malthouse & Li, 2017). This is possible by leveraging advanced technologies as well as integrating big data (Patti, Hartley, Dessel & Baack, 2015). Big data is a term which refers to large and accurate databases (Mazzei & Noble, 2017, p. 1.) and in the digital era, integrated marketing communications are very unlikely to be delivered to the right audience without both reliable and up-to-date databases (Zahay, Mason & Schibrowsky, 2009). These databases hold information about individual consumers, which helps the companies create more relevant advertisements and consequently improve their relationship.

Overall, the collected data can either be structured, unstructured or semi-structured (Stimmel, 2015, p.153). On one hand, structured data is based on predefined data models and is easily stored, understood, and analyzed as it has predefined data models (Stimmel, 2015, p.153). This data can include names, dates, addresses etc. On the other hand, unstructured data does not have a predefined data model and meaningful connections between the data cannot be derived (Stimmel, 2015, p.153). It typically includes text-heavy information, images, video etc. Semi-structured data is a combination of both structured and unstructured data (Stimmel, 2015, p.153).

2.1 Consumer Data

Companies gather information about and directly from their consumers with the intention to improve their marketing activities (CMA, 2015). This collected information is referred to as consumer data. Burby & Atchison, (2007, p. 110) categorize consumer data into primary and secondary types.

Primary types of data include all behavioural, attitudinal and competitive data (Burby & Atchison, 2007, p. 110). Secondary data types are not as commonly used as the primary data by the companies, which is why they are named in such a way (Burby & Atchison, 2007, p. 110). Nevertheless, their impact is still significant. As secondary types of data are considered consumer interaction data, third-party research, usability benchmarking and community-sourced data (Burby & Atchison, 2007, p. 110). Both types of data are further explained as follows.

1.1.1 Primary data types

Behavioural data makes clear how users act during their website journey, including where they came from and what they clicked or interacted with (Burby & Atchison, 2007, p. 110). This type of data is based on the history of the user's clicks or more precisely, the stream of clicks and is usually used to predict the user's behaviour in the future. It gives us information on the average customer lifetime value, history of purchases, duration of the website visit etc. Moreover, this data is used primarily when conducting the analysis of online data and companies use it to support the rest of the collected data. Even though behavioural data gives us insights on how the user behaves online it does not give us clear justifications on why certain actions are undertaken (Burby & Atchison, 2007, p. 110).

Attitudinal data compliments the behavioural data by explaining the user's motivation behind the behaviour during their website visit (Burby & Atchison, 2007, p. 110). This data is gathered from consumer feedback, such as online reviews as well as focus groups and surveys (Burby & Atchison, 2007, p. 110). With attitudinal data, we can derive the consumer’s preferences, sentiments, motivation, challenges as well as their overall satisfaction (Al-Debei, Akroush & Ashouri, 2015, p. 707). Furthermore, consumer's attitudes can be measured through electronic word of mouth or consumer’s trust (Al-Debei, Akroush, & Ashouri, 2015, p. 707).

Competitive data gives us information on the competitor’s website performance, and it is provided from third party networks (Burby & Atchison, 2007, p. 114). This type of networks gathers vast amounts of data on the consumer’s Internet use and later on release it as reports. It is important to note that the data which is gathered by third party networks, is not as accurate as the behavioural or attitudinal data collected by the company itself on their own website (Burby & Atchison, 2007, p. 114).

1.1.2 Secondary data types

Consumer interaction data is the data collected during the interaction with the consumer. An example of such data is the call center data (Burby & Atchison, 2007, p. 116). Such data can provide valuable insights on the consumer’s overall experience with the company and helps to better understand what the customer is looking for. Based on this data, companies are able to tailor their websites, to better fit the consumer’s needs and consequently improve the consumer’s journey (Burby & Atchison, 2007, p. 117).

Third-party research is a great way for a company to receive information on the latest trends within their industry and other insightful information, such as strategic practices (Burby & Atchison, 2007, p. 117). Companies can get such information relatively fast and at an affordable price. However, the information within the research is generalized and intended for a wider use i.e., multiple companies can buy it. Therefore, such research does not provide enough information which would help a specific company to achieve a competitive advantage. One of the biggest third-party research providers is Nielsen Norman Group (Burby & Atchison, 2007, p. 117).

Nielsen Norman Group defines usability as “a quality attribute that assesses how easy user interfaces are to use” (Nielsen, 2013). Furthermore, usability benchmarking is observing how people behave and interact on different websites (Burby & Atchison, 2007, p. 117). It provides insights on how the competitors are performing by comparing the usability of the company’s website to the one of the competitors. Overall, with benchmarking we are able to evaluate consumer experience in relation to other companies that are trying to do the same thing by focusing the companies’ efforts on efficiency, consumer loyalty and consumer satisfaction (Burby & Atchison, 2007, p. 117).

Nowadays, across the Internet individuals gather and create online communities based on mutual interests and preferences (Burby & Atchison, 2007, p. 117). The data which is generated through these online communities is actually referred to as community-sourced data. Community-sourced data can be found across Internet websites, where people share their genuine opinion about a specific product, service and/or a brand (Burby & Atchison, 2007, p. 117). These communities can be a great data source through which consumer brand perception can be measured.

1.2 Web Data Collection Mechanisms

In the online world there are numerous data collection mechanisms including but not limited to JavaScript, CSS, HTML and others. However, for the purpose of this master thesis only the ones which are specifically inherent to online advertising will be explored in-depth.

For example, cookies are considered as an "essential technology" in online advertising which supports the distribution of consumer information. Jimenez, Arnau, Hoyos & Forne (2017, p. 2.) categorize user tracking mechanisms employing cookies into first- and third-party mechanisms. First-party mechanisms include all cookie activities carried out by advertisers who gather and mine first-hand consumer data (Jimenez, Arnau, Hoyos & Forne, 2017, p. 38). Valuable data which can be collected in such a way includes gender, preferences, social interactions and shopping behaviour patterns.

While first-party tracking is directly triggered by consumers, third-party tracking is caused by indirect, non-consented transactions (Jimenez, Arnau, Hoyos & Forne, 2017, p. 38). These transactions are formed by contents integrated within first-party websites from which consumer information is further disclosed with third parties. It is important to mention that apart from cookies, third-party tracking can also be developed through social plug-ins which potentially leak consumer browsing data to various social networks (Roesner, Rovillos, Kohno & Wetherall, 2012; Jimenez, Arnau, Hoyos & Forne, 2017, p. 38).

Cookies enable personal data sharing though Cookie matching (CM), which is a technology that helps the online advertising platforms and web trackers to identify visitors on the web (Jimenez, Arnau, Hoyos & Forne, 2017, p. 38). In fact, with the CM technology, it is possible for advertisers to map cookies on their own, based on the previously gathered user data (Ghosh, Mahdian, McAfee & Vassilvitskii, 2015). The omnipresence of CM across the Web has been also noticed in the experiments carried out by Bashir, Arshad, Robertson and Wilson (2016). They find that highly targeted advertisements are strictly based on shared information.

Contrary to the past where the level of personal data employed by cookies was very low, nowadays, cookies base their tracking mechanisms solely on personal data (Jimenez, Arnau, Hoyos & Forne, 2017, p. 38). In fact, they are classified as primary tracking mechanisms, enabled with a capacity which is difficult to erase. For advertisers who are trying to prevent the "traditional tracking", there are also the so-called Flash cookies (Jimenez, Arnau, Hoyos & Forne, 2017, p. 39). These cookies have a big storage size, non-default expiration and browser independent storage. McDonald and Cranor's (2012) research discover that the practice of respawning deleted cookies had become notably less used. In Table 1, we identify the most commonly used cookies to track users, however, not all existing tracking technologies are based on cookie data.

Table 1: Comparison of the types of cookies that are typically used to track users

	HTTP cookies	**Flash cookies**	**HTML 5 cookies**
Maximum storage size	4KB	100KB	5MB
Level of persistence	Low	Medium	High
Storage location	Within the browser	Outside the browser	Within the browser
Difficulty to delete	Low	High	High
Installation	Native	Through a plug-in	Native
Access level	One browser	Multiple browsers	One browser

Adapted from Jimenez, Arnau, Hoyos and Forne (2017, p. 40).

For instance, a tracking technology which supports personalized advertisements is Fingerprinting (Jimenez, Arnau, Hoyos & Forne, 2017, p. 39). Contrary to the previous mechanisms, this one does not run-on cookies and thus, cannot be deleted. This means that it can be tracked online at all times and can be used to trace some of the already deleted cookies.

Another technology is Canvas fingerprinting. Tracking mechanism mainly used by data aggregators, which allows creating a fingerprint from of the consumer's browser via HTML5 Canvas element (Jimenez, Arnau, Hoyos & Forne, 2017, p. 39). This type of element might be used on visible images or text within the consumer's browser. The technology can be blocked only under the condition - the domain of the provider is familiar, as distinct browser parameters can be kept (e.g., installed plug-ins) in order to generate user-specific fingerprints (Jimenez, Arnau, Hoyos & Forne, 2017, p. 39).

Finally, one of the most universal tracking technologies used in online advertising is the HTML5 local storage. Contrary to Flash cookies or HTTP, this type of tracking has much bigger capacity and doesn't expire or depend on the browser (Jimenez, Arnau, Hoyos & Forne, 2017, p. 39). With HTML5 Local Storage, first and third parties can save data within the browser which stays there even if the user deletes the existing cookies (Jimenez, Arnau, Hoyos & Forne, 2017, p. 39).

1.3 Web Data Analysis

Web analytics gives the company insights on users' behaviour across websites and mobile applications by translating it into data which can be later analyzed (Beasley, 2013, p. 2). With the help of it, marketers are able to track the degree of effectiveness of their campaigns. Burby, Brown and WAA Standards Committee (2007, p. 3) define web analytics as a technique that collects, measures, analyzes and reports users' data from websites and applications.

We can observe web analytics from a micro and macro perspective (Kaushik, 2010, pp. 70–73). Macro analysis gives a broader view and is usually done before the micro analysis. With the help of it companies can get information such as their website traffic or abandonment rate. The micro analysis shows a more detailed view on the user's behaviour like for example when they add something in their shopping cart (Webster, 2014).

Defining clear and quantifiable goals is crucial for a company to get measurable results (Flores, 2014, p. 4.). Based on metrics such as key performance indicators (KPIs), companies are able to define goals (Waisberg & Kaushik, 2009). A KPI can either be a count or a ratio. While the count is a single number (e.g., total sales), the ratio is normally a count divided by a count (e.g., conversion rate). For all metrics, it is presumed that they are connected to a human visitor's action (Burby, Brown & WAA Standards Committee, 2007, p. 4). For the metrics to be efficiently applied, the company has to align them with their unique needs (Järvinen & Karjaluoto, 2015, p. 117). However, metrics alone do not have derivable insights without dimensions. Dimensions provide context for the metrics by giving "a fundamental dimension of visitor behaviour or site dynamics" (e.g., a country of origin for the user) (Burby, Brown & WAA Standards Committee, 2007, p. 4).

After the KPIs are defined, the company can proceed with data collection. The collected data needs to be accurate and stored in a database in order to perform the data analysis smoothly (Waisberg & Kaushik, 2009, p. 5.). In addition, it is of utmost importance for the data to be well-understood for the changes to be correctly implemented (Waisberg & Kaushik, 2009). The flow of steps in the web analytics process can be seen in Figure 2. For marketing analytics to be effective, it is best to carry out the process repeatedly as there is little gained value when the process cycle is carried only once (Waisberg & Kaushik, 2009).

Figure 2: Steps in the web analytics process

Adapted from Waisberg & Kaushik (2009, p. 1).

Web analytics stimulates growth within the online marketing world, by enabling marketers to calculate their work effectiveness through metrics (Beasley, 2013, p. 2.). For instance, they can get data which gives insights on how much money was spent to obtain particular visitors by analysing the number of website visitors which end up buying something on the website.

1.3.1 Metrics and KPIs

Selecting the right metrics and key performance indicators is crucial if a company wants to measure the effectiveness of their marketing communications (Chaffey & Ellis-Chadwick, 2012, p. 203). Not only do they give insights on the current set of circumstances, but also, they help with the planning process of future marketing communications as well as its outcomes (Chaffey & Ellis-Chadwick, 2012, p. 203). The metrics can be divided into standard clickstream metrics such as conversion rate, time spent on the webpage, bounce rate or exit rate and into basic metrics used to evaluate the response of a marketing campaign, such as click-through rate or cost-per click (Kaushik, 2010, p. 37–56).

The standard clickstream metrics refer to the visitor's clicks on the company's website (Dale Wilson, 2010). In web analytics, a user's visit to a website is called a session (Wang, Shen, Chen & Wedman, 2011, p. 23). The user session lasts from the moment a visitor enters a website until he/she leaves. However, if the visitor is not active for a certain amount of time, the session will end automatically - depending on the web analytics tool that is being used. Sessions can also be looked at as interactions of a visitor with the website and all the subpages on it (Burby & Atchison, 2007, p. 240). Unique visitors are a comparable metric to user sessions. With the help of cookies, unique visitors are counted only once, taken in account a longer period of time. The problem with this kind of metrics is that when the user deletes the browsing cookies and access the website once again, he/she will be considered as a unique visitor (Kaushik, 2010, p. 38).

Marketers can use basic metrics to evaluate the response of their marketing campaign. A click-through rate (CTR) is used to measure the performance of an ad and it is defined as a ratio between the number of times an ad has been shown to people to the number of times it has been clicked on (Google Ads Help, n.d.). Similarly, a view-through rate can be used to measure the "number of completed views of a skippable ad over the number of initial impressions" (Google Support, n.d.). Furthermore, cost-per-click (CPC) is the actual click cost on a specific advertisement (WordStream, n.d.). A high click-through rate can potentially reduce the company's cost-per-click rate.

All metrics which the company decides to use should be aligned with their business performance and measurable in an easy manner (Trammell, 2016). Although these are things companies should always keep in mind, they should also be aware that the metrics are applicable on an individual level and most likely differ in each company (Järvinen & Karjaluoto, 2015). Therefore, metrics should always be unique in order to be effective.

1.3.2 Tools for Web data analysis

When a company is gathering data, producing analytics and improving the efficiency of key business processes, it means that the company is leveraging the evidence-based strategy approach (Nakatani & Chuang, 2011). The adoption of this approach does not only seek a vast amount of data, but advanced analytical data processing capacities as well. These capabilities are deliverable with the use of web analytics tools as they "collect click-stream data, track users' navigation paths, process and present the data as meaningful information" (Nakatani & Chuang, 2011, p. 172).

Web analytics tools can be differentiated depending on their characteristics. For example, one way to categorize them is based on the data collection methods: page tagging or transaction log files analysis (Waisberg & Kaushik, 2009; Nakatani & Chuang, 2011, p. 172). Page tagging gathers data by utilizing invisible built in JavaScript code within web pages (Nakatani & Chuang, 2011, p. 173). This means that when an individual visits a webpage with an embedded JavaScript code, the code gathers data about the "site visit" and later sends it to an in-house database or to a web data gathering centre. Transaction log files contain data such as the time duration of the transaction or the requestor's IP (Nakatani & Chuang, 2011, p. 173). After this data has been recorded, a web analysis software is utilized to analyze the log file.

Another way to categorize web analytics tools is by the ways the functions of web analytics are accessed (Nakatani & Chuang, 2011, p. 174). They can be accessed as a software as a service (SaaS), as a software which is installed in-house or via an app service provider (ASP). The third example on how to classify these tools is to make use of web site access devices such as non-mobile or mobile web analytics (Nakatani & Chuang, 2011, p. 174). When deciding on the tool, the company should take into consideration which access devices do their target consumers use. Measuring the time lag between data gathering and the actual available analytics can be the fourth way to categorize web analytics tools (Nakatani & Chuang, 2011, p. 174). While some tools need more time to translate the gathered data to the user (15 minutes or more), others can pull data almost immediately (Nakatani & Chuang, 2011, p. 174).

There is a great deal of tools, both free and paid, used for web analytics. The most common ones include Google Analytics, Yahoo Web Analytics, Facebook Insights, Twitalyzer, KissMetrics, Compete and etc. (Dubois, 2020).

Google Analytics is by far the most popular tool for clickstream analysis with a rough estimation of website usage between 30 and 50 million worldwide (McGee, 2015). It works mainly by using page-tagging as a data collection method, making it relatively easy to use (Dubois, 2020). This tool is completely free and is an easy way to generate in-depth statistics about visitors to the company's website: where they are coming from, what is their journey on the website, how often do they re-visit the website and many other insights. Currently, it is being employed by over 50% of the top 10.000 websites worldwide (Dubois, 2020). Yahoo Web Analytics offers similar insights as Google Analytics, however, the surveying has a greater depth of knowledge. Unlike Google Analytics, the tool also enables companies to import cost of goods information (both raw and real-time data) and is better when it comes to profiling, filtering or customization (Dubois, 2020). Companies who have mastered the Google Analytics tool and are looking to explore more in-depth with their analyzes, often turn to Yahoo Web Analytics (Dubois, 2020).

Facebook Insights is a social analytics tool for companies who consider Facebook as part of their business (Dubois, 2020). It offers aggregate data such as follower count, likes or comments on posts and is a simple, free tool to use. The tool also enables companies with an option to prepare custom, group reports (e.g., based on the country of origin or age) and measures ad efficiency (e.g., click-through rate, engagement rates, post or page reach) (Facebook Analytics, n.d.). Finally, Facebook Insights allows companies to calculate the customer lifetime value (Facebook Analytics, n.d.) and is the best tool to help the engagement with consumers (Dubois, 2020). Twitalyzer, a free Twitter analytics tool, works in a similar way, giving a perspective on the company's page impact on consumers: number of followers, retweets or the account's overall engagement frequency in conversations (Dubois, 2020).

Due to the multiplicity of available tools, all with a variable price and level of quality, companies might have difficulties verifying the tools' reliability (Nakatani & Chuang, 2011). Depending on the tool, the required data to generate the analytics may not be under the company's control and can be gathered during a longer time framework. Therefore, the process of choosing a proper web analytics tool which meets the company's needs is extremely important (Nakatani & Chuang, 2011 p. 172).

2 AD PERSONALIZATION AND THE PRIVACY PARADOX

2.1 Online Advertising

With the support of technology, the Internet became the main communication channel across the world (Wei, Jerome & Shan 2010). Online advertising can be defined as a marketing strategy that is based on the use of the Internet. The main goal is to acquire and increase the amount of website traffic as well as to target and deliver messages to the appropriate audience (Techopedia, 2018). In the past, traditional channels such as newspapers, television and radio had a prevailing presence in the advertising media. Nowadays, online advertising is the main driver in many, if not all advertising initiatives (Kotler, Armstrong, & Opresnik, 2018, p. 29). It is a well confirmed fact that online advertising grew at a much faster rate than traditional advertising channels.

Goldfarb and Tucker (2011a) differentiate online advertising channels from the traditional ones from two aspects: measurability and targetability. In a digital environment, the ad responsiveness is easily tracked and therefore more measurable (Goldfarb & Tucker, 2011a, p. 5,). Moreover, given the possibility to individually track and target the users, marketers are able to achieve a higher targetability with online advertising. All online advertisements such as social media ads, display ads or search engine ads have traits of measurability and targetability (Goldfarb & Tucker, 2011a, p 5.). In 2020, ad spending in the digital advertising market is forecasted to reach 345.948 million US$, which is almost 40% more, compared to the ad spending in 2017 (Statista, 2020).

Furthermore, online advertising is not only about laying down an ad somewhere on the Internet and expecting to have immediate positive results. Online advertising is about building a campaign, by combining various unique elements which maximize its effectiveness (WordStream, n.d). These elements can include text and visual ads, landing pages, sponsored content or remarketing. Naturally, not every campaign should include all elements, however, a campaign is always more effective when these elements are combined rather than when they are alone.

Text and visual ads are the most basic elements of online advertising (WordStream, n.d). While text-based ads are commonly in the form of pay-per-click ads, visual ads take the form of online banners. The latter are also referred to as display ads. Google AdWords offers advertisers both text-based and display ads (Google Ads Help, n.d.). Further, companies use specialized webpages which individuals are redirected to when they click on a specific ad (WordStream, n.d). These webpages are also called landing pages and are used to showcase particular products which have also been displayed on the initial ad.

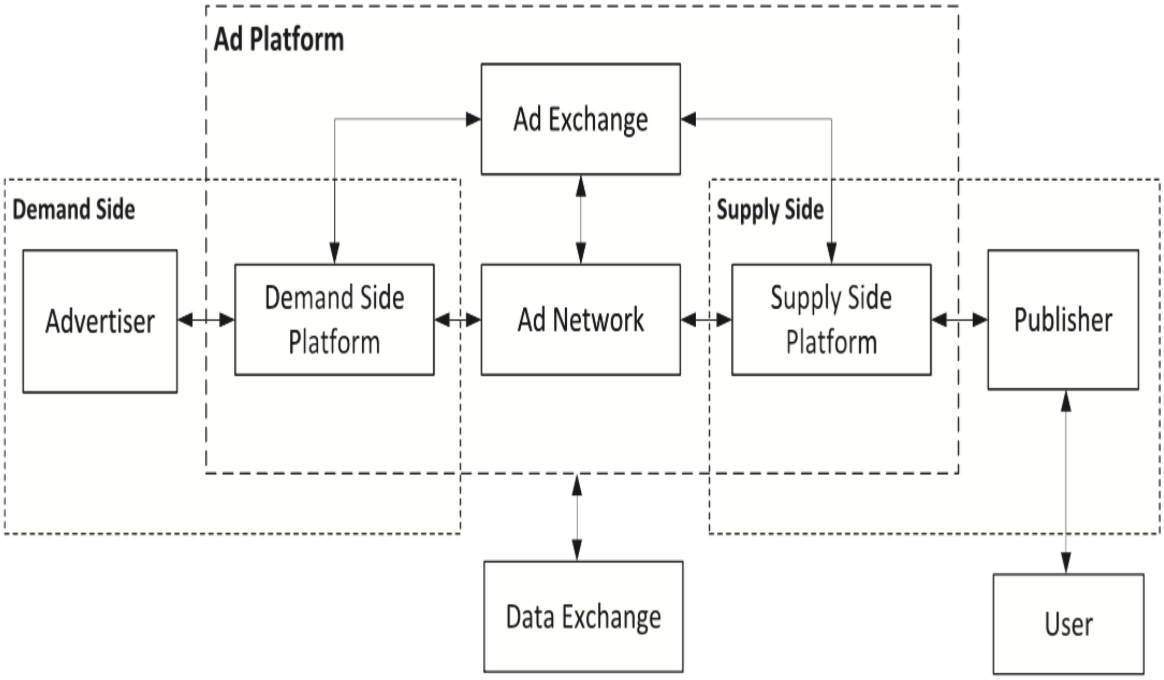
Another element which advertisers have at their disposal to use in their online advertising campaigns is sponsored content (WordStream, n.d). This type of content can either take a form of native advertising or sponsored adverts on social media platforms such as Facebook or Instagram. Finally, one of the most important elements that advertisers can leverage is remarketing. Remarketing helps advertisers show ads to other websites to visitors who have abandoned their own website before acting (e.g., to complete purchase) (WordStream, n.d). This element can be adapted to search, display and/or social media advertising campaigns and help advertisers increase their website traffic by serving as a "reminder" to the visitor.

The appearance of new players in the online advertising world causes the industry's infrastructure to become more and more complex (Jimenez, Arnau, Hoyos & Forne (2017, p. 34). Although there are certainly new players, we can still pinpoint three components which drive the key roles in online advertising (Jimenez, Arnau, Hoyos & Forne 2017, p. 34).

In particular, they include advertisers, publishers as well as ad platforms and they all have a clear goal: showing the appropriate ad to the appropriate user. While players such as advertisers and publishers stand for the demand and supply ends within the economic model controlling an online advertising service (Evans, 2009), the actual interchange between them is possible via an intermediate infrastructure – ad platform (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). Even though user data is the driver for decision-making in online advertising, users themselves are not directly regarded to take part within the industry's infrastructure. This is mainly due to the fact that at the end of the day, they are not the ones who receive the revenues from the business (Jimenez, Arnau, Hoyos & Forne 2017, p. 34).

Figure 3 helps us visualize the interactions between the players in the ad platform scheme in a more detailed manner. The advertisers in the scheme are in fact companies, which are the paying for an ad so that their products or services can be promoted (Yuan, Abidin, Sloan & Wang, 2012). Their advertisements are shown to internet users on particular webpages that provide content, such as search engines or blogs which are also referred to as publishers. Publishers have designated positions on the previously mentioned webpages, where such advertisements are displayed.

Figure 3: Disaggregated ad platform scheme and interactions between players



Source: Jimenez, Arnau, Hoyos and Forne (2017, p. 35).

Technically, the advertisers could directly arrange with the publishers to place their ad on their webpage, however, that would not be as successful as it is crucial to have ad platforms as an intermediate (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). Ad platforms are the connecting factor between the demand side – advertisers and the supply side – publishers (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). They help increase the efficiency of the advertisement by matching it with the right audience, according to the gathered data and user's profile. Ad platforms consist of interrelated services such as demand-side platforms, ad networks, ad exchanges and the supply-side platforms (Jimenez, Arnau, Hoyos & Forne 2017, p. 34).

While demand-side platforms work with the advertisers to help them pick the right users to display the ad, ad networks help them with the selection of an appropriate ad space (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). Such networks are for example GoogleAd-Sense or PulsePoint. Furthermore, ad exchange platforms combine multiple ad networks and therefore the available ad space of the publishers, to give the advertisers the possibility of bidding for an ad space (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). Based on this, advertisers can determine the amount they are willing to spend for a particular ad space and the one who offers the most is and is the highest bidder is able to display the ad. Such process of distributing the ad via different parts of the ad platform helps the ad to gain better results. On the other side of the ad platform scheme, supply-side platforms are the ones helping the publishers by managing their available ad space and providing it to the advertisers (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). They are also the ones in charge of targeting the ad to the appropriate consumer.

The last, yet highly important part of the process is data exchange. Data aggregators are essential for this part, as they are the ones collecting and mining all the data about the users (Jimenez, Arnau, Hoyos & Forne 2017, p. 34). In order for the supply and demand side to make appropriate marketing and targeting decisions, data aggregators share the collected information with them (Jimenez, Arnau, Hoyos & Forne 2017, p. 34).

2.2 Ad Personalization

The advertising industry has reached a point where consumers are overexposed to different marketing messages, coming from traditional and digital channels (Schreiner, Rese & Baier, 2019). Because of the vast number of different messages, consumers are starting to avoid all the advertising clutter and are reaching for ad blocking software (Schreiner, Rese & Baier, 2019). As already discussed in the previous chapters, one of the ways how marketers are trying to improve that negative response and improve the effectiveness of their marketing communications is by following one-on-one marketing communication strategies, where it is essential that they adapt their marketing mix to a consumer as an individual (Arora et al., 2008).

One-on-one marketing can either be found in a form of customization or personalization (Arora et al., 2008). The main difference between these two forms is that in customization, the consumer itself is the one requesting a customized product or service (Montgomery & Smith, 2009), while in personalization, it is up to the marketer to determine the appropriate marketing mix that is considered suitable for a particular individual (Arora et al., 2008). In our thesis, we will focus on the personalization part of the one-on-one marketing strategy, in particular personalization in online advertising.

Ad personalization focuses on an individual consumer, by tailoring the ads according to his or her preferences (Bleier & Eisenbeiss, 2015a; Keyzer, Dens & Pelzmacher, 2015). Consumers can see personalized advertisements in a form of promotional electronic newsletters, product recommendations (Awad & Krishnan, 2006), social media advertisements (Keyzer, Dens & Pelzmacher, 2015), banner advertisements and mobile advertisements (Bang & Wojdynski, 2016). The creation of a personalized advertisement is not doable without the consumer's data, collected with the help of tracking mechanisms or provided from the consumer directly (Awad & Krishnan, 2006).

Li (2016) differentiates between actual personalization on one hand and perceived personalization on the other. While actual personalization happens when a company uses consumer collected data to create a personalized advert, perceived personalization occurs when the consumer is the one who decides whether a delivered message does or does not address his/her preferences. In the latter, it might be the case of a generalized advert, which reflects the consumer's preferences and thus results in perceived personalization (Li, 2016).

Primarily, personalization is based on consumer's data, followed by the company's ability to collect and analyze that data (Chellappa & Sin, 2005). Murthi and Sarkar (2003) develop their view on personalization in more detail with a three-stage process. First stage is learning, which focuses on getting information about a consumer's preferences (Murthi & Sakar, 2003, p. 1346). The data itself might be provided directly from the consumer or collected through consumers online activities. Second stage describes the matching (Murthi & Sakar, 2003, p. 1346). In particular, the stage is based on applying the gathered knowledge from the previous step which enables to create offers that fit consumers preferences. This is best done through targeted messages, product recommendations or in some cases, even personalized prices. The last, third stage is all about evaluation and tracking performance of the personalization methods used in the previous steps (Murthi & Sakar, 2003, p. 1346). In terms of personalized online advertising the last, evaluating stage is tracked with measurable results such as a click-through rate (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015), which we will be using in our thesis to track ad effectiveness.

Furthermore, with the development of machine learning, personalization methods are becoming more impressive year after year (Evergage, 2020, p. 1.). Evergage's annual study on personalization conducted in 2020 shows that 94% of marketers are using personalization as a part of their marketing strategy to achieve better customer experience, customer loyalty and an increase in return on investment. Besides, consumers also benefit from personalization with more relevant advertisements (Gironda & Korgaonkar, 2018), better products and/or services (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015) and a lower cognitive load.

Various studies have highlighted the positive results of personalization in advertising by improving the effectiveness of the ad (e.g., Pavlou & Stewart, 2000; Tam & Ho 2005; Kalyanaraman & Sundar 2006; Noar, Benac, & Harris 2007; Sohl & Moyer 2007, Arora et al. 2008; Walrave, Poels, Antheunis, Van den Broeck & Van Noort, 2018). As seen in Table 2, there are different positive effects of personalization in different types of online channels.

Table 2: Overview of the effects of personalization in online advertising

Channel	Measure	Source / Studies	Additional Insights, results
Email Marketing	Click-through-rate (CTR)	Postma & Brokke (2002)	A doubled click-through-rate in case of personalized email.
		Singh, Singh & Shriwastav (2018)	Average click-through rate of personalized email was 18% compared to overall average rate of 8.9% for non-personalized email.
		Ansari & Mela (2003)	Increase in click through rate for 62% for a personalized e-mail
Social Media Networks	Click-through intention	Keyzer, Dens and Pelsmacker (2015)	Increased click through intention for a moderately personalized advertisement, by increased perceived ad relevance
	Brand engagement	Shanahan, Tran, Taylor (2019)	Perceived personalization highly influences brand engagement and attachment, achieving 80% better results than non-personalized
		Walrave, Poels, Antheunis, Van den Broeck & Van Noort, 2018	Better attitude and brand engagement towards the highly personalized ad in case of personalized advertisements.
	Click-through-rate (CTR)	Bleier and Eisenbeiss (2015b)	Overall personalization strongly increases click-through of a banner and highly personalized banners achieve better results. Authors connect it to timing and placement as further development.
	Attention	Bang & Wojdynski (2016), Malheiros et al. (2012)	Personalized advertisement attracted more attention of the consumers and for a longer period of time.
Mobile advertising	Open rate (number of views), Attitude	Xu, Liao and Li (2008)	Higher number of views of personalized advertisements as well as better attitude.

Source: Own work.

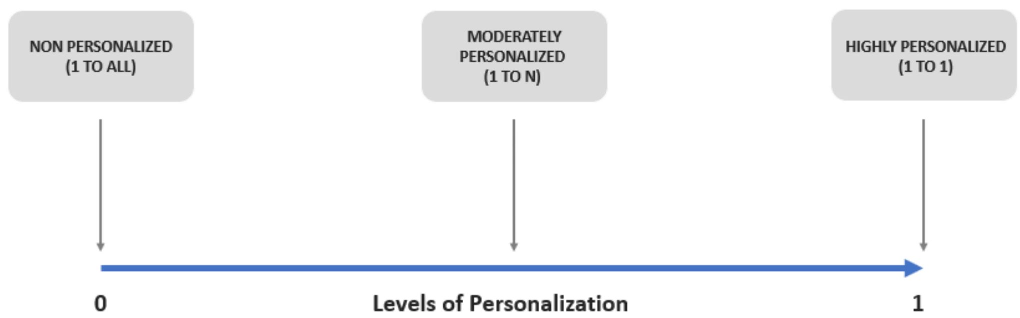
Postma and Brokke (2002) studied email marketing personalization and found a double increase in the click-through rate of personalized emails compared to non-personalized ones. Bleier and Eisenbeiss (2015b) observed personalization in banner advertising and found positive results of personalized messages with increased click-through-rate (CTR), if shown to the user right after his/her visit on a specific webpage. Further, Keyzer, Dens and Pelsmacker (2015) studied personalization on Facebook and also noticed an increase in the click-through intention, when the ad was perceived as relevant.

Bang & Wojdynski (2016, p. 872) examined personalization in terms of consumer's attention and concluded that personalized advertising grabs more attention, for a longer period of time, compared to non-personalized. In fact, the level of attention becomes even higher when consumers are under high cognitive pressure. With the increase in mobile advertising, personalized ads are observed to cause less negative response, as a result of the higher value the consumer receives i.e., more valuable information (Baek & Morimoto, 2012). Based on this, perceived personalization advertisements trigger less skepticism and consequently have lower avoidance rates.

2.2.1 Levels of personalization

Ad personalization can be divided into three levels: non-personalized, moderately personalized or highly personalized, depending on who the targeted receiver of the message is as seen in Figure 4 (Li, 2016; Perez & Steinhart, 2014). Non-personalized ads include messages that are not addressed to any specific target. Further, moderately personalized ads are messages that address a group of people who share similar characteristics. Lastly, highly personalized ads target the audience individually (Li, 2016). Bang et al. (2019) however, take a two-stage personalization approach, omitting the non-personalized step and focusing either on the individual or on the wider audience as a group.

Figure 4: Levels of personalization



Adapted from Arora et al. (2008, p. 310).

It is important to stress that the level of personalization is highly correlated to the individual's situation. Walrave et al. (2018) have observed that higher personalized ads on social media networks received better responses to moderately personalized in the age group of adolescents. On the contrary, Perez and Steinhart (2014) find that when using consumer’s social identity information, the moderate level of personalization yields better results than non-personalized or highly personalized. This is due to the fact that using consumer sensitive information in order to provide a highly personalized message triggers privacy concerns. Similarly, a study by Aguirre, Mahr, Grewal, Ruyter and Wetzels (2015) is also resulting in a decreased click-through rate in case of high personalized messages, including sensitive financial information being used without consumer’s knowledge.

Personalization leads to many positive benefits for the company, however in some cases it also results in an emergence of consumers’ privacy concerns. With this considered, marketers need to be aware that personalization can bring positive as well as negative effects for the company if not used and implemented properly (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015).

2.2.2 Ad relevance

Ad relevance plays an important factor in online advertising as it measures how related consumers feel towards a certain product or service and how much it responds to their needs (Jung, 2017). Perceived relevance is connected not only to consumers cognitive responses, but also their behaviour (Jung, 2017). It was found that personalized advertisements are perceived to be more relevant to consumers compared to non-personalized ones (Xia & Bechwati, 2008) and consequently receive a more positive response (Pavlou and Stewart 2000; Iyer, Soberman & Villas-Boas, 2005; Kalyanaraman and Sundar 2006; Arora et al. 2008; Anand & Shachar, 2009; Noar, Harrington & Aldrich, 2009).

Celsi and Olson (1988, p. 211) define personal relevance or self-reference as a “perceived linkage between an individual's needs, goals, and values (self-knowledge) and their product knowledge (attributes and benefits)”. The more those elements connect to consumer’s values or needs, the stronger the personal relevance emotions become. Self-referencing was initially studied in connection to psychology (Liu, 2015) and the link itself between ad relevance and consumer’s positive reactions can be explained with the help of self-referencing theory (Jung, 2017).

Positive reactions occur due to consumers' deep knowledge about themselves, which then leads them to numerous associations related to the advertised products (Mayers-Levy & Peracchio, 1996). According to Mayers-Levy and Peracchio (1996), self-referencing increases the number of associations and helps the consumer to recall an ad. Further, self-relevance helps motivate the consumer to elaborate a message and consequently increase the ad persuasion (Jung, 2017). Similarly, to some research findings on the levels of personalization, when a message is too complex and requires more cognitive load, the overall ad effectiveness is lower and evokes reactance (Mayers-Levy & Peracchio, 1996). Contrary to this, when the message is less complex and therefore triggers a low cognitive load, the ad becomes more effective.

Furthermore, previous studies have shown a positive impact of self-reference on the consumer’s recall (Debevec, Spotts & Kernan, 1987), attention, understanding, as well as search and shopping behaviours (Celsi & Olson, 1988). Similar positive results have been found in mobile advertisements with self-relevance positively affecting message complexity, response rate and acceptance of the ad message itself (Jung, 2017).

2.3 Personalized Marketing Communication Strategies

When talking about personalization marketers use different strategies and/or techniques to deliver personalized marketing messages. In the following subchapter, we identify and analyze the most common personalization strategies used by companies.

2.3.1 E-mail marketing personalization

With 78% of marketers using it as a part of their marketing strategy, e-mail marketing stands as one of the most commonly used personalized marketing communication tools (Evergage, 2020). It is also one of the personalization tools which has been observed the most in literature (Strycharz et al, 2019, p.644). Companies use email marketing as a channel to gain new consumers as well as to obtain the existing ones and interact with them more often (Sahni, Wheeler & Chintagunta, 2016).

Personalization in email marketing has become a standardized way of email delivery from marketer’s perspective (Strycharz et al, 2019). One of the most basic examples is including the consumer's name in the greeting of the message. In more advanced personalization techniques marketers use demographic data or behavioural data to personalize the content of the email itself (Strycharz et al, 2019, p. 644).

Postma and Brokke (2002, p. 142) conclude that using personalization in e-mail marketing positively affects the click-through rate and expect for the average click-through rate to double when using personalization, compared to non-personalized e-mail message. Furthermore Sahni, Wheeler and Chintagunta (2016) imply that the use of personalization in e-mail marketing shows long term positive effects by increasing consumer’s recall of seen information. Their research also shows an increase in the email’s open rate as well as a lower unsubscribe rate in cases where the subject line includes the consumer’s name (Sahni, Wheeler & Chintagunta, 2016). Similarly, Singh, Singh and Shriwastav (2018) discovered that average click through rate of personalized email was 18% compared to overall average click through rate of 8.9% for non-personalized.

In addition, White et al (2008) examine the levels of personalization used in e-mail marketing in cases where the consumer does not understand the reason for the use of his/her information. In these situations, he does not find an increase in the consumer's click-through intentions when using e-mail personalization, but in fact a decrease.

2.3.2 Social media advertising

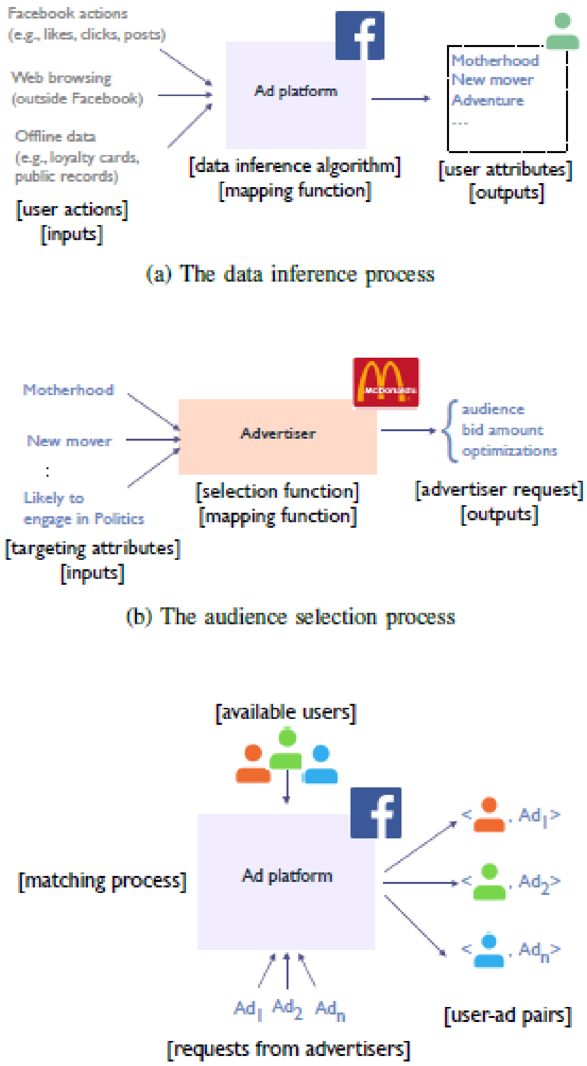
Social media spending has been growing year by year. Chief marketing officers reported an increase in budget spending on social media by 56% in the last 3 years (CMO survey, 2020, p. 20). Marketers are aware of the potential of social media and they consider it one of the essential channels to present and raise awareness about their products (Shareef et al, 2019). With the help of social media, companies have the chance to target their consumers faster and at a lower price (Keyzer, Dens & Pelsmacker, 2015).

Compared to other personalization techniques, social media advertising offers marketers information about consumer's likes, tags and comments (Strycharz et al, 2019, p.644). Advanced machine learning techniques and algorithms have reached a point where marketers are able to predict the consumer's preferences (based just on his/her Facebook likes) better than his/her best friend (Youyou, Kosinski & Stillwell, 2015). Consumers share more detailed information on social media than elsewhere, which allows marketers to create more personalized messages (Keyzer, Dens & Pelsmacker, 2015). That is one of the reasons why social media is a great place for researching how consumers react to personalized advertising.

Out of all social media platforms, Facebook is achieving the highest growth (Shareef et al, 2019). With its 2.7 billion active users per month, it is considered as the biggest among the social networks (Statista, 2020). Facebook offers marketers to choose between two types of advertisements - those that are positioned on the right side of the page and those that are less noticeable, by being implemented somewhere along the consumer's newsfeed (Aguirre, Roggeveen, Grewal & Wetzels, 2016). The ones which are shown in the consumer's newsfeed are in the same style as the rest of the posts, making it less interruptive and consequently resulting in a higher click-through rate. Some ads can be extremely relevant and created in such way that consumers do not even realize that they are in fact viewing an ad (Aguirre, Roggeveen, Grewal & Wetzels, 2016).

The overall ad receiving process on Facebook is relatively easy and can be explained in three stages (Andreou et al., 2018). As seen in Figure 5, the first step includes the platform's collection of consumers' information and definition of their attributes. Further, the next step is in the marketers' hands, who has to define the ad's target audience and the budget they are willing to spend for a bidding price. Last step is called user-ad matching, involving an auction on adverts to distinguish which ad will be shown to which consumer (Andreou et al., 2018, p. 3).

Figure 5: Ad receiving process



(a) The data inference process

(b) The audience selection process

(c) The user-ad matching process

Source: Andreou et al. (2018, p. 3).

Facebook offers marketers to target their consumers in different ways. One of those ways is with the help of characteristics that are collected by Facebook itself (Andreou et al., 2018). With this method, that Andreou et al. (2018) call traditional Facebook targeting, companies target their potential consumers by picking from existing collected characteristics such as their demographics or interests. In addition, Facebook collects data from their consumers not just based on their profile information or likes, but also consumers' activities outside the app such as consumers websites visits (Andreou et al., 2018). However, there are also some consumers who do not share their personal information on social media and yet they still get targeted with the help of second degree targeting. Such type of targeting uses information of the consumer's friends, assuming they share similar preferences (Jung, 2017).

Another way Facebook lets companies target their consumers is with data broker targeting. Data brokers help Facebook with information that is more sensitive and harder to get to, such as consumers' income or past purchase behavior. The last and more recent targeting technique is personally identifiable information (PII) targeting. This method helps companies target their consumers based on the existing data that they have about them from other channels, such as their name or phone number (Andreou et al., 2018).

As a further matter, perceived personalization on social media has proven to positively affect consumers by achieving higher brand attachment, engagement with the ad (Shanahan, Tran & Taylor, 2019), ad credibility and attitude (Tran, 2017, p. 240). Additionally, perceived personalized social media ads, compared to other marketing channels, have more chances to be rated higher due to the interactive nature of social media platforms (Shanahan, Tran & Taylor, 2019). Another one of the positive effects of personalized advertisement on social media is also a higher click-through intent in cases where consumers are aware of the company's data collection methods as opposed to the cases where the consumers are not aware of the methods (Agguire et al, 2015, p. 41). In the latter, the click-through intention actually decreases.

2.3.3 Mobile advertising

In the last quarter of 2019, more than half of the world's web traffic was generated through mobile devices and one third of the worldwide ad spending came from mobile advertising (Ryu & Park, 2020). That is more than twice more of what advertisers spend on desktop advertisements, which indicates how important mobile advertising has become in the eyes of marketers. Even though personalization in terms of applications' content and notifications has not been well documented in literature, it is still considered as a new phenomenon (Strycharz et al, 2019, p. 645).

While initially mobile advertising was based mostly on SMS and MMS ads (Ryu & Park, 2020), nowadays, marketers can reach consumers with the help of applications and push notifications as they allow them to target them with highly personalized content (Tong, Luo & Xo, 2020). Mobile apps are broadly used by consumers on a daily basis to communicate with friends, shop, pay and browse the web (Tong, Luo & Xo, 2020). In fact, consumers prefer using applications compared to browsing the mobile web, because they are easier to search through (Kang, Mun & Johnson, 2015, p. 210).

With the help of built-in trackers and sensors, mobile phones provide marketers with instant hyper context data (Tong, Luo & Xo, 2020). This means that they have information regarding the consumer's location and timing, as well as who they are with. In addition, they also gather information about consumer online behaviour, which together gives them insights into consumer's cross channel patterns (Tong, Luo & Xo, 2020). Location information is extremely important in mobile advertising and it is specific for mobile devices. One of the ways marketers use it is by targeting consumers who are nearby their shop with notifications, ads or coupons (Grewal, Bart, Spann & Zubcsek, 2016). This potentially increases the consumer's purchase intentions.

2.3.4 Online behavioural advertising

Online behavioural advertising (OBA) or targeting is a technique based on collected data during customer's online browsing activity and aims to create more relevant as well as individually tailored advertisements (Boerman, Kruikemeier & Borgesius, 2017, p. 364). The level of personalization in online behavioural advertising differs on the amount of data that is being collected. While for the creation of some ads only one activity or search term is used, for others it might involve a combination of different consumer information (Boerman, Kruikemeier & Borgesius, 2017, p. 365).

One of the ways data is gathered in OBA is through cookies. Cookies can be defined as documents which include text and are stored on a customer's device from which he is visiting the webpage (Smith, Noort & Voorveld, 2014, p. 15). They help to process certain functionalities of the webpage, while they also help the advertiser keep track of the webpages the consumer visits. In fact, visited webpages serve as the grounds for the advertisers to create customer profiles of expected interests (McDonald & Cranor, 2010). These profiles make it easier for the advertiser to target and show the ad only to the consumers who are more prone to buying a certain product based on their past online behaviour.

Online behavioural advertising can be explained through a simple case. Firstly, the consumer is searching for a specific topic online, cars for example. Those webpage visits are tracked and the advertising company behind presumes that this consumer is into cars. The consumer will further on be targeted with car adverts while browsing the web. Similarly, different people will be targeted with different display adverts, based on the history of the web pages they have visited (Boerman, Kruikemeier & Borgesius, 2017, p. 363).

2.4 Online Trust

From a psychological perspective, trust is based on the individual's positive presumption about the intentions of the other party and the willingness to be vulnerable towards them (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015). Based on these positive presumptions, any adverse actions by the other are omitted and the overall complexity is reduced (Gefen, 2000).

Commonly, one of the most valuable elements of any relationship is the limit to which the concerned participants trust one another (Bleier, Goldfarb & Tucker, 2020). Trust can be defined as the "willingness to rely on an exchange partner in whom one has confidence" (Moorman, Zaltman & Deshpande, 1992, p.315) where confidence is developed as the result of one's belief in the other's integrity and reliability (Morgan & Hunt, 1994; Bleier &

Eisenbeiss, 2015a). In a consumer-company context (McKnight, Choudhurry & Kacmar, 2002), trust relates to the consumer's reliance on a company's "competence, benevolence and integrity" (Bleier, Goldfarb & Tucker, 2020, p. 7).

Bleier and Eisenbeiss (2015a) observe that trust can diminish privacy concerns triggered by personalized online ads while keeping all other parameters to stay unchanged. Pursuant to this understanding, trust can influence the probability level of consumers utilizing personalized services. As trust is the pillar of any social interaction, when all sides take part in the interaction, it is assumed that they will all take responsibility for their promises (Okazaki, Li & Hirose, 2009). More importantly, it was found that trust mediates the consumer's perception of the company's marketing efforts (Bleier and Eisenbeiss, 2015a), therefore, if companies plan on gathering and using personal information, online trust is crucial (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015).

In fact, when consumers lack information about retailers in the online domain, trust frequently serves as the single factor on which consumers plan their purchase decisions (shown in Urban, Sultan & Qualls, 2000; Urban, Amyx & Lorenzon, 2009; McStay, 2011; Bleier & Eisenbeiss, 2015a). Bleier & Eisenbeiss (2015a) explain that trust can make consumers feel that their personal information is safe in the database of the retailer and thus can lower the level of privacy concerns. In addition, their freedom of independent choice is appreciated more than the company's suggestions under low trust state (Clee & Wicklund, 1980; Bleier & Eisenbeiss, 2015a).

2.4.1 The importance of trust in consumers' willingness to disclose information

Morgan and Hunt (1994) find that any misuse of personal information inevitably ends with a loss of trust between the involved parties. Trust embodies reliance on someone and includes vulnerability on the side of the trustor (Schoenbachler & Gordon, 2002, p. 5). In the context of data-driven marketing, consumers can be seen as vulnerable in terms that they do not have absolute knowledge nor have control over the usage of their personal data (Schoenbachler & Gordon, 2002, p. 5).

Generally, even if one marketer's intentions do not include controlling consumers' data, many consumers might still not be familiar with the type or amount of data being gathered or the way it is being used (Schoenbachler & Gordon, 2002 p. 6). Certainly, there are companies who can act opportunistically and risk isolating their relationships with consumers for their database and growth (Schoenbachler & Gordon, 2002 p.6). Trust is a crucial driver in diminishing risk perceptions of such behaviour in relationships (Schoenbachler & Gordon, 2002 p.6). Therefore, the establishment of relationships between companies and consumers is highly dependent on developing "solid grounds" for trust. If the relationship is developed and trust is present, the consumer feels less vulnerable and discloses more personal information (Schoenbachler & Gordon, 2002, p.6).

Research has shown that trust initiates a willingness among consumers to share personal information to companies in different contexts (e.g., Hoffman, Novak & Peralta, 1999; McKnight, Choudhury & Kacmar, 2002; Schoenbachler & Gordon, 2002; Anderson & Agarwal, 2011; Bleier, Goldfarb & Tucker, 2020 p. 8). It is notable that the feelings of trust towards companies have to be present in almost every situation for the consumers to disclose personal information (Schoenbachler & Gordon, 2002, p.3).

2.4.2 The importance of consumer trust for companies

All business and social interactions hold a level of uncertainty when it comes to the counterpart's behaviour (Bleier & Eisenbeiss, 2015a). A complex situation can occur when one cannot control nor foresee which actions the other will undertake (Gefen, 2000). In such situations, trust plays a key role, especially when it comes to environments which are not fully governed by certain regulations or rules (Luhmann, 1979; Fukuyama, 1995; Olivero & Lunt, 2004; Bleier & Eisenbeiss, 2015a). In fact, Golembiewski and McConkie (1975, p. 131) claim that "there is no single variable which so thoroughly influences interpersonal and group behaviour as does trust".

The significance of trust for companies whose primary activities rely on consumer data, has been analyzed in a large stream of research papers in academic literature (e.g., Urban, Sultan & Qualls, 2000; Sheehan & Hoy, 2000; Urban Amyx & Lorenzon, 2009; Bleier, Goldfarb & Tucker, 2020). Within the e-commerce environment, Bleier and Eisenbeiss (2015b) have exposed trust in the retailer as one of the factors which carry a key role as it is highly affecting the consumer's purchase decisions.

Primarily, trust relies on various e-commerce factors such as: incentives, lack of utility, overall satisfaction and most importantly, privacy concerns (Pavlou, 2003; Okazaki, Li & Hirose, 2009). Further, it influences the consumers' usefulness perceptions when it comes to the marketing efforts by retailers' Bleier and Eisenbeiss (2015b). In fact, consumers consider retail websites to be more useful when they trust specific sellers (Bleier and Eisenbeiss, 2015b). This is due to the awareness of seller's integrity and reliability when it comes to detrimental behaviour (Gefen, Karahanna & Straub, 2003). Lastly, trustworthiness is an essential factor which determines whether online personalization is economically favorable for companies (Kalaignanam, Kushwaha & Rajavi, 2018; Bleier, Goldfarb & Tucker, 2020). If retailers are perceived as trustworthy, their click-through rates are consequently improved and personalization becomes economically beneficial (Bleier & Eisenbeiss, 2015a).

Therefore, it is crucial for companies to evaluate their consumers' perceptions of trustworthiness before engaging in particular (intensive) data-marketing activities (Bleier, Goldfarb & Tucker, 2020).

2.5 Consumer Data Privacy in Online Advertising

How privacy is defined and what its specific relation to other values is, has been disputed for a long time. Westin (1967, p.7) defined it as “the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others”. Although hard to conceptualize, this definition has been well accepted in organizational literature and has been used as a basis to explain what consumer information privacy actually deals with. In particular, it is concerned with the rights of those consumers whose information is at stake (Okazaki, Li & Hirose, 2009, p. 64). In practice, data privacy or information privacy is highly dependent on various elements such as regulations, culture and sectors within the industry (Milberg, Burke, Smith & Kallman, 1995; Andrews, 2002; Culnan & Bies, 2003; Malhotra, Kim & Agarwal, 2004).

Nowadays, consumer’s personal information is considered as a key factor in market-based economies (Norberg & Horne, 2014). From loyalty programs to mobile applications and websites, personal information combined with behavioral data is widely requested from users in order to receive appropriate benefits for some (if not all) of their online purchases (Norberg & Horne, 2014). For example, to carry out orders, eCommerce websites normally seek for basic data such as name, phone number, payment information and address from the users. However, when it comes to exchanges that may occur on other website sources, the requested personal information might be even more substantial (Norberg & Horne, 2014). If an individual would want to open a bank account online, apart from the basic information, he or she would also be required to provide more vulnerable, private information such as a Tax ID number, Social Security number and/ or an ID number.

2.5.1 Consumer privacy concerns

The psychological processes consumers go through when companies collect their personal data are called privacy concerns (Martin, Borah & Palmatier, 2017). Privacy concerns are the consumer’s perceptions and attitudes towards their privacy (Smith, Milberg & Burke, 1996) and are the proxies for measuring the consumer’s feelings towards their privacy (Malhotra, Kim & Agarwal, 2004). Norberg and Horne (2014) believe that consumers’ reaction towards information solicitations in marketing exchanges is highly dependent on the kind and amount of personal data being gathered.

If privacy concerns were to be observed from a theoretical point of view, they can be directly connected to the consumer’s individual values which influence their reaction to personalized advertisements (Stone et al. 1983). Consumers who experience a lower degree of privacy concerns are more likely to find some kind of benefit in return when faced with a personalized message (Stone, Gardner, Gueutal, & McClure, 1983). Contrariwise, the ones who confront with a higher degree of privacy concerns, will not be comfortable if they were to be exposed to a personalized message. Culnan (1995) discovers three elements which are closely connected to the consumer's knowledge in terms of data deleting procedures. These elements include direct marketing experience, privacy concerns and finally, demographics.

For many years, companies have been storing and using consumer information from their database to tailor marketing and advertising campaigns. These databases, normally, held market-level information instead of personally identifiable information (PII) (Phelps, Nowak & Ferrell, 2000, p. 28). According to Nowak and Phelps (1995), market-level information was never the primary cause for privacy concerns as it only includes general consumer information which normally illustrate characteristics of a specific market segment or a consumer group (Phelps, Nowak & Ferrell, 2000). They claim that fragmented consumer markets, technology advances, as well as the demand for a bigger economic efficiency are incentives for broad use of PII. Therefore, one of the most important pressure points is personal privacy (Smith, Milberg & Burke, 1996). This can be derived as well from the communication process, which gathers unprecedented volume of web consumer information and indefinitely stores it for future use (Okazaki, Li & Hirose, 2009, p. 64).

Smith, Milberg and Burke (1996, p. 169) developed a scale which measures individuals' information privacy concerns about organizational practices. It is a 15-item scale, measuring privacy concerns on four different dimensions: collection, unauthorized secondary use, errors and improper access to personal information. In order to include Internet-specific privacy dimensions as measuring means, Malhotra, Kim and Agarwal (2004) further developed the scale by proposing three differentiating dimensions which also encompass traditional marketing: collection, awareness of privacy practices and control. For its basis they used the social contract theory and they further supported the scale's validity with two empirical studies.

The base theory lays out a rationale on how society, as a whole, aligns itself with the mutual beneficial principals of justice (Macneil 1974, 1980; Okazaki, Li & Hirose, 2009). It implies that the consumer information sharing rules should always make clear to the consumer both the exchange purpose and the potential harms that may occur (Martin & Murphy, 2016).

Privacy concerns trigger feelings of vulnerability simultaneously, whenever companies gather and use consumers' personal data (Martin, Borah & Palmatier, 2017). Scharf (2007) found that all negative consumer reactions from data usage originate from consumer's feeling of unease towards potential harm or feelings of privacy violation. This type of anxiety is preferred to actual data abuse or financial distress (Martin, Borah & Palmatier, 2017). From a legal point of view, consumers can be harmed by data infringement even if their own data wasn't mishandled (Fisher, 2013). Thus, instead of concentrating solely on damages, it is crucial to understand consumers' vulnerabilities (Martin, Borah & Palmatier, 2017).

2.5.2 Understanding consumers' vulnerabilities

Vulnerability indicates exposure towards wrongdoing or harm (Smith & Cooper-Martin, 1997) and when we speak of consumer data vulnerability, we are referring to the consumer's privacy and their level of tolerance when breaching that privacy with harmful data practices (Martin, Borah & Palmatier, 2017). Usually, companies who store consumer data have "detailed digital dossiers about people" and possess the ability to "widespread the transfer of information between a variety of entities" (Solove, 2003, p. 2). In order to prevent this and to reduce their vulnerability, consumers limit themselves with whom and how they disclose personal information (Martin, Borah & Palmatier, 2017).

To keep the feeling of control, consumers might even adopt certain courses of actions such as falsifying and/or excluding data (Lwin & Williams, 2003; Lwin et al. 2007; Norberg & Horne, 2014). With these actions, their perception of disclosure data management is better when receiving benefits of specific transactions. Both falsifying and excluding data can have substantial negative effects over companies whose operations are data-driven and primarily depend on consumer data (Norberg & Horne, 2014).

All the same, companies continue to collect and hold vulnerable consumer data which consequently increases the level of vulnerability and privacy concerns among consumers (Tucker, 2014; Martin, Borah & Palmatier, 2017). For instance, a data breach vulnerability influences consumers' perceptions of harm liability as it suggests that a company who has stored their data was subjected to a data breach (Martin, Borah & Palmatier, 2017). In this case, the absence of control is particularly concerning to consumers, even in cases where not everybody who's digital dossier has been affected undergoes a form of victimization.

Further, it can also happen for the perceptions of vulnerability to grow when similar data breaches occur at close competitors of the company where the consumer's data is already stored (Martin, Borah & Palmatier, 2017). This is due to the effect titled spillover vulnerability. The spillover effect arises from the consumer's perceptions where if a data breach already occurred at another company similar to the one in question – the possibility of happening in the latter is interpreted as highly likely (Martin, Borah & Palmatier, 2017). Martin, Borah and Palmatier (2017) have found that a local company one consumer normally uses, the spillover effect causes low level vulnerability perceptions compared to the one of data breaches.

Data manifest vulnerability happens with the misuse of consumer data, directly harming the consumer (Martin, Borah & Palmatier, 2017). Consumers experience actual harm as a result of activities including harm and fraudulency (Martin, Borah & Palmatier, 2017). Even though the experienced actual harm is not on a big scale, such occurrence only fuels perceptions of data vulnerability (Martin, Borah & Palmatier, 2017). Therefore, perceptions of privacy violation and the threat's undetermined complexity, tend to have larger influence than the actual personal data misuse itself (Solve, 2003; Scharf, 2007; Anderson, 2013; Martin, Borah & Palmatier, 2017).

2.6 Privacy Threats Inherent to Online Advertising

The main triggers for consumer privacy threats are tied with the capabilities and infrastructure of ad platforms (Jimenez, Arnau, Hoyos & Forne, 2017). Almost every personalized ad indicates that companies are voluntarily inclined towards leveraging consumers' information knowledge, gathered by tracking their browsing activities. (Anand & Shachar, 2009; Bleier & Eisenbeiss, 2015a). In fact, the business model itself of online advertising relies on the vast collection of personal information (Jimenez, Arnau, Hoyos & Forne, 2017). Jimenez et al. (2017) highlight that many online advertising platforms practice advanced levels of user targeting which neglect consumer privacy and might support personal data leakage.

In modern advertising, there are various tracking mechanisms used by companies to gather and mine user data: HTTP and flash cookies, canvas fingerprinting and HTML5 local storage (See Table 3). All mechanisms can evoke privacy concerns; thus, it is not striking that the majority of consumers do not want highly adapted ads to their online behaviour (Turow, King, Hoofnatle, Bleakley & Hennessy, 2009; Guild, 2013; Bleier & Eisenbeiss, 2015a).

Table 3: Tracking mechanisms used in modern online advertising

	User single-out effectiveness	**Have led to lawsuits**	**Easily erasable**	**Usage level**	**Are intrusive**
HTTP cookies	High	No	Yes	Extended	No
Flash cookies	High	Yes	No	Extended	Yes
Canvas fingerprint	Low	Yes	No	Limited	Yes
HTML5 local storage	High	Yes	No	Growing	Yes

Adapted from Jimenez, Arnau, Hoyos and Forne (2017, p. 40).

Mainly, there are two reasons why cookies incentivize privacy concerns among consumers: they indefinitely store the collected personal data (Olejnik & Castelluccia, 2016) and they enable personal data sharing though Cookie matching (CM) (Jimenez, Arnau, Hoyos & Forne, 2017, p. 38). In fact, with the CM technology, it is possible for advertisers to map cookies on their own, based on the previously gathered user data (Ghosh, Mahdian, McAfee & Vassilvitskii, 2015).

The omnipresence of CM across the Web has been also noticed in the experiments carried out by Bashir, Arshad, Robertson and Wilson (2016), where they find that highly targeted advertisements are strictly based on shared information. Contrary to the past where the level of personal data employed by cookies was very low, nowadays, cookies base their tracking mechanisms solely on personal data (Jimenez, Arnau, Hoyos & Forne, 2017, p.38). In fact, they are classified as primary tracking mechanisms, enabled with a capacity which is difficult to erase.

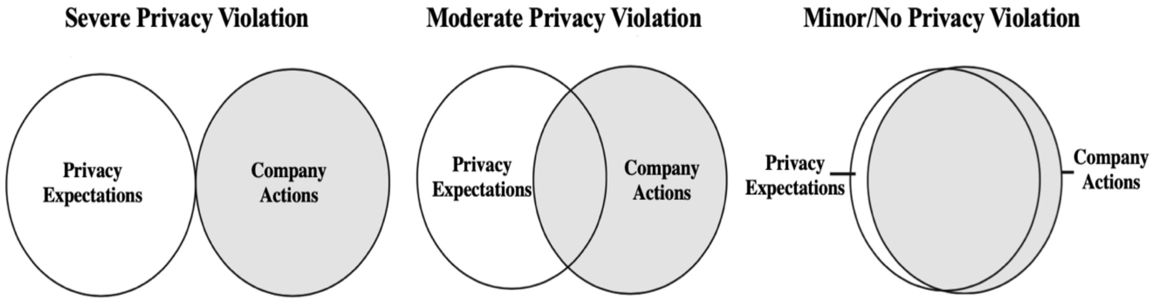
2.7 Perceived Privacy Violation

According to Wright and Xie (2019), the consumer determines the privacy violations depending on their perceived control over "when, how and to what extent information about them is communicated to others" (Pollach 2005, p. 222). In essence, people are willing to share personal information with both known and unknown recipients in order to foster social bonds or establish individual identities (Mothersbaugh et al., 2011; Acquisti et al., 2015; Wright & Xie, 2019).

Research has shown that consumers often form privacy expectations and perceptions of privacy violation, despite the presence of privacy policies (Martin, 2015). To avoid perceptions of privacy violations, Wright and Xie (2019), demonstrated the significance of the alignment between privacy expectations and companies' actions (See Figure 6). In particular, they explore the roles of consent types, explicit and implied, in terms of the alignment.

Consent types are essential in order to determine the perceptions of privacy violation among consumers and their response to notices on data sharing (Wright and Xie, 2019, p. 125). An explicit consent is a clear, straightforward agreement to certain terms or policies, whilst implied consent is an indirect agreement gained during the interaction with the company (Wright and Xie, 2019, p. 125). Opposite of implied consent, an explicit one helps the consumer form clear, distinct privacy expectations and matches the alignment between the consumer expectations and the company actions (Wright and Xie, 2019, p. 125).

Figure 6: Degree of perceived privacy violation based on the alignment between privacy expectations and company actions



Adapted from Wright and Xie (2017, p. 126).

Consumers will often feel that their rights have been violated, if marketers do not follow a certain, expected behaviour pattern (Milne & Gordon, 1993; Okazaki, Li & Hirose, 2009). Martin (2016) points out that contextually dependent norms often dictate the consumers' expectations when it comes to their privacy. He draws special attention to the so-called "negotiated agreement" which occurs between companies and consumers. This agreement implies that during the interaction with the companies, consumers shape certain expectations with regards to the company's data management. That is, for it to be adhering to privacy norms (Wright & Xie, 2019).

Turow et al. (2009) show that 84% of the consumers do not want tailored ads based on their tracked online behaviour on websites different from the one they are visiting. In fact, even if the altered ads are on the website the consumer is currently visiting, they will most likely trigger the feeling of privacy violation, if the banners are found as privacy-invasive (Goldfarb & Tucker, 2011b, 32). Aguirre, Mahr, Grewal, Ruyter & Wetzels (2015) found a steep decline in the tailored ad click-through rate when consumers became aware that the company has collected personal data without their consent.

To which extent advertisements influence the perceived privacy violation and prompt privacy concerns is highly dependent on the sensitivity of personally identifiable information they are built on (Nowak & Phelps, 1992; Bleier & Eisenbeiss, 2015a).

2.8 Perceived Privacy Control

In order to achieve a higher communication distinctiveness, companies include vast amounts of personal data within their targeted ads (Ansari & Mela, 2003). However, this may push consumers to "fall" into a psychological state called reactance (White et al.,2008). When a consumer finds himself/herself within such state, it means they have a perception that their freedom is being threatened (Brehm, 1966).

According to Tucker (2012, p. 327) reactance is a process "where consumers resist something, they find coercive by behaving in the opposite way to the one intended, which is in this case not finding the ad appealing." White et al. (2008, p. 48) find that psychological reactance might occur when there is a high level of personalization and the consumer has not received any specific reasons for the use of their personal data. Building on this study, Tucker (2014) points out that reactance can be in fact diminished through privacy controls.

Overall, people are prompted to control the level of personal information disclosure (Altman, 1975; Wright & Xie, 2019). When it comes to usage of consumer data for marketing purposes, Foxman and Kilcoyne (1993) conclude that companies often claim that use of such data results with a more effective marketing service to the community as a whole, even if it causes slight inconvenience for some consumers along the process. With this, the issue of unequal control over the personal data arises, as the companies presume, they have the "owner rights" over any information they managed to obtain during the communication with the consumer (Foxman & Kilcoyne, 1993).

Studies have shown that when consumers feel loss of control over their personal data, they feel vulnerable towards the advertising company and as a consequence, manifest privacy concerns (e.g., Raab & Bennett, 1998; Dinev & Hart, 2004; Bandyopadhyay, 2011; Bleier and Eisenbeiss, 2015a). Foxman and Kilcoyne (1993) categorize the privacy states of users with two key elements in mind: control and knowledge. In particular, they differentiate the states based on who controls the user data and whether users are actually knowledgeable about data gathering and privacy rights. We summarize the types of privacy states in Table 4.

Table 4: Types of privacy states

	Consumer has control	**Others have control**
Informed consumer	The consumer is aware of potential privacy threats/issues and is able to determine if and how the personal data will be used.	The consumer is aware of potential privacy threats/issues but may not have the right to say if and how the personal data will be used.
Non-informed consumer	The consumer is not aware of their privacy rights. They assume the providing of personal data is mandatory, therefore, they do not exercise control over information release.	The consumer is (not) aware of their privacy rights and may (not) have a say on how the data is collected and used.

Adapted from Foxman and Kilcoyne (1993, p. 107).

Often, privacy control criteria are determined according to both quantity and quality of data potential attackers might gather about consumers (Jimenez, Arnau, Hoyos & Forne, 2017). According to Changa et al. (2014), the term itself defines an idea that affects how a person feels towards their ability to control the release of their information. They suggest that it is highly associated with perceived risk in a given situation, meaning that if the perception of control is high, the situation is perceived as less risky. Therefore, the consumer's reaction is positive.

Previous studies indicate that when people feel in control of information disclosure, they tend to answer more favorably to highly custom-built marketing communications (Norberg & Horne, 2014; Martin & Murphy, 2016). This was also confirmed in a study done by Tucker (2014), where it was found that when people experience greater privacy control settings, they respond positively to targeted and personalized ads.

Malhotra et al. (2004) argue how privacy concerns are evoked when consumers perceive deprivation of control over how companies gather and use their personal data. This was also supported with field data in a study done by Tucker (2014). In particular, he uses the case of Facebook where the company granted its users (almost) absolute control over their profile privacy settings (Bleier, Goldfarb & Tucker, 2020). The outcome of granting their users these privacy rights is seen in the effectiveness increase of personalized ads located on the social media platform. These findings complement the ones of Dinev and Hart (2004), where they show that the perception and capability of control over the usage of their personal data consequently lowers the level of privacy concerns. In addition, increased perception of privacy control results with an increase in purchase intentions (Phelps, Nowak & Ferrell, 2000).

However, there might be some countervailing outcomes by granting privacy control rights (Bleier, Goldfarb & Tucker, 2020). Due to the complexity of data gathering and mining by companies nowadays, there is a growing unease that consumers cannot manage their privacy in an effective manner (Nissenbaum, 2011; Solove, 2012; Bleier, Goldfarb & Tucker, 2020). It can also be the case where consumers might be more vulnerable even though they have more privacy control (Bleier, Goldfarb & Tucker, 2020). If consumers perceive a complete control over their data, they will be more inclined towards sharing sensitive data (Brandimarte, Acquisti & Loewenstein, 2012; Mothersbaugh et al., 2012).

Therefore, companies may afford to increase or decrease the level of control depending on the information category and the existing level of consumers' trust (Bleier, Goldfarb & Tucker, 2020).

2.8.1 Privacy regulations and their influence over consumers

To reduce privacy concerns, consumers might turn to lawmakers to enforce more rigorous privacy regulations (Smith, Milberg & Burke, 1996; Bleier, Goldfarb & Tucker, 2020).

Without present regulations, privacy altogether might diminish over time and consequently come at high cost for consumers (Rust, Kannan & Peng, 2002). Privacy regulations aim to "limit the extent to which firms can track and use consumers' personal information" (Bleier, Goldfarb & Tucker, 2020, p. 5).

There are several motives why the consequences of privacy regulations have been well investigated in online advertising literature. Primarily, the sole nature of online advertising is such that it needs to be constantly observed and studied (Goldfarb & Tuckerb, 2011, 32). Further, being among the first sectors to leverage digital data also triggered to be among the first to undergo systematic regulation efforts (Bleier, Goldfarb & Tucker, 2020). Lastly, because there is a notable quid pro quo relationship between the effectiveness of online advertising and the usage of consumer data (Evans, 2009; Lenard & Rubin, 2010; Bleier, Goldfarb & Tucker, 2020).

A recent, significant regulation which addresses consumers' privacy concerns is the General Data Protection Regulative (GDPR) enforced in Europe on May 25, 2018. The directive aims to strengthen the individuals' security by unifying the data protection whilst addressing the export and utilization of personal data within and outside the EU (European Commission, n.d.). In particular, GDPR helps alleviate the consumers' concerns about potential privacy invasions and expands the scope of the definition of personal information (Bleier, Goldfarb & Tucker, 2020).

Even though Xu, Teo, Tan and Agarwal (2012) claim government regulations influence the level of perceived privacy violation, there is still some ambiguity when trying to capture the influence of privacy regulations over online advertising (Bleier, Goldfarb & Tucker, 2020). This is due to the fact that it is not difficult to omit, if there is any actual consequence from the shortfall of advertising effectiveness. Moreover, this ambiguity is often caused by policy debates on what kind of effects there are for consumers when online advertising markets work efficiently (Benkler, Faris & Roberts, 2018).

2.8.2 Privacy regulations and their influence over companies

The effect of privacy regulations over companies has been documented in many instances in online advertising literature (Baumer, Earp & Poindexter, 2004; Goldfarb and Tucker, 2011b).

For instance, Goldfarb and Tucker (2011b) investigated the effects of the first considerable European legislation, the E-Privacy Directive (EC/2002/58) which addressed the use of consumer data in online advertising. The directive enforced limits to which advertising companies can track consumers' online browsing behaviour and restricts the vast collection and usage of data across other websites (Bleier, Goldfarb & Tucker, 2020). The collected data held 3.3 million responses where the respondents were exposed to online banner advertising campaigns (9.596 in total) and measured the influence this regulation has over advertising effectiveness within the European Union compared to the rest of the world (Goldfarb and Tucker, 2011b; Bleier, Goldfarb & Tucker, 2020). With the enforcement of this specific regulative it was found that online banner ads were 65% less effective among the respondents compared to other countries where no such regulative is present.

Similar to Goldfarb and Tucker (2011b), Jia et al. (2018) analyzed GDPR's influence over investments in new and emerging technological companies in the short-run. The results show that the conditions for innovators – entrepreneurs have become more difficult in Europe compared to the US because of regulatory enforcement (Bleier, Goldfarb & Tucker, 2020). Meaning that, investments in EU ventures have significantly decreased opposed to the US ones (Bleier, Goldfarb & Tucker, 2020).

The self-regulation of the advertising industry has also been analyzed by Johnson et al. (2018) through the AdChoices program. This program (set in motion in 2010) introduced consumers with a "choice and notice" on the use of their personal data for advertising motives: Consumers can learn how their browsing activities are used for the modelling of personalized ads, by simply clicking on AdChoices logo included in advertisers display banner ads (Bleier, Goldfarb & Tucker, 2020, p. 5). In addition, the program also allows consumers to opt out from having their data gathered and applied for personalized advertising purposes.

On one hand a "choice and notice" is surely beneficial for consumers, however, on the other hand it was found that asking smaller companies to notify and obtain an agreement from consumers to gather, store and use their data is actually a disadvantage (Campbell, Goldfarb & Tucker, 2015). This is due to the fact that companies who offer sort of "easily" valid benefits to consumers in exchange for their personal information, presumably gain consent more effortlessly in contrast to smaller companies, who usually gather information in a more precise manner. Thus, both smaller and new companies are the ones who are likely endure cost the most by the "notice and consent", as they do not have history of persuasive scale of value exchanged for consent (Campbell, Goldfarb & Tucker, 2015; Bleier, Goldfarb & Tucker, 2020).

Nevertheless, one thing is evident: there is a trade-off between the leverage of consumer personal information and the ad effectiveness (Evans, 2009; Lenard & Rubin, 2010; Bleier, Goldfarb & Tucker, 2020).

2.9 Unraveling the Privacy Paradox

Norberg and Horne (2014) argue that, if consumers want to receive benefits in online personalized advertising, they must give something in exchange – their personal information. Consumers are torn between receiving better services and products, in exchange for providing and disclosing their personal information (Norberg, Horne & Horne, 2007).

Nevertheless, the idea of a free gift or service often wins over the perceived privacy risk that comes along with it (Karwatzki, Dytynko, Trenz & Veit, 2017).

Consumers state that they are anxious about the privacy of their personal information (Kokolakis, 2017), however their actions are the opposite of their concerns when it comes to sharing their personal data in exchange for benefits (Norberg, Horne & Horne, 2007). This term is known as "privacy paradox" and is used as a referral to the disconnect between the consumer's privacy preferences and the actual information disclosure behaviour (Martin & Murphy, 2016; Barth & Jong, 2017). Decisions and evaluations about the trade-off between the risk and benefit are highly dependent on an individual's view on privacy evaluation and on their general view of sharing personal information (Karwatzki, Dytynko, Trenz & Veit, 2017). Often, the personal information consumers disclose is in exchange for solicitations (Milne & Gordon, 1993).

Researchers are facing difficulties when studying the paradox due to the difference in privacy perceptions within different segments, as well as the variety of different measuring techniques (Norberg, Horne & Horne, 2007). While some studies are challenging the existence of the paradox (Young & Quan-Haase, 2013; Blank et al., 2014; Lutz and Strathoff, 2014), others are trying to find evidence to prove the contrary (Acquisti & Grossklags, 2005; Norberg et al., 2007; Carrascal, Riederer, Erramilli, Cherubini & Oliveira, 2013). As a result, different theories can be found in the literature which support and explain its existence. In the following chapter, we explore in-depth the ones which we came across more often than others.

2.9.1 The privacy calculus theory

Consumers may tolerate privacy concerns caused by certain marketing practices only if the perceived value which is being received is on an adequate level (Sheehan & Hoy, 2000). In literature, this is explained through the privacy calculus theory and it is a type of decision making which can be conceptualized as a cost versus benefit comparison (Gironda & Korgaonkar, 2018).

This theory is built on the economical perspective of a consumer as a "homo economicus" - an economic human (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015). This theoretical approach proposes that privacy information disclosure is a cognitive concept (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015) and it presumes that a consumer acts in a way to maximize his/her benefits (Gerber, Gerber & Volkamer, 2018). They calculate their potential loss of privacy compared to disclosure of their information (Kokolakis, 2017).

Even though personalized adverts do not bring a cost in terms of money for the consumer, they are based on a great amount of data, which is in fact a privacy cost for the consumer (Gironda & Korgaonkar 2018). Other potential costs might occur such as privacy violation, online bullying, or potential stealing of consumers identity (Bandara, Fernando & Akter, 2017). However, in return for paying that cost, consumers receive benefits in the form of personalized products and services, online product recommendations (Bandara, Fernando & Akter, 2017), financial rewards or social benefits (Smith et al., 2011; Bleier, Goldfarb & Tucker, 2020), as well as adverts that are more relevant to their needs (Gironda & Korgaonkar 2018). Their final decision is therefore based on the trade-off result (Kokolakis, 2017), thus when the benefits are higher than the perceived risk, they will reveal their private information, even if privacy concerns occur (Bandara, Fernando & Akter, 2017).

For instance, Chellappa and Sin (2005) employed the privacy calculus theory to observe whether consumers would trade off privacy concerns with perceived benefits of personalized products and/or services. They find that consumers considered personalization benefits to be much higher than privacy concerns (Bleier, Goldfarb & Tucker, 2020). Similarly, Schumman, Wangenheim and Groene (2013) observe that consumers may agree to targeted ads if they receive free Web services in return. Consequently, researchers have started to carry out inquiries to examine the monetary value consumers put on their privacy (Hann, Hui, Lee & Png, 2002; Hirschprung, Toch, Bolton & Maimon, 2016). In particular, the monetary value placed on the secondary personal data usage (Bleier, Goldfarb & Tucker, 2020).

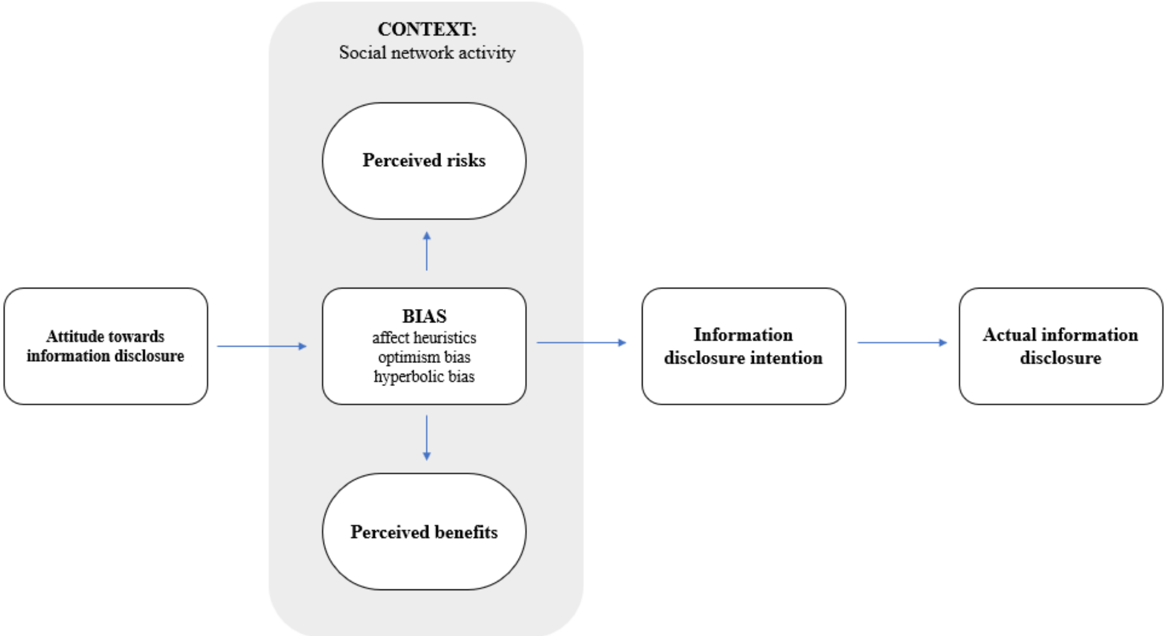
2.9.2 The bounded rationality theory & decision biases

Different studies suggest that the privacy calculus theory does not take into consideration all the associated factors when it comes to consumers' decision-making (Gerber, Gerber & Volkamer, 2018). Since consumers do not have enough information, the trade-off estimation cannot be done properly (Gerber, Gerber & Volkamer, 2018). This implies that when there is not enough sufficient information to make an informed decision, individuals might not have the cognitive ability to determine the actual privacy threats and disclosure benefits i.e., determine the trade-off (Kokolakis, 2017). This term is also known as bounded rationality.

Consumer decision-making process is often accompanied with various cognitive biases, so actual consumer behaviour might in fact not be as initially intended (Gerber, Gerber & Volkamer, 2018). Figure 7 presents what is the actual connection between the variables affect risk versus benefit estimation during biased judgment. Most commonly addressed biases in organizational literature are: affect heuristics, optimism bias and hyperbolic bias.

Kokolakis (2015) exposes affect heuristics as one of the most accepted biases when discussing consumer behaviour and decision-making. Due to affective impressions, consumers make quick decisions, which influence their judgment towards associated risks of information disclosure, as well as the judgment towards the benefits (Kokolakis, 2017). This results in underestimation of potential risks for the things the consumer likes and overestimation of potential risks, connected to the things the consumer does not like (Slovic, Finucane, Peters & MacGregor, 2002).

Figure 7: Risk versus benefit estimation under biased judgement



Adapted from Barth & Jong (2017, p. 1045).

Decision making is also affected by optimism bias, based on which individuals tend to think they are less vulnerable compared to others, when it comes to their privacy (Kokolakis, 2017). Thus, they assume their privacy is not at risk, which might in fact increase the risk of exposure (Barth & Jong, 2017; Flender and Müller, 2012). Furthermore, consumers' privacy decisions are associated with hyperbolic discounting, which is also referred to as immediate gratification bias (Gerber, Gerber & Volkamer, 2018).

Consumers are not able to forecast their future decision-making, since their decisions are based on their preferences, which are not consistent with time (Kokolakis, 2017, p. 130). They will therefore prefer receiving a smaller benefit soon, than wait for a large benefit later in the future. Nevertheless, if all the benefits are available only in the long term, an individual will choose the bigger benefit over the smaller one (Barth & Jong, 2017). This particular bias results in poor estimation of potential privacy risks in the future in order for the consumer to receive an instant benefit (Barth & Jong, 2017; Flender and Müller, 2012)

2.9.3 The social theory

The arrival of social media channels has highly affected the social lives of individuals, in particular the way they disclose their personal information (Blank et al., 2014). Blank et al. (2014) observe that users must share their information on social media networks, regardless of their privacy concerns, if they want to sustain their social network persona. This paradox in which users often find themselves, can also be explained through the social theory.

Lutz and Strathhoff (2014) present a double-sided perspective to online social networks: as a community and as a society. In the former, there are groups of members that are a part of a community, connected through emotional ties and implicit rules. While the latter, groups members on rational estimations, followed by explicit rules and contracts. As social networks are in fact private companies, they also have a system which works on determined rules and policies (Kokolakis, 2017, p. 128).

In general, when a user is present on social media networks, they can be placed within one of the two aforementioned perspectives. For example, a user is said to be a part of the community when their behaviour is mainly driven by emotions instead of rationality (Kokolakis, 2017, p. 128). This user's feelings of belonging to a community more often wins over the calculated risks of privacy intrusion. Contrary to these users, the ones which are a part of the society evaluate the privacy threats and take into consideration possible damages.

The way individuals behave and make privacy decisions is highly connected to the social environment they belong to (Gerber, Gerber & Volkamer, 2018). Their behaviour and decisions might be associated with the culture they originate from, in particular whether it is collectivistic or individualistic. In both environments, the individual's decisions may be influenced by the opinion of others to a certain extent. In fact, Flender and Müller (2012) observe that sharing personal information on social networks can trigger social pressure on an individual, when their partner tends to share personal information. Sometimes, data disclosure can even be referred to as a social stigma for the users who decide not to share their personal information and are thus considered to be hiding something (Hull, 2015; Gerber, Gerber & Volkamer, 2018).

Therefore, there is no doubt that social factors highly affect the actual behaviour of users on social media, whilst the expressed attitude "reflects the unbiased opinion of the respective individual" (Gerber, Gerber & Volkamer, 2018, p. 230).

2.10 Ad Transparency

Consumers lacking awareness of data collection techniques that marketers use often result in privacy concerns (Kim, Barasz, & John, 2018). Overall, public surveys show that in fact consumers would like to be more informed about data collection and usage done by companies (Karwatzki, Dytynko, Trenz & Veit, 2017). In the past years this particular topic has gained more public acknowledgement (especially from the media), which has consequently increased the awareness of privacy violations (Treiblmaier & Pollach, 2007).

By using transparent practices, companies can improve that awareness and inform their consumers which and how the information is being collected, as well as the ways it can be deleted (Karwatzki, Dytynko, Trenz & Veit, 2017). With this, transparency would not only positively impact privacy concerns, but it would also benefit consumers' trust (Treiblmaier

& Pollach, 2007; Karwatzki, Dytynko, Trenz & Veit, 2017) and the feeling of privacy control (Karwatzki, Dytynko, Trenz & Veit, 2017).

Increased consumers' vulnerability is one of the reasons why companies have turned to more transparent approaches in the past years (Kim, Barasz, & John, 2018). Similarly, to Facebook's clickable icon on top of their advertisements stating, "Why I am seeing this ad?", other companies use practices which alert consumers that privacy standards are being met or inform them about tracking activities (Kim, Barasz, & John, 2018).

Aguirre, Mahr, Grewal, Ruyter & Wetzels (2015) investigated ad transparency and its influence on personalization and found an increase in the click-through intention for more personalized adverts, when the company used overt data collection techniques. Kim, Barasz and John (2018) came across similar results which show that consumers are more likely to interact with an advertisment which displays acceptable information collection techniques. Covert data techniques on the other hand trigger vulnerability in consumers and their click-through intentions decrease (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015).

Moreover, a study by Awad and Krishnan (2006) raises a concern for companies that those consumers who value transparency more are also the ones who are the least inclined to online profiling. These customers are also named as privacy fundamentalists, since they place a high value on their data and are not willing to share it easily. Therefore, they propose for companies to target the consumers which are willing to share their information for profiling purposes and are less sensitive with their data sharing (Awad & Krishnan, 2006).

3 RESEARCH HYPOTHESES

3.1 Ad Personalization and Click-throughs

With the advanced data collection technologies, marketers are able to create individualized offers as a part of their one-on-one marketing communication strategy (Tam & Ho, 2005). Ad personalization focuses on the consumer as an individual, with ads that are based on the consumer's preferences (Bleier & Eisenbeiss, 2015a). Personalized advertisements are not only more likable, but also more memorable (Howard & Kerin 2004), thus their effectiveness is higher (Arora et al. 2008; Tam & Ho 2005). Various studies have highlighted the positive results of personalization in advertising by improving the effectiveness of the ad (e.g., Pavlou & Stewart, 2000; Tam & Ho 2005; Kalyanaraman & Sundar 2006; Noar, Benac, & Harris 2007; Sohl & Moyer 2007, Arora et al. 2008; Walrave et al., 2018).

A way to measure an advertisement's effectiveness is through the click-through rate. Previous studies are showing positive effects of personalization on the click-through-rate in email marketing (Postma and Brooke, 2002), banner advertising (Bleier and Eisenbeiss, 2015b) and social media advertising (Keyzer, Dens & Pelsmacker, 2015). Based on this previous research we therefore hypothesize that:

H1: Ad personalization and the likelihood of the click-through have a positive relationship.

3.2 Ad Personalization, Click-throughs and Ad Relevance

Ad relevance plays an important role in online advertising. It is based on the individual's personal relevance (i.e., self-reference) and its role is to measure how related consumers feel towards a certain product or service and how much it responds to their needs (Jung, 2017). Sundar and Marathe (2010) find that the increase in personal relevance is the main factor which positively influences personalization.

As it was already proven that when an ad is personalized and therefore based on an individual's specific preferences, it is also seen as more relevant. The better the perception of ad relevance, the more personalized messages cause behavioral changes (Rimer and Kreuter, 2006). Thus, we assume that if an ad is personalized there is better perception of ad relevance consequently leading to more click-throughs:

H2: Better perception of ad relevance mediates the relationship between ad personalization and the likelihood of the click-through.

Self-referencing was initially studied in connection to psychology (Liu, 2015) and the link itself between ad relevance and consumer's positive reactions can be explained with the help of self-referencing theory (Jung, 2017). As we already mentioned, the appeal of the ad is influenced by personalization as the consumer perceives the message to be closer to his or her interests or needs (Malheiros, Jennett, Patel, Brostoff & Sasse, 2012). Moreover, it was found that personalized advertisements are perceived to be more relevant to consumers compared to non-personalized ones (Xia & Bechwati, 2008). Therefore, we can assume that:

H2a: Ad personalization and ad relevance have a positive relationship.

Previous studies have shown a positive impact of self-reference on the consumer's recall (Debevec, Spotts & Kernan, 1987), attention, understanding, as well as search and shopping behaviours (Celsi & Olson, 1988). Simultaneously, personalized messages are easier to process because of self-referencing and consequently be perceived as more relevant. Personalized advertisements are also perceived to be more relevant to consumers compared to non-personalized ones (Xia & Bechwati, 2008) and consequently receive a more positive response (Pavlou and Stewart 2000; Iyer, Soberman & Villas-Boas, 2005; Kalyanaraman and Sundar 2006; Arora et al. 2008; Anand & Shachar, 2009; Noar, Harrington & Aldrich, 2009).

If a message is seen as more relevant, it causes better message processing and, in the end, better persuasion to click-through (Tam & Ho, 2005; Rimer & Kreuter 2006; Bright & Daugherty, 2012). Based on this, we hypothesize:

H2b: Ad relevance and the likelihood of the click-through have a positive relationship.

3.3 Ad Personalization, Click-throughs and Perceptions of Privacy Violations

As previously mentioned, research has shown that if consumers are not aware how a company managed to collect data and tailor an advertisement corresponding to their preferences, they will feel violated. In fact, Tucker (2014) explains through the reactance theory that the rise of concerns comes from the consumer's resistance to an ad they find enforced. The reactance theory captures the consumer's "reactance" as a motivational state in which they show resistance towards coercive situations and act contrary to the way intended (Brehm 1966, 1989; Clee & Wicklund 1980; Tucker, 2014).

H3: Increased perception of privacy violation mediates the relationship between personalization and the likelihood of a click-through.

What differs online information privacy transactions from the offline ones is the fact that all forms of electronic access leave a virtual trail (Chellappa & Sin, 2005). This particular trail enables companies to form fairly accurate consumer profiles with basic and harmless information. Chellappa and Sin (2005) point out that personalization is very difficult to achieve if consumers do not provide preference information.

Meaning, whenever consumers share preference information in order to receive some kind of personalized tangible or intangible benefit, they experience loss of privacy (Chellappa & Sin, 2005). Therefore, we hypothesize:

H3a: Ad personalization and perceived privacy violations have a positive relationship.

Turow et al. (2009) show that 84% of the consumers do not want tailored ads based on their tracked online behaviour on websites different from the one they are visiting. In fact, even if the altered ads are on the website the consumer is currently visiting, they will most likely trigger the feeling of privacy violation, if the banners are found as privacy-invasive (Goldfarb & Tucker, 2011b, 32). Aguirre, Mahr, Grewal, Ruyter and Wetzels (2015) found a steep decline in the tailored ad click-through rate when consumers became aware that the company has collected personal data without their consent.

Information disclosure, purchases, or click-throughs as marketing's objectives are more likely to happen when consumers have a perception of liberty to choose (Martin & Murphy, 2016). With this we can argue that enforced ads will likely result in a negative response or in other words, avoidance of the ad and no click-throughs:

H3b: Perceived privacy violation and click-throughs have a negative relationship.

3.4 Ad Personalization, Perceived Privacy Violations and Control

Often, privacy control criteria are determined according to both quantity and quality of data potential attackers might gather about consumers (Jimenez, Arnau, Hoyos & Forne, 2017). According to Changa et al. (2014), the term itself defines an idea that affects how a person feels towards their ability to control the release of their information. They suggest that it is highly associated with perceived risk in a given situation, meaning that if the perception of control is high, the situation is perceived as less risky.

It was observed that the feeling of control can diminish vulnerabilities and emotional violation in the context of data privacy (Martin & Murphy, 2016). The theory of planned behaviour explains how a person's attitudes combined with perceived control and norms, leads to behaviour intentions and consequently behaviour (Ajzen & Fishbein, 1980). Behavioural research has also indicated that reactance can be reduced if the consumer has a perception of control (Taylor, 1979). This means that by strengthening privacy control, firms could improve the performance of their online ads (Tucker, 2014).

The perception of the privacy being violated can be in fact reduced through the perception of privacy control. Xu, Teo, Tan and Agarwal (2012) suggest that perceived privacy control is the focal mechanism through which course of actions such as government regulations, industry self-regulation and self-protection influence the level of perceived privacy violation. To find out if this is indeed the case, we propose to test the following hypothesis:

H4: Increased perception of privacy control suppresses the relationship between ad personalization and perceived privacy violation.

3.5 Trust, Perception of Privacy Violations and Click-throughs

From a psychological perspective, trust is based on the individual's positive presumption about the intentions of the other party and the willingness to be vulnerable towards them (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015). Based on these positive presumptions, any adverse actions by the other are omitted and the overall complexity is reduced (Gefen, 2000).

If retailers are found as trustworthy, they can benefit from personalized ads and consequently improve their click-through rates (Bleier & Eisenbeiss, 2015a). Lack of trust on the other hand, can create a negative effect and evoke privacy concerns (Bleier & Eisenbeiss, 2015b). Consumers who have low trust are prone to suspicion towards companies trying to anticipate their actions, as they perceive them as predators who are only looking to maximize their profit instead of aiding them during their selection task (Bleier & Eisenbeiss, 2015a). More importantly, it was found that trust mediates the consumer's perception of the company's marketing efforts (Bleier and Eisenbeiss, 2015a), therefore, if companies plan on gathering and using personal information, online trust is crucial (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015).

In many instances, the sensitivity of the requested consumer information triggers privacy concerns and reduces trust (Malhotra, Kim & Agarwal, 2004; Okazaki, Li & Hirose, 2009). This is due to the fact that such requests cause suspicion within the consumer's eyes. However, once present, trust can diminish the level of perceived privacy violation as consumers are likely to foresee negative consequences of engaging with a specific advertiser (Okazaki, Li & Hirose, 2009). Thus, we propose the following hypothesis:

H5: Trust in retailers amplifies the relationship between the perception of privacy violation and the likelihood of a click-through.

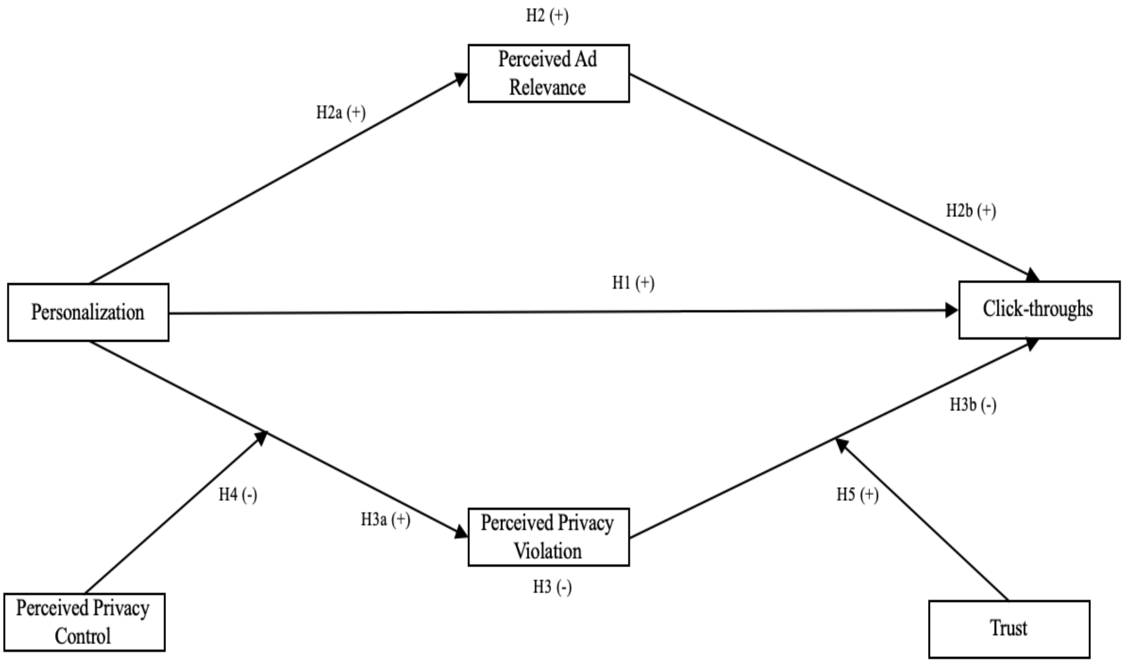
3.6 Conceptual Model

We expect that the relationship between personalization and the likelihood of click-throughs is positive. Further, we also assume that this relationship is mediated by the perceptions of ad relevance and privacy violations. From previous literature (e.g., Tam & Ho, 2005; Tucker, 2014) we learned that these two variables are crucial when exploring what has influence over the relationship between personalization and the likelihood of click-throughs. It was found that the more personalized the advertisement the more the overall perceptions will be that the advertisement is relevant, inducing click-throughs. However, simultaneously if there is an increased level in perceptions of privacy violation it will not result in click-throughs.

Furthermore, by including perceived privacy control as a variable, it is anticipated the vulnerabilities and the overall perception of violations in the context of data privacy will be reduced. Trust also acts as a variable which is able to diminish the perceptions of privacy violations, finally resulting in click-throughs.

Figure 8 illustrates **the hypotheses in the conceptual model**. This figure helps us visualize and summarize the expected relationships among the constructs. In the conceptual model, only selected relationships are included, e.g. we explore the effects of perceived privacy control on the relationship of personalization and privacy violation only, although this moderator can influence other relationships in our model as well. Similarly, for trust, we focus on its effects on the relationship between perceived privacy violations and click-throughs only. We chose to look at the arising effects over these two relationships only as they were also present in the studies in our literature research.

Figure 8: Conceptual model of hypotheses development



Source: Own work.

4 RESEARCH DESIGN AND METHODOLOGY

The empirical part of this thesis is built on the basis of primary research and involves qualitative and quantitative data: in-dept interviews and a survey-questionnaire. In the following subchapters, we will discuss the structure of both chosen methods and the description of the samples. In addition, a summary of the demographic analysis for the respondents will be presented.

4.1 Qualitative Research

As the subject matter of our thesis is understanding both the consumer's and the company's perspective on data collection and personalized advertising, the in-depth interviews were considered as the most appropriate method to make use of the companies' perception (Malhotra, 2002; Churchill & Iacobucci, 2005). In particular, we chose in-depth interviews as they allowed us to gain more detailed insights on the company's situation in connection to our research topic (Boyce & Neale, 2006). Contrary to the quantitative research, this technique gives a chance to dive deeper in the topic with a smaller group of participants i.e., one-on-one. Moreover, in-depth interviews enable a more relaxed environment for the interviewee as opposed to when they have to fill out a survey-questionnaire (Boyce & Neale, 2006).

4.1.1 Description of the structure of the in-depth interviews

With a predetermined format, the interview has a structured nature, and each interviewee was asked the same 10 questions. The questions were selected and structured in a way that enables us to gain the company’s perspective and dive deep on the topic: usage of consumer data for marketing purposes. Thus, we were looking at all factors that are connected to the topic such as: data types, data gathering methods, analysis tools and data employment. All interviews were carried out on the phone and their time duration varied between 45 minutes and 1 hour.

Before starting with the interview, an introduction to our research and how the provided information will be used was given. After the introduction, the interview starts with questions which gather some general information about the company, such as industry type, size and age. Within this part, we also identify the interviewee's current position within the company, as well as the department where his/her role is based. Further on, we move on with the questions.

In the first two questions, the interviewee was asked whether the company in general gathers consumer data and if so, which department within the company has that responsibility. With the third question, we get knowledge on the most common channels the company uses to collect data. The types of consumer data (e.g., demographic, social etc.) which is being gathered is explored within the fourth question. Further, with the fifth question we are able to learn which are the most frequently used tools to analyze the consumer data. In the sixth question we ask whether the company’s marketing decision-making is driven by consumer data and if so, which are these decisions.

While questions one through six are based on consumer data itself, questions seven through ten explore how this data is used in the company’s marketing communications, in particular for the purpose of ad personalization. With questions seven and eight, we familiarize whether the company uses personalized advertisements and if so, which personalized techniques are practiced for their marketing communication.

Further, we ask the interviewees to express their personal, professional opinion on the benefits of personalized ads compared to the non-personalized ones. Finally, with the tenth question, we discover if the company has previously tested how the different levels of personalization affect their consumers.

4.1.2 Description of the sampling methods

There were various factors that were taken into consideration when trying to decide which companies we would contact for the in-depth interviews. For example, we were very cautious to reach out to companies within different industries, as well as have a different size. This is because we were trying to observe whether these two factors actually play a role and cause differences on whether a company will decide which data to collect and how to use it. Further, whether the decision to use personalized ads as part of their marketing communication might also depend on the aforementioned factors.

In order to have the right answers to our questions, we used the purposive sampling technique. For the purposive sample we created a list of possible interviewees who were experienced in our topic of research and worked within companies that were a part of our network. The list included individuals which are marketing employees and have a title of a chief marketing officer (CMO). When that list was exhausted, we reached out to appropriate candidates via LinkedIn.

Initially, we targeted marketing specialists from 20 different companies. However, when we reached out to some potential interviewees and discussed the interview's purpose, we received negative feedback connected to the companies' confidential policies. The root cause for it was in fact the introduction itself, in particular, the part where we give the interviewees the possibility to disclose their name and/or the company's. It seems that when there is such an option, it causes negative reactance as they are always afraid that if not stated or guaranteed clearly, the name disclosure might be leaked somewhere and cause confidentiality conflicts with the company itself. In addition, due to the questions' sensitive nature, revealing such confidential information is considered as a breach of contract within most companies. Taking this into consideration, we decided to move forward with an approach that does not give the potential interviewees the possibility to disclose neither their or their company's name. Additionally, we assured them that the gathered information will only be used for the purposes of our research and would not be distributed nor used by any third parties.

Due to the limited timeframe, we carried out 6 interviews. Even though this sample is not considered to be statistically large enough, we find that with this number of interviews we were still able to derive valuable insights for our topic.

4.2 Quantitative Research

As a part of our quantitative research, we used a survey questionnaire which was carried out with the help of the online survey tool, 1ka (www.1ka.arnes.si). We decided to use this tool for the purpose of our thesis as it is bilingual (English and Slovenian) and it allowed us to design and analyze the collected data at no cost. The survey itself was created on September 6th, 2020 and tested with 20 respondents until September 8th. This period was considered as a test period, as it allowed us to identify any potential question misinterpretation. Officially, the data gathering took place online, from September 14th until October 12th, 2020.

Furthermore, the survey questionnaire consisted of 20 questions and its estimated duration was approximately 7-8 minutes. In order to analyze the collected data, the following tools were used: 1ka for the basic demographic analyses, Excel 2019 for data filtering and visualization of results and Statistical Package for Social Sciences (SPSS) for multivariate analyses (e.g., One-way ANOVA, Classification and Regression Tree).

4.2.1 Description of the structure of the survey questionnaire

The survey questionnaire's structure is composed out of seven blocks. These blocks were structured in a way that makes the results comparable to previous studies. As there was no previous research which observes altogether the consumer's perceptions on ad personalization, trust, privacy and ad relevance, we had no choice but to develop the survey questionnaire according to multiple studies which touch upon each topic.

The survey questionnaire started with a welcome screen, with an introduction to the topic and the reason why the survey is being conducted. The first few questions referred to the individual's GDPR consent to collect (demographic) personal data in the survey and the **general usage of social media platforms**. With the first four questions in particular, we were able to learn the sequence of social media usage and classify the respondents to the corresponding sample ("How often do you use social media?"; "Which of the following social media platforms do you use most often?"; "What type of device(s) do you most often use to access social media platforms?"; "How many advertisements (paid messages where the brand is known) have you seen placed on social media platforms in the last two weeks?").

After showing one of the three hypothetical ad scenarios, the participants were given one question which helps us measure the **likelihood of actually clicking on the advertisement.** The question itself was "How likely is that you would click on the ad that you have just seen" and it was constructed based on research such as the one of Aguirre, Mahr, Grewal, Ruyter and Wetzels (2015) and White et al. (2008). Through this question, or more precisely answer, the survey questionnaire participants were able to express their click-through intentions by choosing one of the points on the likelihood ratio scale, varying from "very unlikely" to "very likely".

Further, it is of crucial value that **perceived personalization** is differentiated from actual personalization and therefore measured separately. This was pointed out by Li (2016) as occasionally, personalized advertisements can be perceived as non-personalized ones or the other way around. Keeping this perspective in mind, we were careful to look and determine whether the participants of the survey questionnaire differed in perceived personalization within the three possible ad scenarios. This was done with two-items (Li & Liu, 2017), where the participants had to mark correspondingly the degree to which they believe that the advertisement was based on their preferences ("I believe that the ad I saw is not based on my preferences") and to which degree they believe that the advertisement was created explicitly for them ("I believe the ad I saw was specifically created for me"). In both statements, we used a seven-point Likert scale, (from "strongly disagree" to "strongly agree") as we believe that this scale provides us with more reliability when it comes to measuring the participants' attitudes.

While we measured perceived personalization with two-items, **ad relevance** was measured with the help of a single-item (Xia & Bechwati, 2008; Keyzer, Dens and Pelsmacker, 2015). The survey questionnaire participants were once again supposed to indicate the degree to which they believe that the advertisement presented to them is relevant for their needs ("I believe the ad I saw is relevant for my needs"). For this situation, we used the seven-point Likert scale where participants could mark their degree of agreement or disagreement correspondingly from "strongly disagree" to "strongly agree".

While the very first few questions were mainly focused on click-through intentions, ad personalization and ad relevance, the following question explored the participants overall **perceptions on privacy violations** when keeping in mind the specific ad scenario. We used a 7-point Likert scale which allowed us to measure the perceptions of privacy violations with a statement based on the degree of agreement or disagreement (from "Strongly Disagree" to "Strongly Agree") (Tucker, 2014). The statement itself, straightforwardly asked them to express whether the given ad is intrusive towards their privacy ("I find this ad to be intrusive towards my privacy").

We later on measure the overall **trust** of the participants towards Samsung as a brand. Here in particular, the research of Bleier and Eisenbeiss (2015a) was extremely useful when adapting the 7-point Likert scale (from "Strongly Disagree" to "Strongly Agree"). In a simplistic manner, we once again asked the participants to express their level of agreement or disagreement on whether they find Samsung to be a trustworthy company ("I consider Samsung a trustworthy company").

As privacy is one of the main factors on which our research is based, it was only natural that we would both address and measure the **general concerns** of the survey questionnaire participants, when it comes to their (online) **privacy**. This was done with two-items (statements) placed on a 7-point Likert scale. With the help of previous readings and research, in particular the one of Baek and Morimoto (2012), we were able to put two statements which explore the data privacy concerns of the participants. We asked the participants to mark correspondingly their degree of comfortability when it comes to having their data used and/or shared without permission ("I am uncomfortable having my data used and/or shared without my permission"). Moreover, we asked them to express their feelings of concern when a random advertisement is too close to their previous online activities ("I am uncomfortable when an ad is too close to my online activities").

In the studies carried out by Van Dyke, Midha and Nemati, (2007) and Kim and Kim (2011), the perception of privacy control was measured on the individuals' webpages usage. We adjusted our 7-point Likert measuring scale based on their researches and measured the participants' **privacy control perceptions** with one statement ranging from "strongly disagree" to "strongly agree". The statement allowed them to express their overall state and feeling of control over their personal data in a straightforward manner ("I feel in control of my data").

By using transparent practices, companies can improve that awareness and inform their consumers which and how the information is being collected, as well as the ways it can be deleted (Karwatzki, Dytynko, Trenz & Veit, 2017). To measure **perceptions of ad transparency,** we adjusted our 7-point Likert measuring scale statements ranging from "strongly disagree" to "strongly agree". With the first statement, the participants were able to express their overall awareness on whether they know how the data they share in the online world is being stored ("I am aware of how my shared data is being stored"). While the second statement questioned whether the participant was aware that companies in general have ways to track their online activities ("I am aware that companies have ways to track my online activities."). the third statement challenged whether the participant's awareness of the techniques companies use to gather their data ("I am aware of the techniques companies use to collect my data.").

Further, they were asked to mark their degree of agreement or disagreement on whether they feel informed beforehand that their data is being collected by the companies when they visit their webpages ("I feel informed beforehand that my data will be collected by the company"). In the fifth statement, we asked the participants whether they can actually pick from different options on how their data will be used by the company which acting as a data collector ("I can pick from different options on how my data will be used by the company"). Finally, with the sixth statement, the participants expressed their level of agreement or disagreement with the fact that they can always go back and request or delete by themselves the collected data ("I can always go back and request/delete myself the collected data").

In order to measure the **overall brand attitude** of the participants and check if there any biases might exist when they answered the questions placed in the survey questionnaire, with one-items or in other words, one question. The scale itself was based and further on adjusted correspondingly to the one of Dahlen (2005) as well as to the one of Cruz, Leonhardt and Perzzuti (2017). With the help of a five-point semantic differential scale varying from one to five, with one being "Bad" and five being "Good", the participants expressed their overall attitudes towards Samsung as a brand ("My overall attitudes towards Samsung as a brand are:").

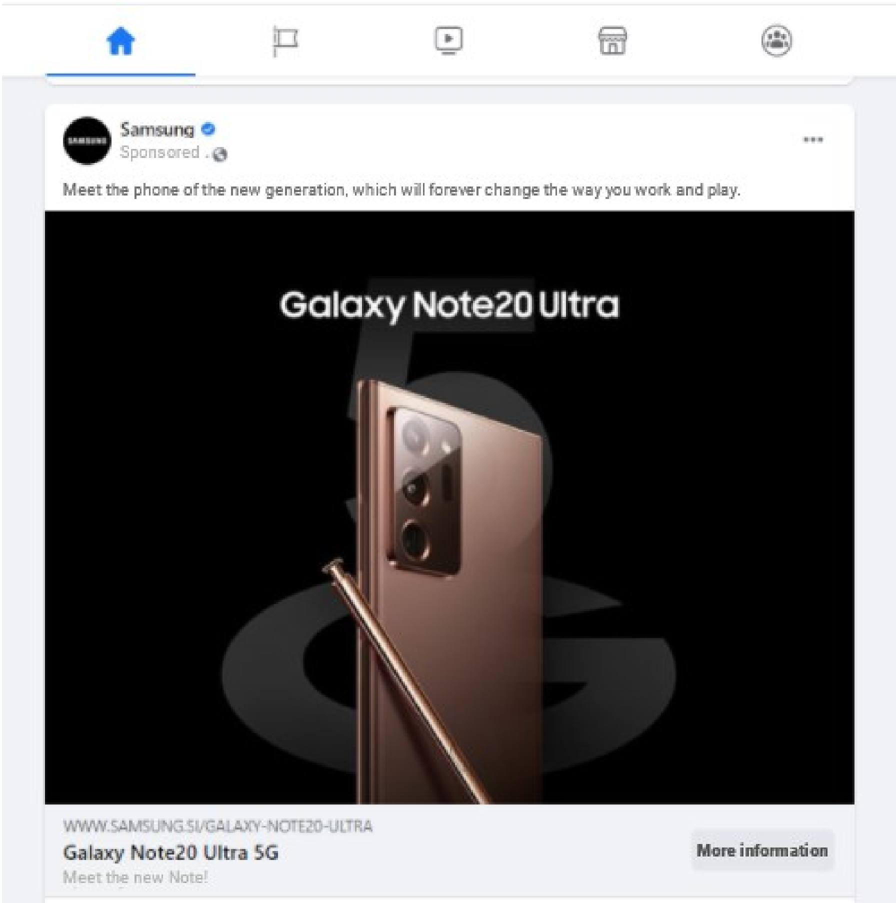
Finally, in order to better understand certain background traits of the respondents, we included **demographic questions** as the end of our survey. In particular, we gathered data about their gender, age, country of origin, type of living community, education and current occupation.

4.2.2 Stimuli

By leveraging Adobe Photoshop, we adapted an advertisement for the Samsung Galaxy Note20 Ultra phone, implemented as part of a user's Facebook timeline (See Figure 9). We selected Facebook due to its popularity and its highest growth among all social media networks (Shareef et al, 2019). As per month it has 2.7 billion active users (Statista, 2020), we assumed that most, if not all, of our survey questionnaire participants will be able to imagine themselves scrolling through a Facebook timeline and encountering an advertisement. All participants seem to have gone through the presented scenario without difficulties, as we did not receive any negative feedback on this. A phone was chosen as a stimulus due to the fact it can be considered as both age and gender neutral.

The survey participants were assigned at random to one of the **three possible ad scenarios**: Non-personalized ad scenario (n=147); Moderately-personalized ad scenario (n=135); Highly-personalized ad scenario (n=122). The ad scenarios were based on a personalization continuum similar to the one of Keyzer, Dens and Pelsmacker (2015), where they put online advertising on a continuum which ranges from no personalization, to more general personalization, to full personalization.

Figure 9: A Samsung advertisement placed on a Facebook timeline



Source: Adapted from a Samsung Facebook advertisement.

In the **non-personalized ad scenario**, the participants were asked to assume that they were on their Facebook profile scrolling at their home page and that at some point they reach an advertisement of a Samsung Galaxy Note20 Ultra phone. In this scenario, the participant would not have any previous online (private) messaging or browsing activities related to mobile phones, Samsung Galaxy Note20 Ultra or the brand itself.

Furthermore, in the **moderately-personalized ad scenario**, the participants were asked to assume that they visited Samsung's webpage and that they browsed through some of the available mobile phones. Shortly afterwards they were supposed to assume that they logged onto their Facebook account and encountered the advertisement of a Samsung Galaxy Note20 Ultra phone on their homepage.

Finally, in the **highly-personalized ad scenario**, the participants were asked to assume that they were discussing with their colleague the new Samsung Galaxy Note20 Ultra phone in their private online messages. At that point, they were also asked to assume that they have never browsed the web for this specific phone. Shortly afterwards, they would be on their Facebook homepage and would encounter an advertisement of the Samsung Galaxy Note20 Ultra phone.

4.2.3 Description of the sampling methods

During the first stage of the sampling process, we have used two non-probability sampling methods: voluntary and convenience sample. With the voluntary technique, we were able to gather data by sharing the survey questionnaire on LinkedIn and Facebook, kindly asking people to participate. This technique is based on self-selection, meaning that the sample is created out of individuals who voluntarily take part in the research.

Meanwhile, with the convenience technique we distributed the survey among people who were easy to reach via a personal message, such as family and friends, as well as acquaintances. For this method, Facebook, LinkedIn and Instagram were used as main distribution social media channels. In addition, we also used traditional channels such as SMS and e-mail.

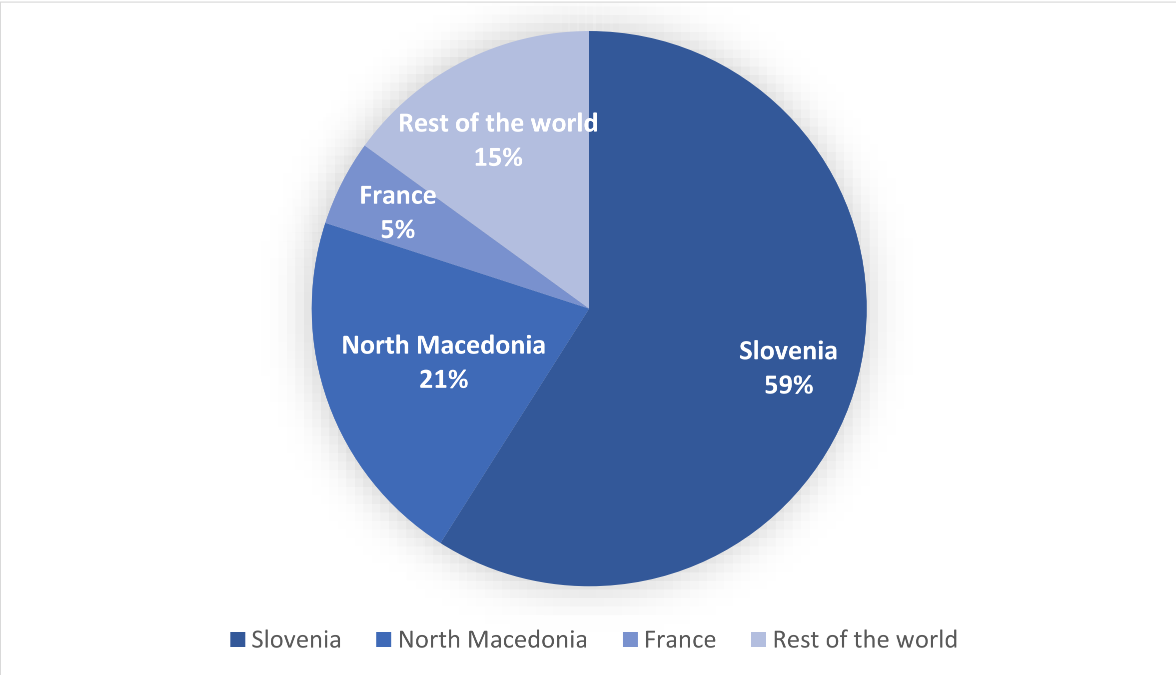
In the second stage of the sampling process the snowballing technique was used. This means that respondents who have already filled out the survey refer the survey questionnaire to contacts within their network (Oxford Reference, n.d.). With this technique we were able to increase the size of our sample. In the end, the number of total surveyed participants which were considered as valid amounted to 479, however we were able to use and analyze only 404 responses, as there were either too many missing variables or the respondents did not choose the appropriate answer to the control question.

4.2.4 Demographic characteristics of the sample

Demographic data such as gender, age, education, current occupation as well as country of origin, helps us to better analyze and understand the background of the sample. Within our sample, 64% of the respondents are female and 35% of the respondents are male. That leaves us with 1% of the respondents who did not want to disclose their gender. Furthermore, the respondents' age group classification yielded the following output: 1% below 19; 85% between 20-29; 11% between 30-39; 1% are between 40-49 and finally, 2% above 50. The high percentage within the 20-29 age group is mainly driven by the fact that we also belong within that group, meaning, our survey distribution network is generally classified there.

As set out in Figure 10, the vast majority of individuals in our sample comes from Slovenia (59%), followed by North Macedonia (21%) and France (5%). The remaining number of respondents (in total of 15%) are coming from the following countries: Australia (1), Austria (6), Belgium (1), Bosnia and Herzegovina (4), China (2), Croatia (1), Czech Republic (1), Germany (5), Greece (5), Guinea-Bissau (1), India (2), Ireland (1), Italy (4), Luxembourg (1), Montenegro (4), Norway (2), Pakistan (1), Poland (1), Portugal (1), Romania (1), Russia (2), Serbia (6), Slovakia (1), Spain (1), Switzerland (1), Turkey (2), UK (1), US (2), Uzbekistan (1) and finally, Vietnam (1). In addition, 59% of the surveyed individuals are currently living in a large city, 14% in a suburb near a large city, 21% in a small city or town and 6% marked that they are living in a rural area.

Figure 10: Country of origin

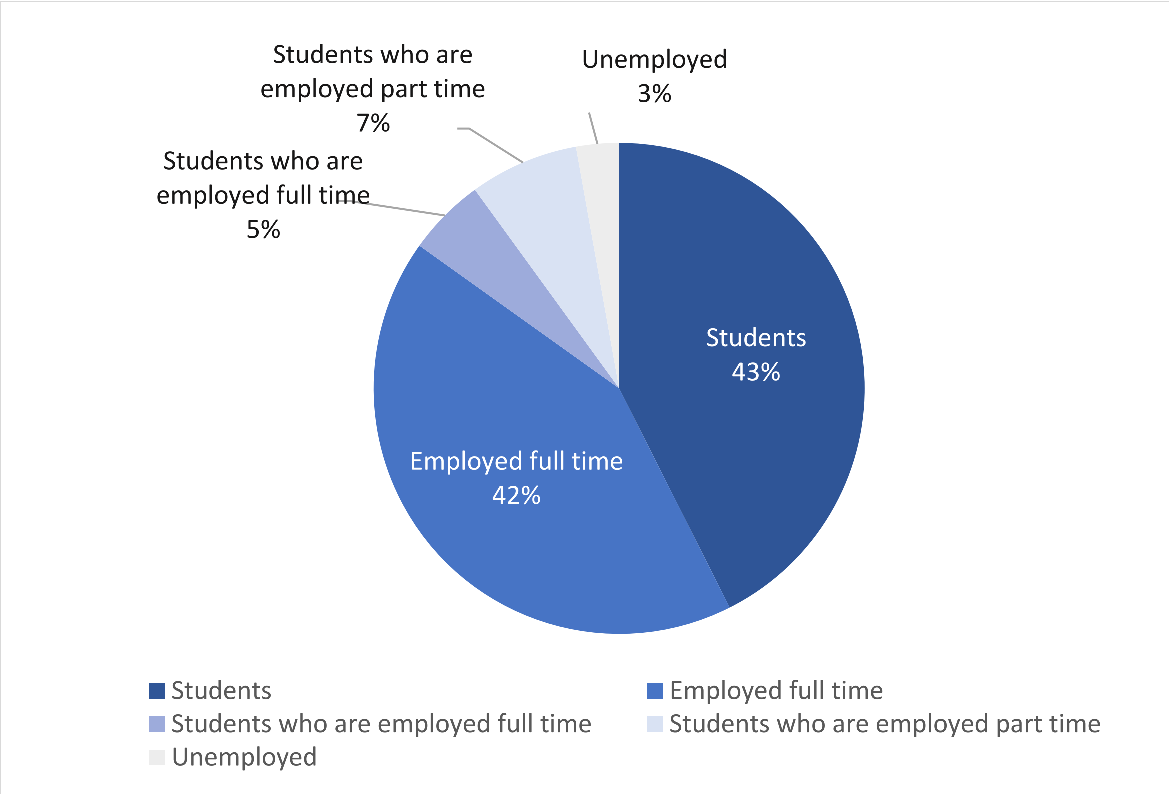


Source: Own work.

Finally, when it comes to the respondents' highest level of education, 64 respondents own a high school degree or equivalent (16%), 221 respondents have obtained a Bachelor's degree

(55%), 116 have received a Master's degree (28%) and 3 respondents preferred not to answer (1%). The current occupation divides them into the following groups: 166 are students, 165 are employed full-time, 14 are employed part-time, 20 are students which are also employed full-time, 28 are students which are at the same time employed part-time, 11 unemployed (See Figure 11).

Figure 11: Current occupation



Source: Own work.

5 RESEARCH RESULTS

5.1 In-depth Interviews

According to the Slovenian company size classification (Zakonodaja.com, n.d), two of the chosen companies are considered as micro (up to 9 employees), three as small (up to 50 employees) and one as a big company (above 250 employees). As we did not have available information regarding the company's profits, our main indicator for size was the number of employees. The companies are present within different industries, including recruitment, e-commerce, sport equipment, retail, financial services and the beverage industry.

Our interview questions were structured to be answered by employees whose role in the company includes using consumer data for marketing purposes (i.e., personalized advertising). With that said, we were targeting specifically employees whose day-to-day tasks encompass leveraging consumer data for putting together the company's marketing communications and whose title is Chief Marketing Officer (CMO). An interesting observation that comes along from our interviews is that the titles of the responsible employees are very versatile from company to company. Our "point of contact" for the interviews were employees who carry a title of chief marketing officer (CMO), brand manager, marketing project manager, marketing specialist and chief executive officer (CEO). The contact which carries a title of a CEO comes from a micro company without an existing marketing department. This suggest that depending on the company's internal structure, the title differs for the same role. An overview of the companies' industry, size and age, as well as the interviewees' position can be found in Table 5.

Table 5: An overview of the companies' industry, size, age and the interviwees' position

Company	Industry	No. of employees	Company's age	Interviewee's position
#1	Sports equipment	15	27 years	CMO
#2	Beverage	600	195 years	Brand Manger
#3	Financial services	20	6 years	Marketing Project Manager
#4	Retail	20	21 years	CMO
#5	e-Commerce	4	10 years	CEO
#6	Recruitment	6	10 years	Marketing Specialist

Source: Own work.

All of these companies gather consumer data for marketing purposes mainly through online channels such as social media, websites, e-commerce and mobile apps. Some also gather consumer data the 'old-fashioned' way - in brick-and-mortar stores, however they say that this technique is not very convenient as it includes more "manual labor" to derive actual consumer insights. One of the companies (See Table 5) which collects data in such way gave us the following answer:

"Since we are present in both brick-and-mortar stores and online, I must admit for our physical store we are not that data-driven. I would say that this is kind of a drawback for our business as it is not as convenient (it is much harder to be data-driven when owning a physical store) and does not allow us to anticipate what the consumers visiting our store would like. We do have types of forms that can be filled out but, this requires much more time and energy from both our employees and customers. However, when it comes to our online presence, we most certainly try to rely our marketing decision-making on consumer data as much as possible." (Respondent #1, 2020).

Another response (See Table 5) which stood out from the others to the question on how the company gathers consumer data worth documenting is the following one:

"Consumer data is always gathered on, or through, the website. Reason is that the customer has to accept our GDPR statement before we allow ourselves to store such data. We motivate and ask customers to register as our members and so submit their personal data through various social media platforms, online advertising and physical shops. In the later, there are still some "Post-it" stickers in physical shops, where sellers write down the numbers of customers, but we try to minimize and eventually ban that." (Respondent #4, 2020).

The reason why the above-mentioned response caught our attentions is that it was the only employee which addresses the GDPR, even though this is a key regulation when it comes to the proper collection of user data within the EU. Moreover, the interviewee also admits that the company tries to "ban" the ways of collecting data in brick-and-mortar stores as it not so convenient.

In general, the collected data within all companies includes demographic, behavioural and social consumer data. Furthermore, on the question of most frequent tools used to analyze the data and turn it into insights, in each interview, Google Analytics was always mentioned as the first tool. This comes naturally as the tool itself is known as the "freemium" service which companies can use to measure advertising ROI and track all consumer activities across multiple channels (Hearn, 2017). Some also use internally developed systems, Customer Relationship Management (CRM) and/or Enterprise Resource Management (ERP).

Not all companies have a specific department responsible for gathering and analyzing the data. In our case, the gathering of consumer data belongs mainly to the marketing department within the company, however, two of the companies also cooperate closely with the research and development department. This seems to be generally driven by the limited capacity of employees, who have more general roles rather than specific ones. In each of the interviewed companies, the gathered consumer data is recognized as an asset as it helps them make better marketing decisions (future goals, targeting etc.) and better user experience (UX). In addition, we found that some of the companies' decisions on new product development and product recommendations are also driven by consumer data. One of our interviewees (See Table 5) also specified in what way the use consumer data. For example, they retrieve data for the geographical area of the user which enables them to adjust the promoting content accordingly. The full answer can be found below:

"Yes. Speaking from e-commerce perspective, we communicate and promote items are most bought or viewed on our website. We use personal data to see, which geographical areas are spending more money and which ones less. That's how we can also adjust the content being promoted in different geographical areas. For example, trail running outfits are more favourable in mountain regions, whereas city running outfits are more favourable in the cities." (Respondent #4, 2020).

An insight which can be derived from these interviews is that ad personalization is or has already been a part of the marketing communication in each company. This means that ad personalization is widely leveraged across different industries and different company sizes. On the benefits of personalized ads compared to non-personalized ones, each of the interviewees answered that personalized ads are better as they are more relevant for the consumer and are more measurable compared to other adverts, however, two of our interviewees gave us answers worth noting:

"Personalized ads "hunt" the consumer with a product or a service that he/she has already expressed interest in. In this way consumers don't lose time searching for the solution, because the solution comes straight to them. The more often the consumer sees the product, the more likely he/she is to convert. Often consumers can be irritated by non-personalized and general ads, and might start to ignore them. However, personalized ads are just the opposite. It is like having a direct sales rep communication by an individual consumer, just that the sales rep doesn't even know about it." (Respondent #4, 2020).

"I strongly believe that personalized advertising has a way better effect than the traditional. As a company that has had such a long advertising history and we have definitely used all of the available media channels to deliver our adverts in the past, we can really see that the personalized ones perform better and are more measurable than for example our tv ads.' (Respondent #2, 2020).

When it comes to the personalization techniques that companies employ for their marketing communication, the ones that are mentioned more frequently than others include retargeting, targeting and e-mail personalization. Interestingly, even though companies do use personalization techniques, they do not seem to be aware which specific ones are used. For example, overall, they were aware which type of data they are using (e.g., demographic), however they did not know the correct term for the used technique in this case i.e., targeting:

"Not sure what is official classification, but we personalize our ad messages and CTA based on target audience of this specific ad." (Respondent #3, 2020)

In addition, we also wanted to learn whether the companies have previously tested the different levels of personalization. Based on their responses, only one out of the six companies have tested moderately-personalized communication versus non-personalized communication. In their case, they tested it through their e-mail newsletter, where moderately-personalized e-mails had a higher open rate than the non-personalized ones. The rest of the companies have however expressed interest to test the effect of different levels of personalization on the effectiveness of the ad.

5.2 Survey-questionnaire

5.2.1 Usage of Social Media platforms

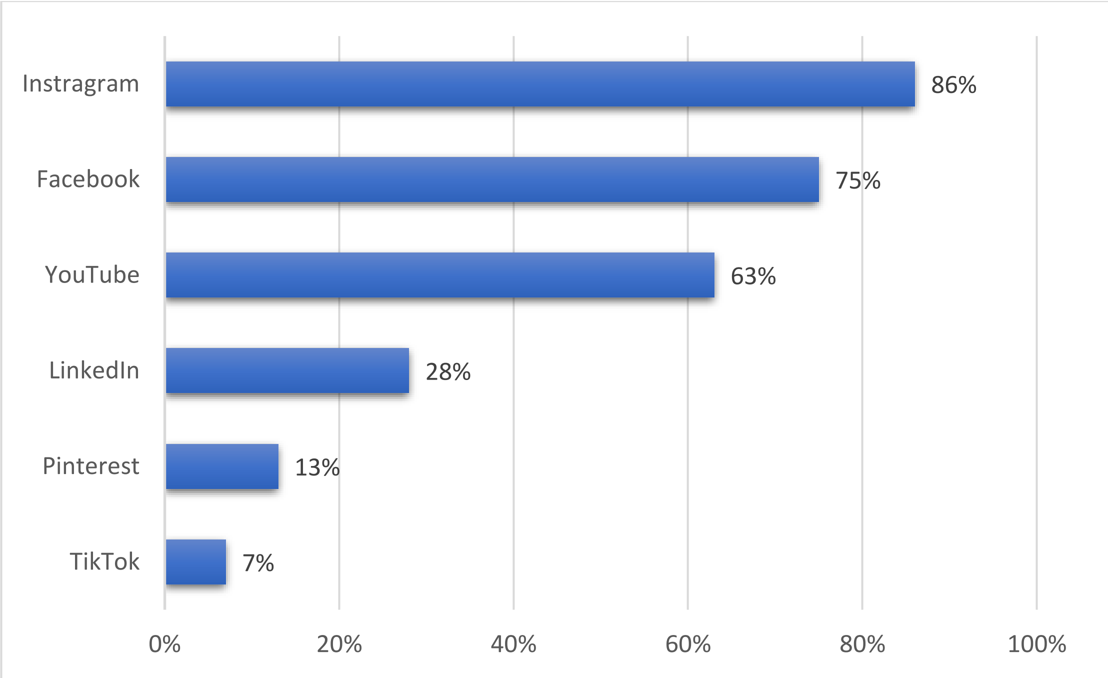
According to the recently enforced law on data collection in Europe (GDPR), any personal data collection needs to be approved from the respondent's side. To be in line with this regulation, our survey questionnaire starts with a question regarding personal data collection. The results of the survey questionnaire show that not all of the respondents consent to have their data used for the analysis. This comes even though within the question's introduction it is stated that data is completely anonymous and will only be used for the purpose of the master thesis.

Furthermore, to our first question on how often the respondents use social media, 97% of them have answered several times a day. The remaining 3% of the respondents use social media once a day. This comes to no surprise as most of our respondents are between the age of 20 to 29, the group considered as the most present on social media channels. In addition, the main channel of the survey's distribution was social media itself.

In the following question, we asked our respondents which social media platforms they use the most often. As our possible choices of social media networks, we included: Facebook, Instagram, YouTube, LinkedIn, Pinterest and Tik-Tok. We included these networks as we believe that they are the ones which are most commonly used in Europe and are used among various age generations. However, the respondents also had the possibility to name additional social media networks they use but cannot be located on our list. In Figure 12 we can observe our results from this question and see that the top three most used social networks on a daily basis among our sample are Instagram with 86%, Facebook with 75% and finally YouTube, with 63%.

Again, we expected these three social networks to be on the top of our "most often used" list, since most of our respondents are in their twenties. Additionally, from the self-reported social media networks that our respondents have named, the ones that were mentioned several times as most often used are Twitter, Reddit and WhatsApp.

Figure 12: Most often used Social Media platforms

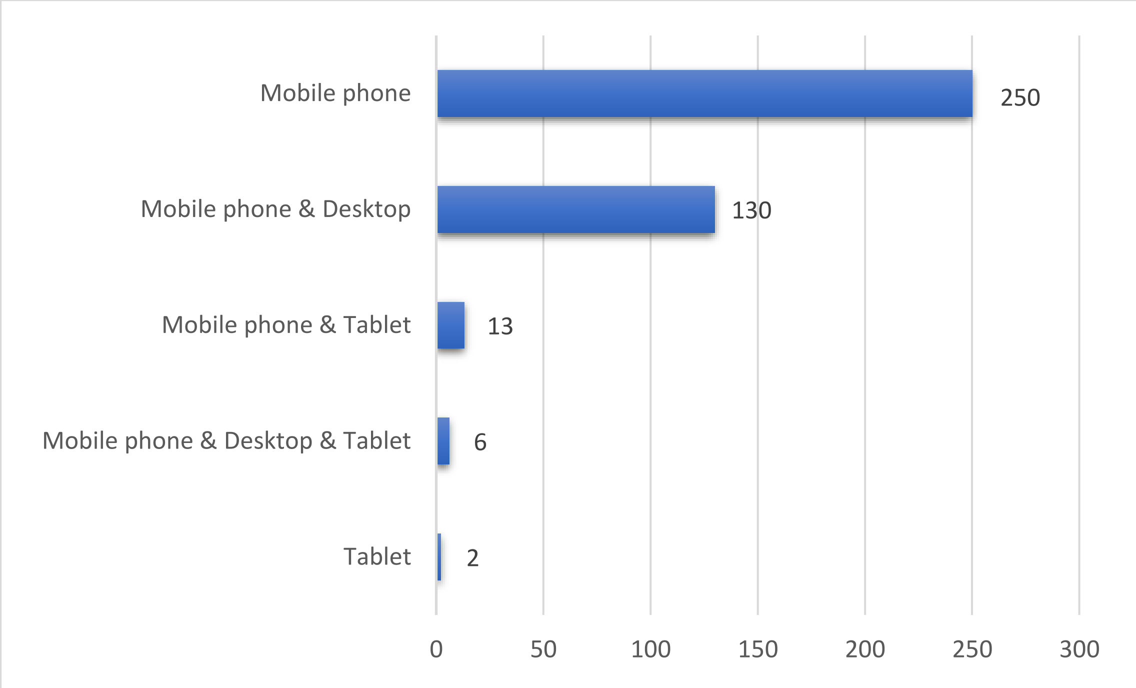


Source: Own work.

Furthermore, we questioned the respondents on the device they use to access the social media platforms. From our sample we can see that the mobile phone can be considered as the "main channel" through which respondents access social media networks. In particular, 250 respondents access social media networks exclusively from their mobile phone, 130 access it from both their mobile phone and their desktop and only 6 respondents use all three devices to access social media networks. The remaining 13 respondents access social media platforms through a combination of mobile phone and tablet, while 2 respondents use only their tablet (See Figure 13).

It was quite foreseeable for us that the mobile phone would be the device which is most commonly used to access social media networks, as nowadays more than half of the world's web traffic is generated through the mobile phone (Ryu & Park, 2020). From our sample, we mark that 321 of our respondents have accessed and solved the survey from their mobile phone.

Figure 13: Usage of Social media by device type



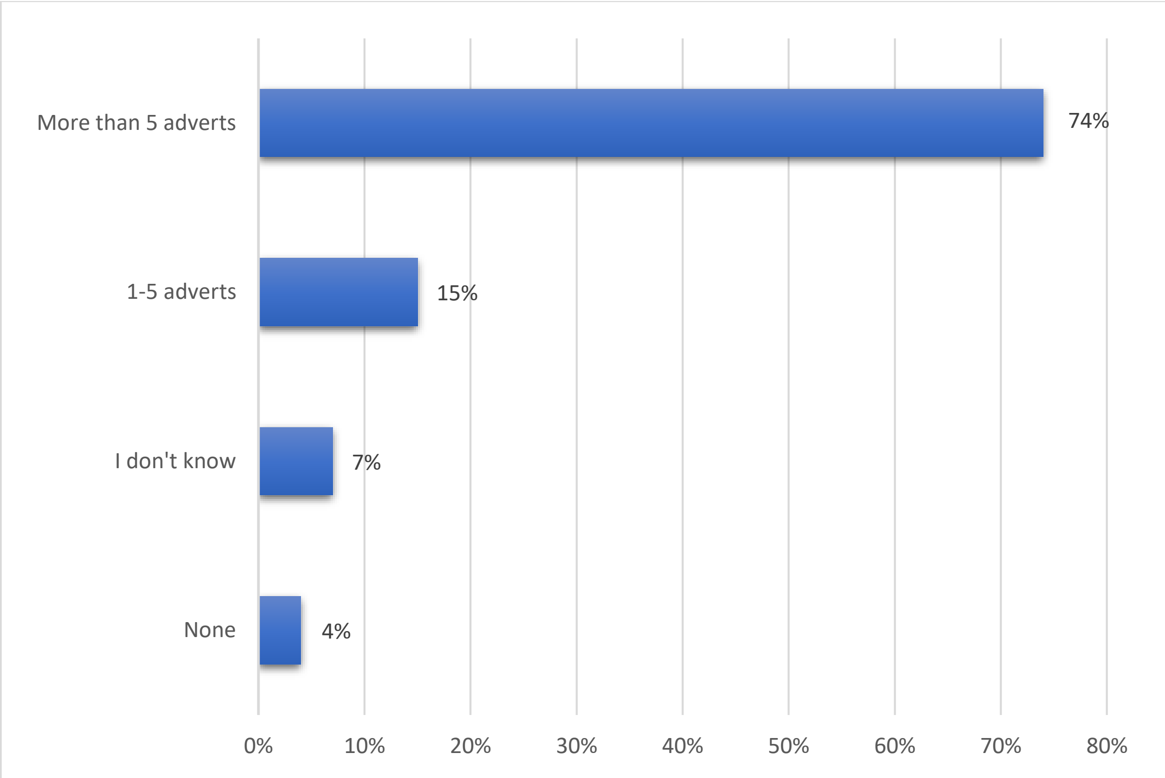
Source: Own work.

5.2.2 Ad awareness on Social Media

Prior to giving the respondents an ad scenario, we decided to check their actual awareness of ads placed across Social Media networks. In particular, we asked them how many paid advertisements they have noticed over the past two weeks on the social networks they are present.

The results show that the majority of consumers are very much aware of the paid advertisements placed on social media. As seen in Figure 14, 74% of the respondents noticed more than 5 paid advertisements, 15% have noticed between 1 and 5, 4% have not seen any paid advertisements and finally, 7% were not aware whether and/or how many paid advertisements they have seen over the past two weeks on their social network platforms.

Figure 14: Ad awareness on Social Media (in the past two weeks)



Source: Own work.

5.2.3 Brand attitudes

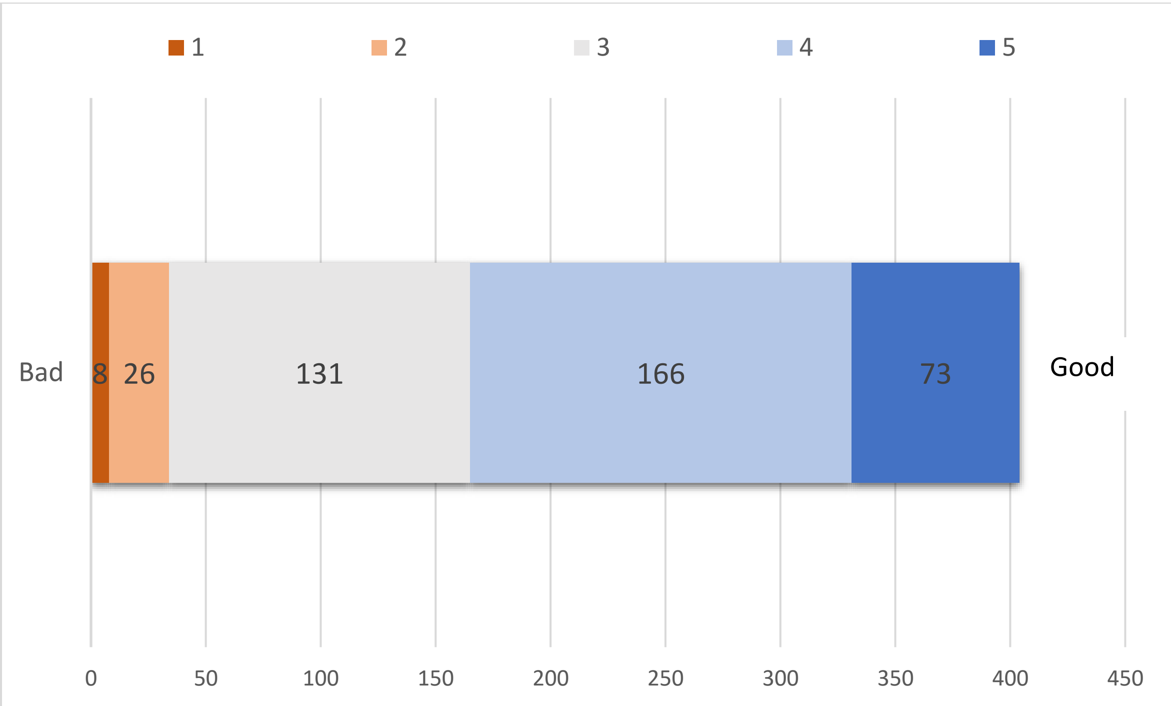
How an individual feels towards a certain brand, more often than never, impacts their behaviour when it comes to click – throughs or even purchase intentions. Moreover, this might create certain biases when it comes to answering questions or expressing level of agreement and disagreement for a certain brand. Since we used a Samsung (phone) advertisement as a stimulus, therefore we set an objective to explore how the participants of our survey – questionnaire feel towards Samsung as a brand.

As illustrated in Figure 15, the **brand attitude** was measured on a scale between one to five, where one equals to bad and five equals to good overall attitude. In other words, we were able to measure the respondents' perspectives with a five-point semantic differential scale as it is most commonly used for psychological measures.

The mean of the sample is 3,67 and it therefore indicates that the respondents have a positive attitude towards Samsung. Our results show that 239 (59%) respondents have answered either with a four or a five. More precisely, 73 (18%) of them have expressed their attitude with the highest number (that is five) and 166 (41%) respondents with the second to highest number (which is four). The ones with a negative attitude towards Samsung as a brand are counted as the ones who have marked either one or two on the scale. This number accounted to 34 (8%). The remaining 131 (32%) respondents have a neutral attitude, meaning neither good nor bad.

As 1ka allows us to observe from **which operating system** the respondents are filling out the survey questionnaire, we notice that 73 (35.5%) of respondents which marked to have a positive attitude towards the brand are in fact Apple users (iOS or MacOSX). The ones which marked to have a bad attitude towards Samsung and are Apple users are 28 (82%) out of the 34 respondents. Interestingly enough, this might be an indication that their response is biased as they might favor Apple more than Samsung. Of course, this is not something we can claim and confirm but might be a viable root cause why these individuals marked to have a bad attitude towards Samsung as a brand.

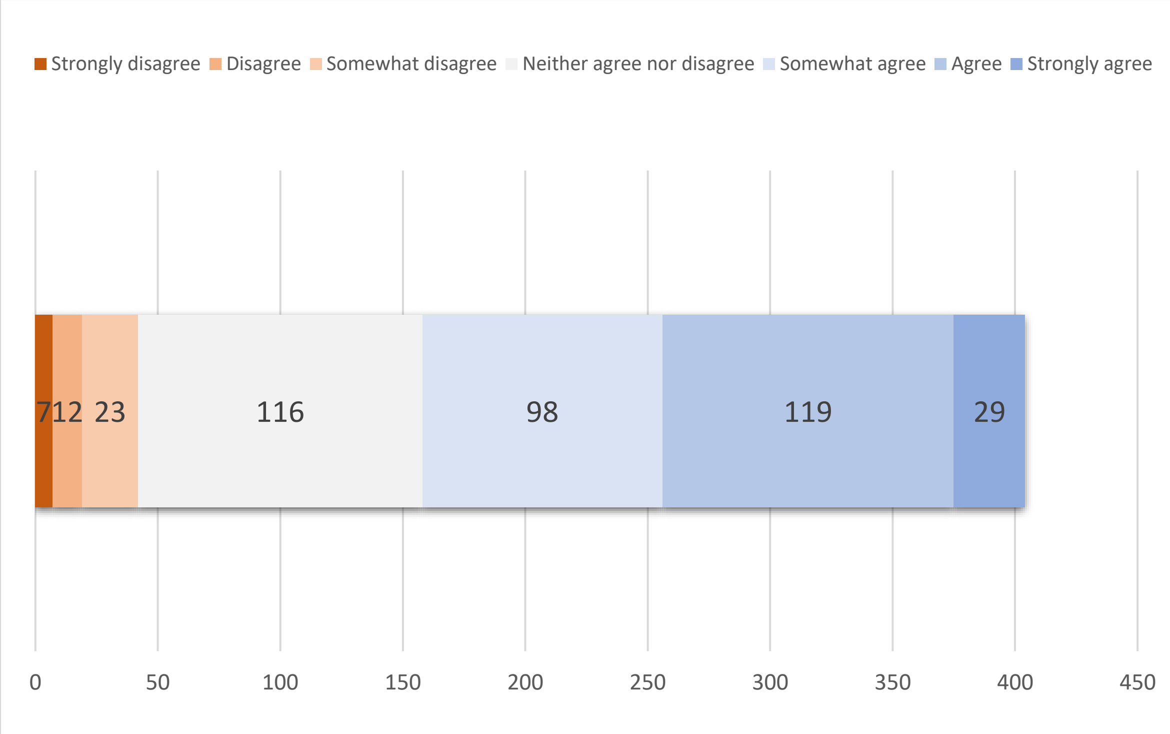
Figure 15: Overall attitude towards Samsung as a brand



Source: Own work.

While we will also test and measure the role of trust when it comes to perceptions of privacy violation and click – through intentions, we also find to be of great value to observe this variable individually. In order to do so, we will now try to derive from our findings what was the participant's attitude towards Samsung as a brand when it comes to trust (i.e., trustworthiness). Respondents were able to express their degree of agreement or disagreement to the statement: *I consider Samsung a trustworthy company*. The results to this statement are set out in Figure 16.

Figure 16: Perceptions of trust



Source: Own work.

Overall, **our findings** are indicating that the majority of our respondents do find Samsung trustworthy (60%). Within the figure, these participants are located on the right, colored in shades of blue. In particular, 98 (24%) of them somewhat agree, 119 (29%) agree with this statement, and 29 (7%) strongly agree. However, there are also respondents who have expressed some level of disagreement. If we take a closer look on the left side of the chart bar (colored with shades of red), we can observe that there are 23 (6%) respondents who have marked that they somewhat disagree, 12 (3%) who disagree and 7 (2%) which strongly disagree with the given statement. The remaining 116 (29%) have expressed a neutral opinion and do neither agree not disagree with the statement.

What we found intriguing to investigate is whether the respondents who marked to have a good attitude towards Samsung as a brand, also marked that they found the brand itself as trustworthy and vice versa. In order to do so, we created a matrix of perceptions of trust versus overall attitude towards Samsung as a brand (See Table 6).

For the purpose of this investigation, we allowed ourselves to group the respondents in a more simplistic manner. By this we mean that we placed the participants who have marked four or five on the scale of attitude towards the brand into one group. Contrariwise, the participants who have marked one or two the scale of attitude towards the brand were placed into another group. In both groups we first filtered on the participants who find the brand as trustworthy and then on the participants who find the brand as untrustworthy. For instance, we considered that respondents who have marked five, six or seven as the ones who do find

Samsung as a trustworthy brand, while the ones who have marked one, two or three as the ones who do not find the brand as trustworthy.

Table 6: Matrix of perceptions of trust versus overall attitude towards Samsung as a brand

	Trust	**No trust**
Good Attitude	190 (94%)	12 (6%)
Bad Attitude	8 (40%)	12 (60%)

Source: Own work.

The results were as anticipated: the ones who have a positive (good) attitude towards the brand Samsung, also find it as trustworthy (94%); the ones who have a negative (bad) attitude towards the brand Samsung, also find the brand as untrustworthy (60%). In addition, this is something we can assert with confidence and we would not lightly disregard that these two variables are positively correlated. Our analysis indicates a positive correlation as the Pearson Correlation coefficient is 0.487 (See Table 7).

Table 7: Correlation analysis

Correlations

		TRUST	ATTITUDE
TRUST	Pearson Correlation	1	.487**
	Sig. (2-tailed)		.000
	N	404	404
ATTITUDE	Pearson Correlation	.487**	1
	Sig. (2-tailed)	.000	
	N	404	404

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Own work.

5.2.4 Perceptions of personalization, privacy concerns and ad transparency

With the aim to explore whether the respondents differ between the **actual personalization and perceived personalization**, like also suggested by Li & Liu (2017), we compared the means of perceived personalization with a combination of two questions: "I believe that the ad I saw is not based on my preferences" and "I believe the ad I saw was specifically created for me". To do so, the first step was to organize the data of the first question for the 7-point Likert scale to be in line with the second question. The second step was to filter the data and group it into non-personalized versus personalized and compare both means (See in Table 8). When looking at the results of the respondents who have received a non-personalized ad scenario, we can see that there were no traces of perceived personalization. However, that was also the case for the respondents who were exposed to a personalized ad scenario, since the mean is just slightly higher. Given the nature of experiment, this was not the best way of addressing this differentiation (not using an actual ad) and our results cannot be used to derive any reasonable insights.

Table 8: Means of perceived personalization by ad type

Type of ad	Mean
Non-personalized	3,51
Personalized (moderately or highly)	4,12

Source: Own work.

Through various public opinion surveys, it was found that people are concerned about privacy threats to a fairly significant extent when it comes to their personal data (Equifax, 1996; Harris & Westin, 1998; Westin, 1997). When it comes to privacy, their behaviour is guided by their past experience in life (Bates, 1964) and it is their knowledge that presents a vital element of perceived control (Kirsch, 1996). Based on that, we wanted to investigate the perceptions of privacy concerns and ad transparency among our respondents.

The **perceptions of privacy concerns** were measured by combining two statements: "I am uncomfortable when an ad is too close to my online activities." and "I am uncomfortable having my data used and/or shared without my permission." The results displayed in Table 8 show that the perceptions of privacy concerns are present among our respondents.

Furthermore, the **perceptions of ad transparency** were measured by combining the following statements: "I am aware of how my shared data is being stored."; "I am aware that companies have ways to track my online activities."; "I feel informed beforehand that my data will be collected by the company."; "I can pick from different options on how my data will be used by the company."; "I can always go back and request/delete myself the collected data." and "I am aware of the techniques companies use to collect my data." As expected, the results of perceived ad transparency are indicating that our respondents think that companies are transparent regarding their collection and usage of data. However, the mean of 4,66 is still not relatively high, which leaves room for the companies to be more transparent when collecting, storing and using the consumer data (See Table 9).

Table 9: Means of perceptions of privacy concerns and ad transparency

Perceptions	Mean
Privacy concerns	5,61
Ad transparency	4,66

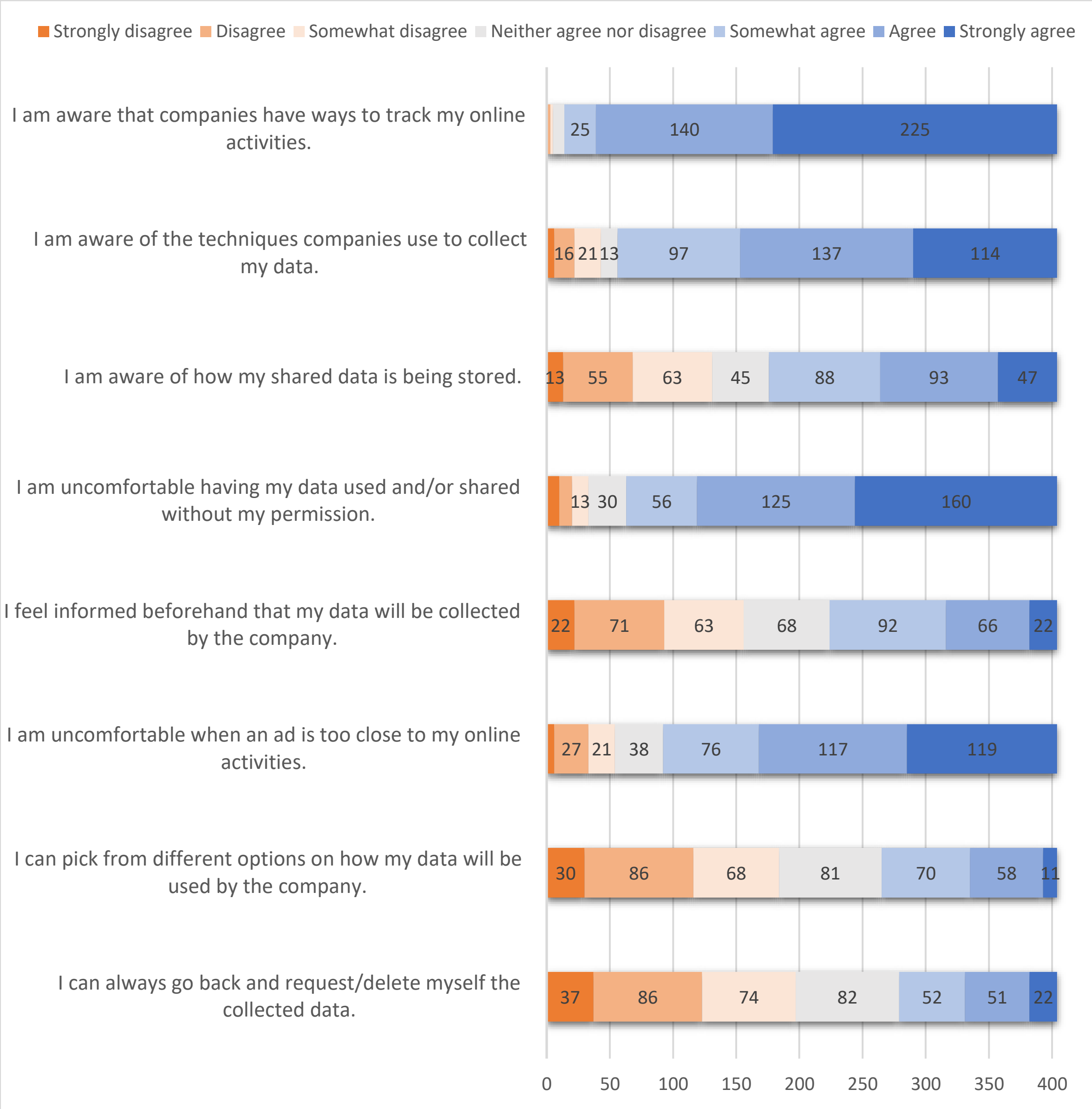
Source: Own work.

Moreover, each individual statement of the perceptions of privacy concerns and ad transparency was analysed (See Figure 17). In the results to the **first statement** "*I am aware that companies have ways to track my online activities*" we can observe that the majority of our respondents agree with the statement to some extent or more precisely 390 of them (97%). The percentage itself is high and clearly indicates that our sample is aware of such data collection practices. Breaking down the data per answer shows that 225 (56%) of the respondents strongly agree with this statement, 140 (35%) agree and 25 (6%) somewhat agree. Only 5 (1%) respondents have expressed disagreement with the given statement, while 9 (2%) of them share a neutral opinion.

The following statement was associated with the previous one and it measures the awareness of the actual data collection techniques: "*I am aware of the techniques companies use to collect my data*". If we would compare and contrast these results to the previous statement, we can see that both have a very high level of awareness on the data practices and techniques, however in the latter this number diminished. Overall, we find 348 (86%) respondents that have answered with strongly agree (28%), agree (34%) and somewhat agree (24%). Contrariwise, there were 47 (10%) of respondents who are not aware of such techniques and 13 (3%) who have expressed a neutral opinion.

In the online advertising world, privacy advocates share the very same concerns when it comes to using personal data: personalized ads might trigger privacy concerns. Our findings reflect such concerns when we observe the results from the *"I am uncomfortable when an ad is too close to my online activities."* statement. More specifically, they show that 312 (77%) find this statement to be true while 54 (13%) find it otherwise. The rest of the respondents remain neutral (9%).

Figure 17: Privacy statements



Source: Own work.

Previous research shows indications that consumers do not particularly have interest in being completely **aware of how their data is being stored** but rather be reassured that the company has an existing privacy policy (Awad & Krishnan, 2006). We explore this ambiguity with the statement "*I am aware of how my shared data is being stored*". The results are showing a closely equally distributed awareness on data storing practices. While 226 (56%) of respondents are still to some extent aware of these practices and have answered with somewhat agree, agree or strongly agree, 45 (11%) have a neutral opinion and the remaining 131 (33%) are not completely or not at all aware of such techniques. These results lean towards confirming what was suggested by Awad & Krishnan (2006).

Furthermore, the consumer determines the **privacy violations** depending on their perceived control over "when, how and to what extent information about them is communicated to others" (Pollach 2005, p. 222). Bearing this in mind, we developed the statement: "*I am uncomfortable having my data used and/or shared without my permission*". As presumed, 341 (86%) of our respondents do agree with this statement, while 33 (7%) feel otherwise. Intriguingly, 30 (7%) respondents have a neutral opinion about it.

Consumers would like to be more informed about **data collection and usage** done by companies (Karwatzki, Dytynko, Trenz & Veit, 2017) and companies are working on this matter by implementing more transparent practices such as informing their consumers which and how the information is being collected, as well as the ways it can be deleted (Karwatzki, Dytynko, Trenz & Veit, 2017). With our next statements we wanted to see if our respondents do detect such transparent practices. For example: *"I feel informed beforehand that my data will be collected by the company*". The results show that there is a similar number of respondents who agree with the given statement to the ones who disagree with it. In particular, 180 (44%) of respondents have replied with a somewhat agree, agree or strongly agree and 156 (39%) of the respondents who have replied with somewhat disagree, disagree or strongly disagree. The rest of the respondents 68 (17%) neither agree or disagree with the statement.

Further, the respondents had to express their **level of agreement to "***I can pick from different options on how my data will be used by the company.*" On the contrary to all the previous questions, there was a prevailing number of negative responses. The results show that 184 (45%) of the respondents do not agree with this statement and have chosen either somewhat disagree, disagree or strongly disagree. There were only 139 (34%) respondents who had reacted positively, by picking somewhat agree, agree or strongly agree. The results of this statement also show a relatively high number of neutral responses - 81(20%) respondents.

Finally, **the last statement** was *"I can always go back and request/delete myself the collected data.*" where once again, the majority of the respondents do not agree with this statement. Out of all respondents 197 (48%) do not agree with the statement and only 125 (31%) agree with it. The rest 82 (20%) respondents neither agree nor disagree. The results of this statement are quite surprising, given the fact that there are ways of consumers to delete some of the collected data themselves, as well as they have the right to request from the company to delete their data. However, it seems that many of our respondents are not aware of them.

5.2.5 Privacy paradox

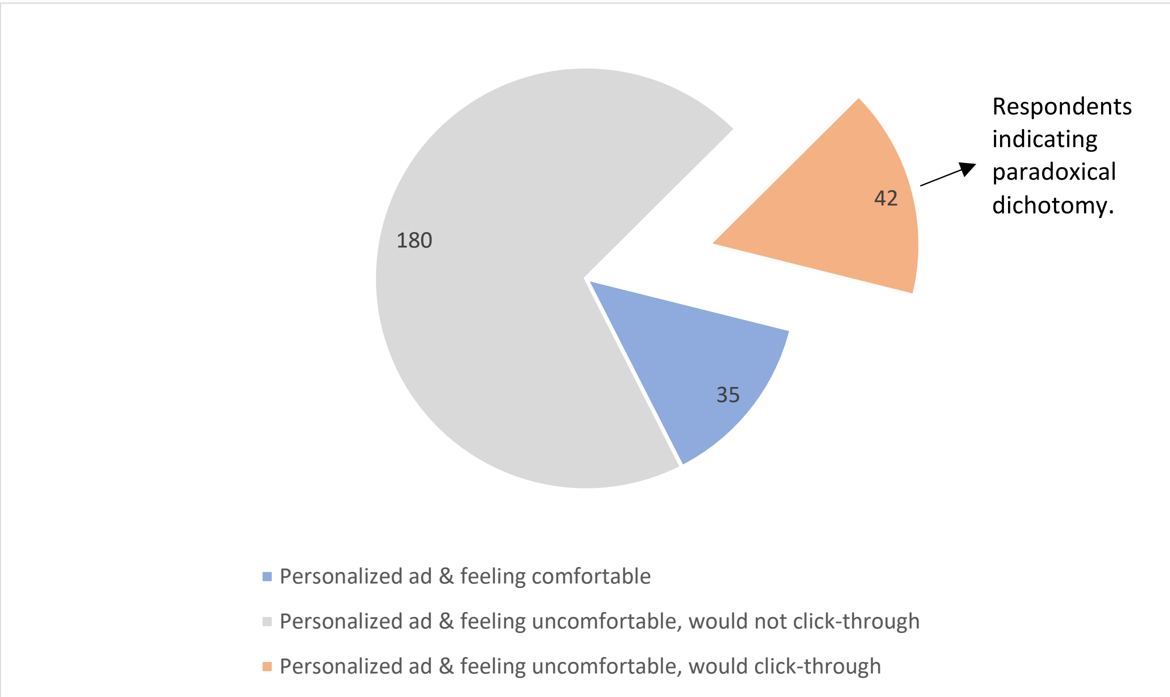
Consumers do not always behave according to what they state when it comes to their privacy preferences. To determine if there are traces of paradoxical dichotomy between the feelings of privacy and the actual behaviour within a personalized setting, we look at the data of the respondents who were actually exposed to a personalized ad in our study. This includes both moderately and highly-personalized adverts as they are both created with the help of consumer data.

In particular, out of 404 respondents, 257 were exposed to such advertisement. As privacy preferences are the base of the paradox, we were interested in how many of those 257 respondents have reacted positively to the statement "*I am uncomfortable having my data used and/or shared without my permission*". All respondents who have reacted to the given statement with a five (Somewhat agree), six (Agree) or a seven (Strongly agree) were taken into consideration. After filtering out the data, we were left with 222 respondents.

The given number indicates that 86% of the respondents which were given the personalized advertisements do not feel comfortable when their data is used or shared without their permission. What is important to note here is that their "fictitious data" was used for the creation of the advertisement itself, which is also clearly given in both of the delivered scenarios. In particular, the moderately personalized advert was created based on the previous browsing history data, while for the basis of the highly personalized advert the information was taken from the respondent's private online messages.

Furthermore, to see if there is some indication that the respondent's behaviour is not in line with what they are claiming, we have checked how many of those 222 respondents also positively reacted to whether they would like to click to the given advert. The final number of those respondents is 42, which adds up to 19% of the 222 respondents (See Figure 18).

Figure 18: Respondents with paradoxical dichotomy



Source: Own work.

Based on these results, we can see that there is a noticeable disconnect between consumer's actual behaviour on one hand and expressed privacy concerns on the other. Meaning, 19% of respondents have still expressed an intention to click on the advert even though they claim that they do not like their data being used without their permission. These results do not prove or deny the existence of the privacy paradox in a straightforward manner, however such percentages should not be neglected.

5.2.6 Ad personalization and click-throughs

H1: Ad personalization and the likelihood of a click-through have a positive relationship

The hypothesis has been developed to observe whether there is a difference in the intention to click-through between situations when an ad is personalized and when an ad is not personalized. In the first step, we differentiated and placed the participants in groups based on the three ad scenarios they got at random: non-personalized (n=147), moderately personalized (n=135) and highly personalized (122). All three groups were compared with *Q7: How likely is it that you would click on the ad that you have just seen?*

To compare the means and test the hypothesis we used a One-way ANOVA in SPSS. Moreover, we carried out a Post Hoc Test (Tukey HSD) in order to have in-depth comparisons between the groups.

This hypothesis can be confirmed since the ANOVA results displayed in Table 10 show that there are statistically significant differences between the groups (p=0.000001).

Table 10: One-way ANOVA for H1

ANOVA

Clickthrough

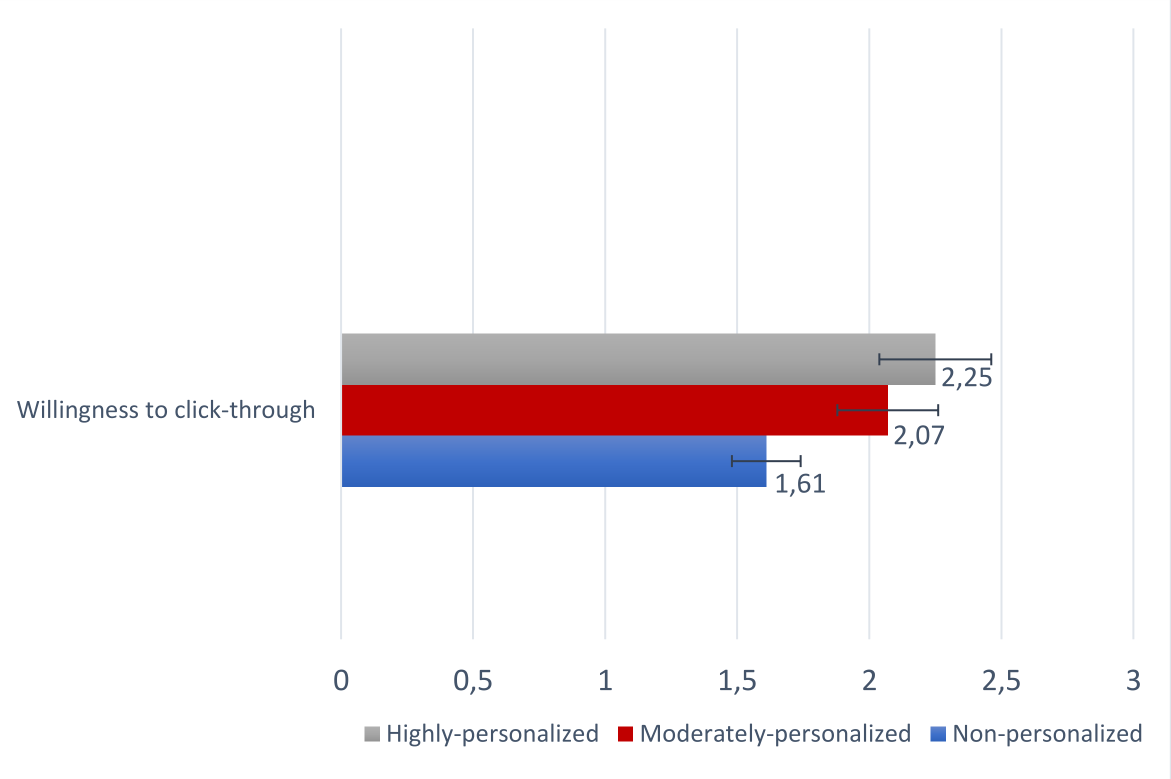
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	29.864	2	14.932	13.911	<.001
Within Groups	430.421	401	1.073		
Total	460.285	403			

Source: Own work.

The post hoc test shows an in-depth view on the P values between each group. We observe that there are statistically significant differences between the click-through intentions in the non-personalized and moderately personalized ad scenario (p=0.0001); likelihood of a click-through between the non-personalized and highly personalized ad scenario (p=0.0002). However, we can observe that there is no statistical difference that is significant between the likelihood of a click-through in the moderately personalized and highly personalized ad scenarios (p=0.317). The outputs of these results can be found in Appendix 4.

If we look at the means between the ad scenarios, we can see that the willingness to click-through is higher when the participants have a moderately personalized ad (mean=2.0667; SD=1.123) or a highly personalized ad (mean=2.2541; SD=1.182), rather than a non-personalized ad (mean=1.6122; SD= 0.797) (See Figure 19).

Figure 19: Willingness to click-through in a non-personalized, moderately personalized and highly personalized ad scenario



Source: Own work.

5.2.7 Ad personalization, click-throughs and ad relevance

H2: Better perception of ad relevance mediates the relationship between ad personalization and the likelihood of a click-through.

This specific hypothesis has been developed to observe whether better perception of ad relevance can influence the relationship between ad personalization and click-throughs. In order to do so, we also developed two sub-hypotheses (H2a and H2b). To compare the means and test the hypotheses, we used a One-way ANOVA test in SPSS. We also carried out a Post Hoc Test (Tukey HSD) in order to have multiple comparisons between the groups.

The hypothesis can be confirmed based on the results which we received from H2a and H2b. Below, there is an in-depth analysis of the outcome of both hypotheses which helps confirm the main hypothesis (H2).

H2a: Ad personalization and ad relevance have a positive relationship.

The hypothesis has been developed to observe the relationship between ad personalization and ad relevance. In other words, we want to test whether participants have a better perception of ad relevance when an ad is personalized versus when an ad is non-personalized. Once more we differentiated and placed the participants in groups based on the three ad scenarios they got at random: non-personalized (n=147), moderately personalized (n=135) and highly personalized (122). All three groups were compared with *Q8b: I believe the ad I saw is relevant for my needs* measured with a 7-point Likert scale (from "Strongly Disagree" to "Strongly Agree").

This hypothesis can be confirmed as the ANOVA results displayed in Table 11 show that there are statistically significant differences between the groups (p=0.008).

Table 11:One-way ANOVA for H2a

ANOVA

AdRelevance

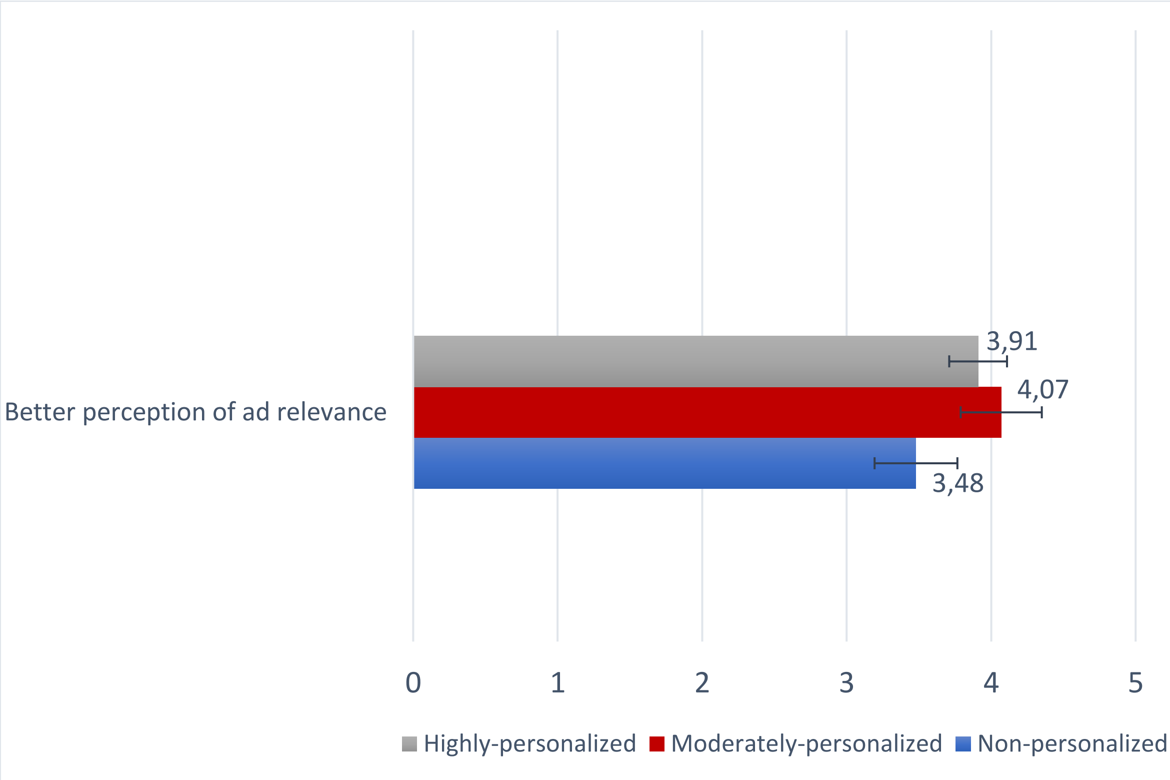
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	26.477	2	13.239	4.901	.008
Within Groups	1083.075	401	2.701		
Total	1109.552	403			

Source: Own work.

Additionally, the post hoc test shows that there are statistically significant differences between: the perception of ad relevance in the non-personalized and moderately personalized ad scenario (p=0.008); perception of ad relevance between the non-personalized and highly personalized ad scenario (p=0.080). However, we can observe that there is no statistical difference that is significant between the perception of ad relevance in the moderately personalized and highly personalized ad scenarios (p=0.725). The outputs of these results are located in Appendix 4.

When we look at the means between the ad scenarios, we can see that the perception of ad relevance is better when the participants have a moderately personalized ad (mean=4.0667; SD=1.64906) or a highly personalized ad (mean=3.9098; SD=1.47712), rather than a non-personalized ad (mean=3.4762; SD= 1.76470) (See Figure 20). We can also notice that in our sample, the participants within the moderately-personalized ad scenario found the ad to be more relevant compared to the ones in highly-personalized ad scenario.

Figure 20: Perception of ad relevance in a non-personalized, moderately personalized and highly personalized ad scenario



Source: Own work.

H2b: Ad relevance and the likelihood of a click-through have a positive relationship.

The hypothesis has been developed to observe whether the relationship between ad relevance and click-throughs is positive. In other words, we want to test whether participants who have perceive an ad to be more relevant are more likely to click-through. In order to do so we used *Q7: How likely is it that you would click on the ad that you have just seen?* measured with a 5-point scale (from "Very Unlikely" to "Very Likely") and *Q8b: I believe the ad I saw is relevant for my needs* measured with a 7-point Likert scale (from "Strongly Disagree" to "Strongly Agree").

For this hypothesis, we grouped the participants who selected strongly disagree, disagree or somewhat disagree into one group named (n=172) and the participants who selected strongly agree, agree or somewhat agree in another group (n=173), as otherwise our samples were not big nor equal enough to show usable results. The rest of the participants which selected neither agree nor disagree were left as a third group (n=59).

This hypothesis can be confirmed as the ANOVA results displayed in Table 12 show that there are statistically significant differences between the groups ($p=7*10^{-11}$).

Table 12:One-way ANOVA for H2b

ANOVA

Clickthrough

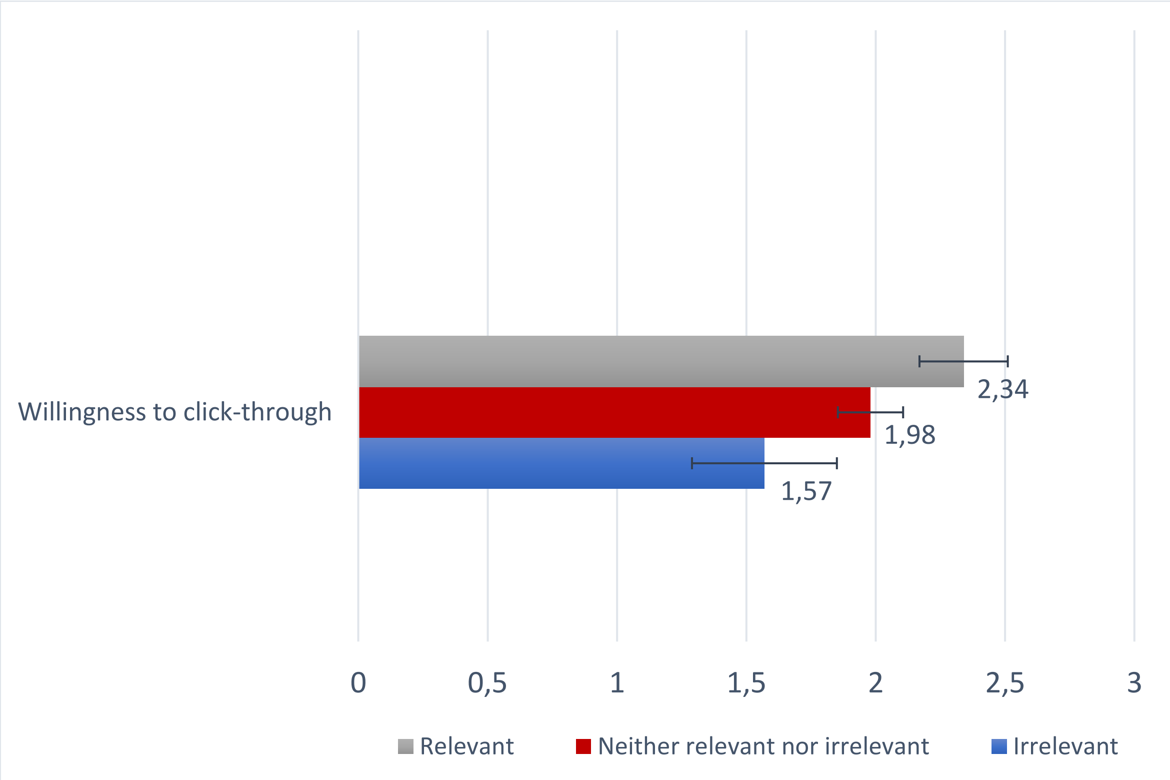
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	50.584	2	25.292	24.755	<.001
Within Groups	409.701	401	1.022		
Total	460.285	403			

Source: Own work.

Moreover, the post hoc test shows that there is a statistically significant difference in the willingness to click-through when there is a better perception of ad relevance ($p=5*10^{-9}$**)** rather when there is not (See Appendix 4). In addition, we can also see that when we compare the willingness to click-through of participants which expressed that they neither find the ad to be relevant nor irrelevant to the ones which found it relevant, we can still see a statistically significant difference ($p=0.05$). This is also the case for the participants who found the ad to be irrelevant compared to the ones who neither found it relevant nor irrelevant ($p=0.019$).

When we observe the means, we can see that the willingness to click-through is higher when the participants find the ad to be relevant (mean=2.3353; SD=1.13751) than when the participants find the ad to be irrelevant (mean=1.5698; SD=0.83828). In Figure 21, we can notice that in our sample, the “gap” between these two means is relatively big. If we would also compare the means between the ones which find the ad to be relevant and the ones which find it neither relevant nor irrelevant (mean=1.9831; SD=1.07465), we can notice that the willingness to click-through is much higher in the former, rather than in the latter.

Figure 21: Willingness to click-through when the ad is found as relevant, irrelevant or neither relevant nor irrelevant



Source: Own work.

5.2.8 Ad personalization, click-throughs and perceptions of privacy violations

H3: Increased perception of privacy violation mediates the relationship between ad personalization and the likelihood of a click-through.

This hypothesis in particular, has been developed to learn whether the increased perception of privacy violation can influence the relationship between ad personalization and click-throughs. In order to do so, we also developed a sub-hypothesis (H3a). To compare the means and test the hypothesis, we used a One-way ANOVA test in SPSS. We also carried out a Post Hoc Test (Tukey HSD) in order to have multiple comparisons between the groups.

The hypothesis cannot be confirmed. Based on the results which we received from H3a, we can confirm that ad personalization and perceived privacy violations do in fact have a positive relationship. However, what blocks us from confirming the hypothesis (H3) is in fact hypothesis H3b. This sub-hypothesis cannot be confirmed due to the lack of statistical significance. Nonetheless, the results are encouraging and are leaning towards findings which confirm the main hypothesis. Below there is an in-depth analysis of the outcome of the sub-hypotheses.

H3a: Ad personalization and perceived privacy violations have a positive relationship.

The hypothesis has been developed to observe whether there is a positive relationship between personalization and the perceptions of privacy violation. Once more, we differentiated and placed the participants in groups based on the three ad scenarios they got at random: non-personalized (n=147), moderately personalized (n=135) and highly personalized (122). The three groups were compared with *Q9b: I find this ad to be intrusive towards my privacy* measured on a 7-point Likert scale.

To compare the means and test the hypothesis we used a One-way ANOVA in SPSS. Moreover, we carried out a Post Hoc Test (Tukey HSD) in order to have in-depth comparisons between the groups.

This hypothesis can be confirmed as the ANOVA results displayed in Table 13 show that there are statistically significant differences between the groups (p=0.001).

Table 13:One-way ANOVA for H3a

ANOVA

AdIntrusiveness

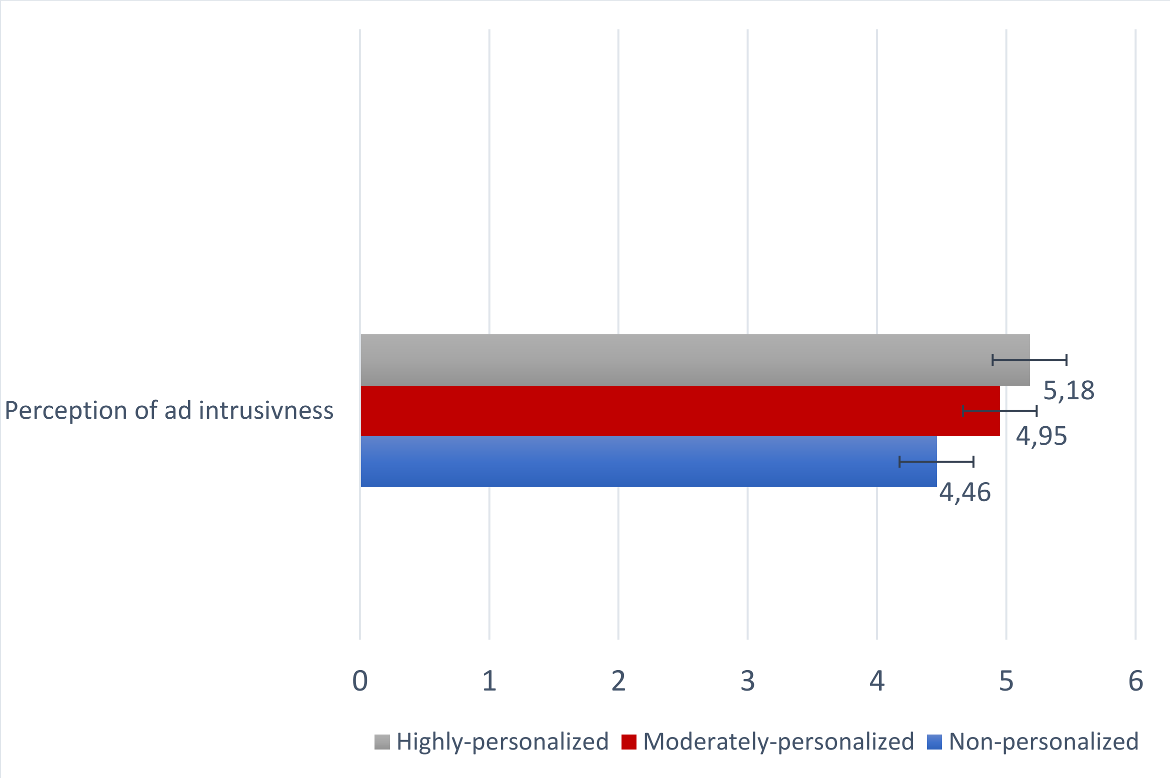
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	36.647	2	18.324	6.636	.001
Within Groups	1107.214	401	2.761		
Total	1143.861	403			

Source: Own work.

In addition, the post hoc test shows that there are statistically significant differences between: perceptions of privacy violations in the non-personalized and moderately personalized ad scenario (p=0.039); perceptions of privacy violations between the non-personalized and highly personalized ad scenario (p=0.001). However, we can observe that there is no statistical difference that is significant between the perceptions of privacy violations in the moderately personalized and highly personalized ad scenarios (p=0.503). The outputs of these results can be found in Appendix 4.

If we look at the means between the ad scenarios, we can see that the perception that the ad is intrusive is greater when the participants have a moderately personalized ad (mean=4.9481; SD=1.67206) or a highly personalized ad (mean=5.1803; SD=1.53212), rather than a non-personalized ad (mean=4.4626; SD= 1.75278.) (See Figure 22). It seems that the more the participants found the ad to be personalized, the more their perceptions of privacy violation grew.

Figure 22: Perception of privacy violation in a non-personalized, moderately personalized and highly personalized ad scenario



Source: Own work.

H3b: Perceived privacy violation and the likelihood of a click-through have a negative relationship.

The hypothesis cannot be confirmed as the ANOVA results displayed in Table 14 show that there are no statistically significant differences between the groups (p=0.642).

Table 14: One-way ANOVA for H3b

ANOVA

Clickthrough

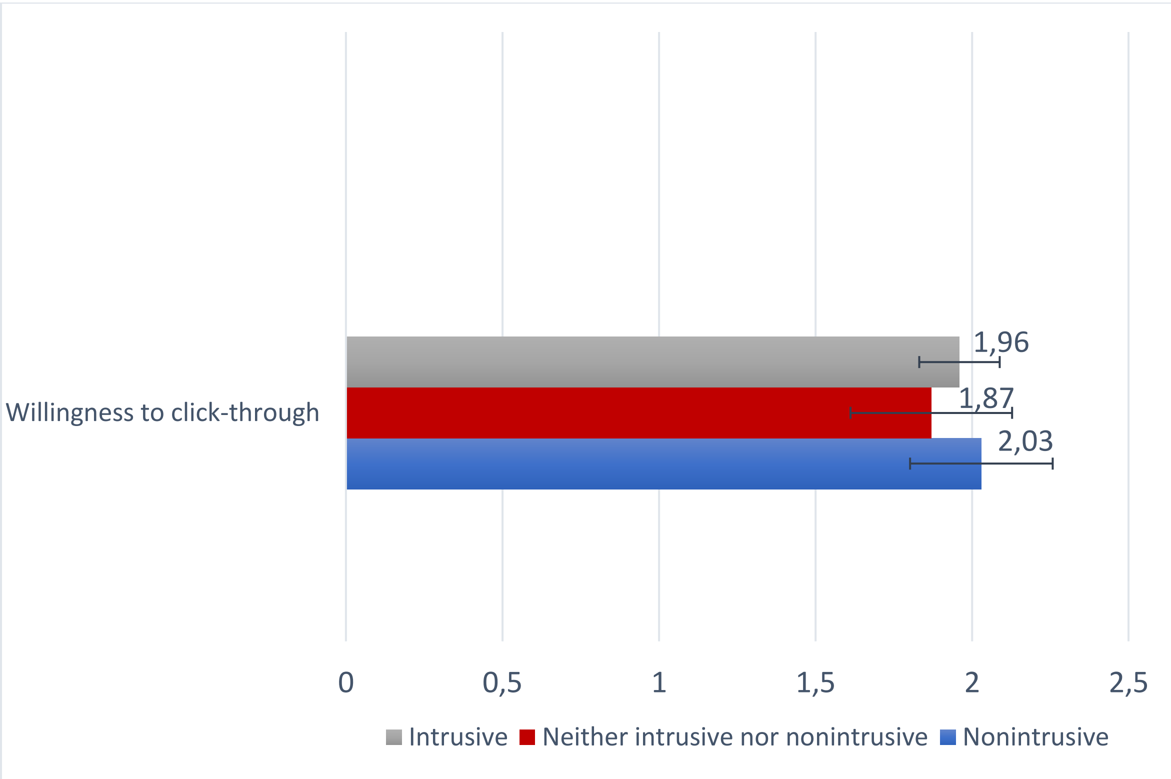
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.017	2	.509	.444	.642
Within Groups	459.268	401	1.145		
Total	460.285	403			

Source: Own work.

Moreover, the post hoc analysis (results are in Appendix 4) shows that there is not a statistically significant difference in the willingness to click-through when there is no perception of ad intrusiveness rather when there is (p=0.813). We can also see, that when we compare the willingness to click-through of participants which expressed that they neither find the ad to be intrusive nor nonintrusive to the ones which found it nonintrusive, we still cannot see a statistically significant difference (p=0.619). This is once again the case for the participants who found the ad to be intrusive compared to the ones who neither found it intrusive nor nonintrusive (p=0.840).

However, if we would observe the means in Figure 23, we could still note that in tendency, the willingness to click-through is higher when the participants find the ad to be nonintrusive (mean=2.0337; SD=1.08134) than when the participants find the ad to be intrusive (mean=1.9579; SD=1.08213). If we would also compare the means between the ones which find the ad to be neither intrusive nor nonintrusive (mean=1.8667; SD=0.99943), we can notice that the willingness to click-through is albeit higher in the former, rather than in the latter.

Figure 23: Willingness to click-through when the ad is found as intrusive, nonintrusive and neither intrusive nor nonintrusive



Source: Own work.

5.2.9 Ad personalization, perceived privacy violations and control

H4: Increased perception of privacy control suppresses the relationship between ad personalization and perceived privacy violation.

The hypothesis was set out to observe whether the perceptions of privacy control influences the relationship between personalization and perceived violation. In particular, does feeling of control over data, reduce the perceptions of privacy violations when there is a personalized ad or does it reduce perceptions of privacy violations when there is a non-personalized ad.

For this hypothesis, first we filtered out the participants into two groups. The first group included the ones which were assigned a personalized ad scenario (both moderately and highly personalized) and the second group the ones which were assigned a non-personalized ad scenario. Later on, we compared correspondingly *Q9b: I find this ad to be intrusive towards my privacy* with *Q11f: I feel in control of my data, both measured on a measured* on a 7-point Likert scale (from "Strongly Disagree" to "Strongly Agree").

In order to test the hypothesis, we used a One-way ANOVA in SPSS and we carried out a Post Hoc Test (Tukey HSD) to have more in-depth information on the samples.

The hypothesis cannot be confirmed as the ANOVA results displayed in Table 15 show that there are no statistically significant differences between the groups (p=0.957).

Table 15: One-way ANOVA for H4 (personalized setting)

ANOVA

Intrusiveness

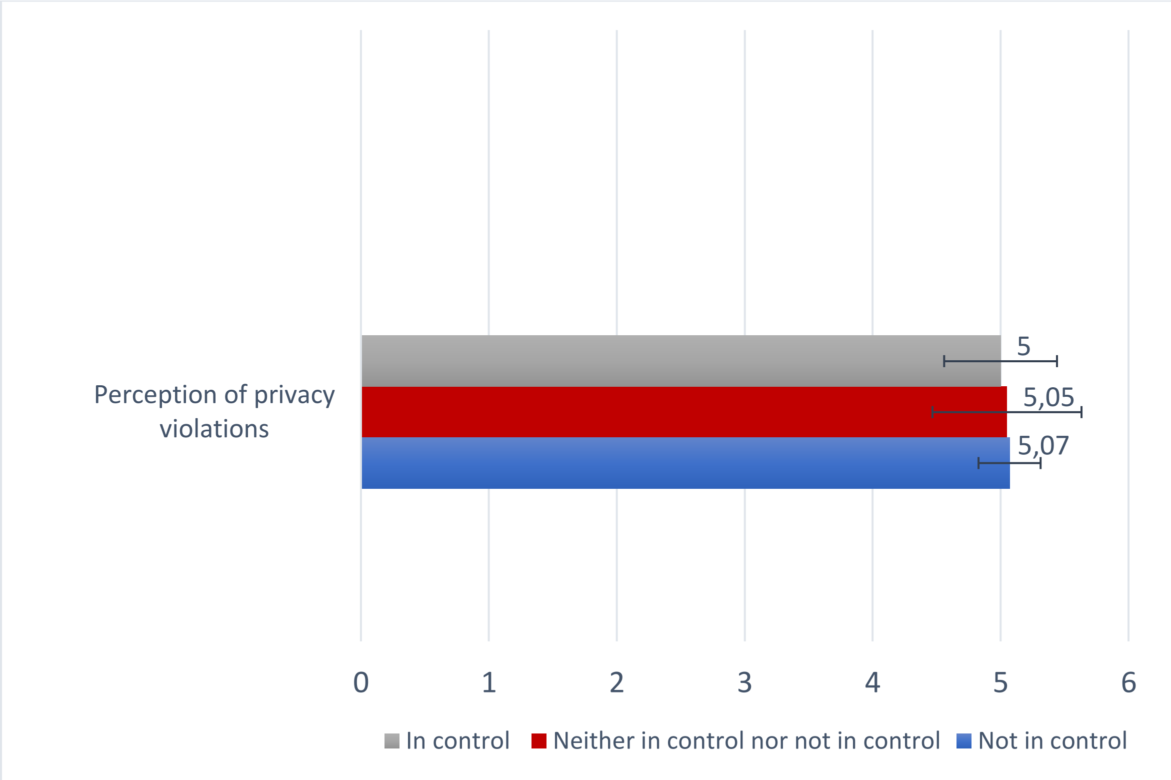
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.227	2	.113	.044	.957
Within Groups	661.898	254	2.606		
Total	662.125	256			

Source: Own work.

Moreover, the post hoc test sets out that there is not a difference which is statistically significant in the perceptions of ad intrusiveness between the participants who do not feel in control of their personal data and the ones who do feel in control in a personalized ad setting (p=0.953). The outputs of these results can be seen in Appendix 4.

Even though, if we look at the means, we can observe that the ones which are feeling in control of their personal data also found the ad to be less intrusive (mean=5.0000; SD=1.55183) compared to the ones who feel less in control which found the ad to be more intrusive (mean=5.0765; SD=1.60252) or the ones who neither feel in control nor not in control (mean=5.0541; SD=1.74716) (See Figure 24).

*Figure 24: Perception of privacy violations in a **personalized ad scenario** when the participants feel in control, not in control or neither in control nor not in control of their personal data*



Source: Own work.

Even in a non-personalized setting, the ANOVA results displayed in Table 16 show that there are no statistically significant differences between the groups (p=0.510).

*Table 16: One-way ANOVA for H4 **(non-personalized setting)***

ANOVA

NonpersonalizedIntrusivness

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	4.178	2	2.089	.677	.510
Within Groups	444.366	144	3.086		
Total	448.544	146			

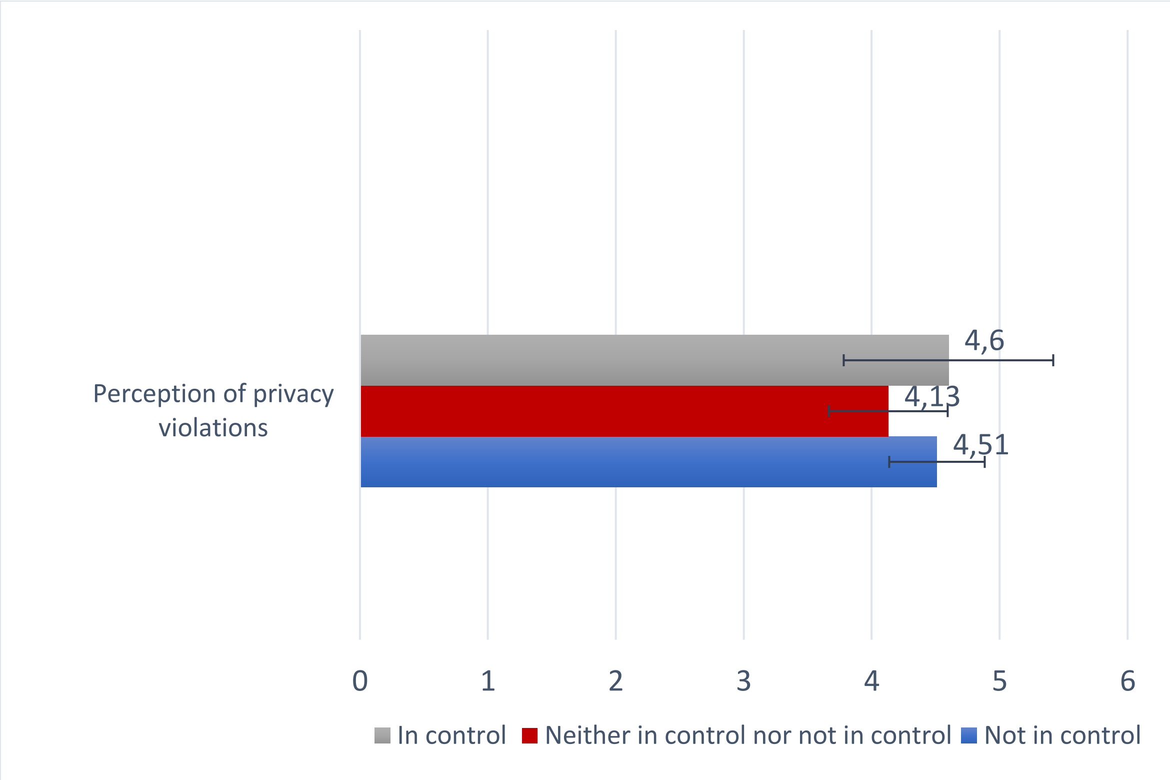
Source: Own work.

The post hoc test located in Appendix 4, indicates that there is not a statistically significant difference in the perceptions of ad intrusiveness between the participants who do not feel in control of their personal data and the ones who do feel in control (p=0.936).

By looking at the means in Figure 25, we can see that the ones which are feeling in control of their personal data also found the ad to be more intrusive (mean=4.6429; SD=2.11195) compared to the ones who feel less in control which found the ad to be less intrusive (mean=4.5111; SD=1.78158) or the ones who neither feel in control nor not in control (mean=4.1379; SD=1.21667).

This tells us that maybe our sample was not big enough to be of statistical significance or that maybe the survey-participants were not "honest" enough when answering this specific question. Therefore, based on our data we cannot make any viable conclusions.

*Figure 25: Perception of privacy violations in a **non-personalized ad scenario** when the participants feel in control, not in control or neither in control nor not in control of their personal data*



Source: Own work.

5.2.10 Trust, perception of privacy violations and click-throughs

H5: Trust in retailers amplifies the relationship between the perception of privacy violation and the likelihood of a click-through.

The hypothesis has been developed to observe whether trust would positively impact the perception of privacy violation as well as the intention to click-through. In particular, to learn if trust can in fact reduce the feeling of privacy violation and therefore result with a click-through.

In the first step, we differentiated and placed the participants in three groups based on the answers from *Q10: I consider Samsung a trustworthy company*, measured on a 7-point Likert scale. We grouped the participants who selected strongly disagree, disagree or somewhat disagree into one group (n=42) and the participants who selected strongly agree, agree or somewhat agree in another group (n=246), as otherwise our samples were not big nor equal enough to show viable results. The rest of the participants which selected neither agree nor disagree were left as a third group (n=116). We compared the groups with Q9b: I find this ad to be intrusive towards my privacy.

In the second step, we used the same groups from Q10: I consider Samsung a trustworthy company, measured on a 7-point Likert scale and compared them with Q7: How likely is it that you would click on the ad that you have just seen? To compare the means and test the hypothesis we used a One-way ANOVA in SPSS. We also carried out a Post Hoc Test (Tukey HSD) in order to have in-depth comparisons between the groups.

This hypothesis can be confirmed as the ANOVA results displayed in Table 17 ($p=2*10^{-7}$ is for privacy violations) and Table 18 (p=0.001 is for click-throughs) clearly show that there are statistically significant differences between the groups.

Table 17: One-way ANOVA for H5 (privacy violations)

ANOVA

AdIntrusiveness

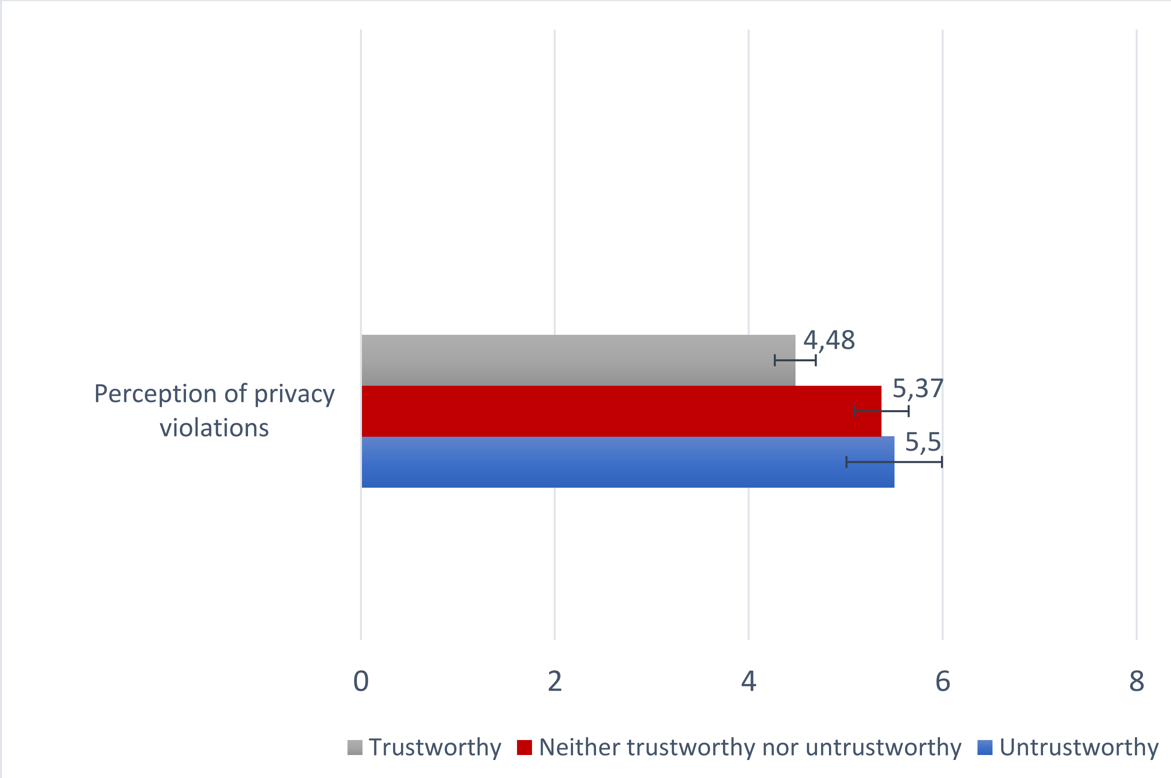
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	82.903	2	41.451	15.667	<.001
Within Groups	1060.959	401	2.646		
Total	1143.861	403			

Source: Own work.

Additionally, the post hoc test identifies that there are statistically significant differences in the perceptions of ad intrusiveness when the brand Samsung is found to be trustworthy (p=0.001) compared to when it is not found to be trustworthy. Furthermore, we can also observe that when we compare the perception of privacy intrusiveness of the participants when they found Samsung to be neither trustworthy nor untrustworthy to the ones which found it as trustworthy, we can see a statistically significant difference (p=0.000005). The results of the post hoc test can be found in Appendix 4.

If we look at the means in Figure 26, we can see that the perception of ad intrusiveness is lower when the participants found Samsung to be trustworthy (mean=4.4797; SD=1.68232) than when the participants found Samsung to be untrustworthy (mean=5.5000; SD=1.58114). Further, when we also compare the means between the ones which found Samsung to be trustworthy and the ones which found Samsung to be neither trustworthy nor untrustworthy (mean=5.3707; SD=1.51818), we can notice that the perception of privacy violations with regards to the advertisement is greater in the latter, rather than in the former.

Figure 26: Perceptions of privacy violations when the brand is found as trustworthy, untrustworthy or neither trustworthy nor untrustworthy



Source: Own work.

Table 18: One-way ANOVA for H5 (click-throughs)

ANOVA

Clickthrough

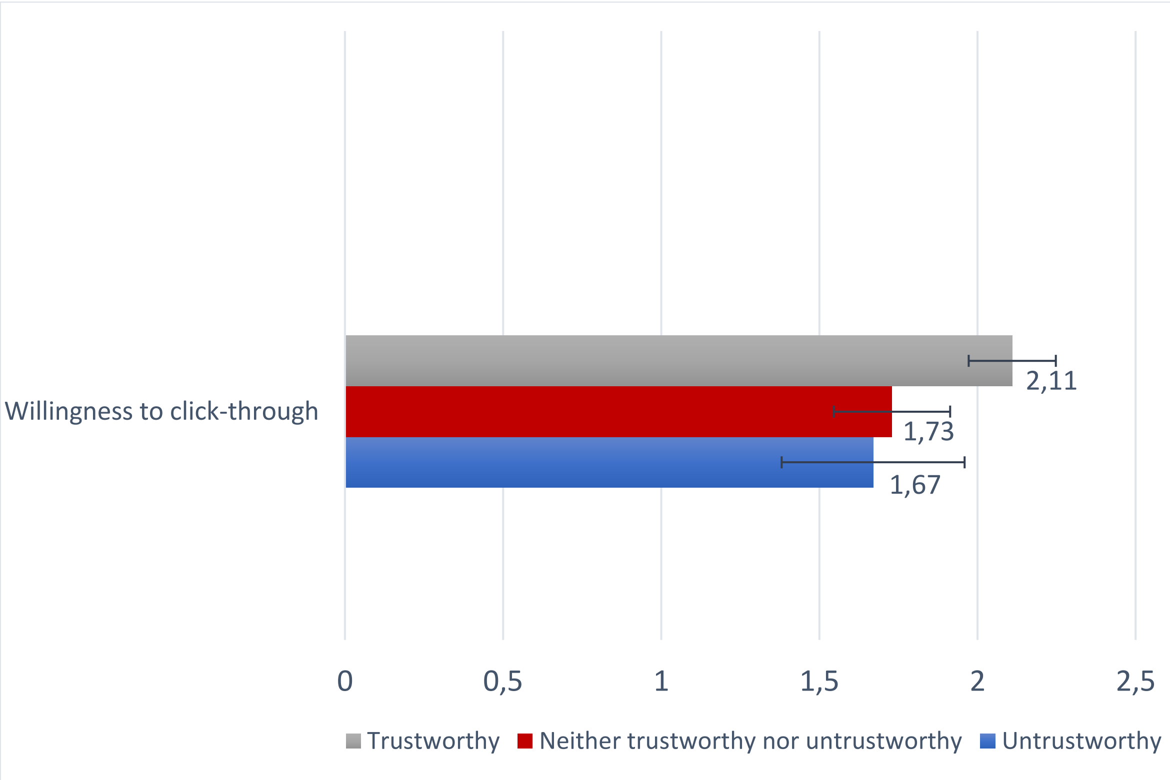
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	15.423	2	7.711	6.951	.001
Within Groups	444.862	401	1.109		
Total	460.285	403			

Source: Own work.

From the results in the post hoc test (found in Appendix 4), we can observe that there is also a statistically significant difference in the willingness to click-through when the brand Samsung was found as trustworthy (p=0.030) rather when there is not. In addition, we can also see that when we compare the willingness to table click-through of participants which expressed that they neither find Samsung to be trustworthy nor untrustworthy to the ones which found it as trustworthy, we can still see a statistically significant difference (p=0.004).

Same goes for trust in connection with click-throughs if we would observe the means. In Figure 27, we can notice that when the participants found Samsung as trustworthy (mean=2.1138; SD=1.09696), their willingness to click-through was higher than the participants who found Samsung as untrustworthy (mean=1.6667; SD=0.92833). If we would also compare the means between the ones which find Samsung to be trustworthy and the ones which Samsung to be neither trustworthy nor untrustworthy (mean=1.7328; SD=0.99876), we can notice that the willingness to click-through is much higher in the former, rather than in the latter.

Figure 27: Willingness to click-through when the brand is found as trustworthy, untrustworthy or neither trustworthy nor untrustworthy



Source: Own work.

A complete overview of the hypotheses' status tested in this research can be found in Table 19. The yielded results of the hypotheses are discussed further in chapter 6 (Discussion and Implications).

Table 19: Summary of hypotheses status

	Hypothesis	Status
H1	Ad personalization and the likelihood of the click-through have a positive relationship.	**Confirmed**
H2	Better perception of ad relevance mediates the relationship between ad personalization and the likelihood of a click-through.	**Confirmed**
H2a	Ad personalization and ad relevance have a positive relationship.	**Confirmed**
H2b	Ad relevance and the likelihood of a click-through have a positive relationship.	**Confirmed**
H3	Increased perception of privacy violation mediates the relationship between ad personalization and the likelihood of a click-through.	**Not supported**
H3a	Ad personalization and perceived privacy violations have a positive relationship.	**Confirmed**
H3b	Perceived privacy violation and the likelihood of a click-through have a negative relationship.	**Not supported**
H4	Increased perception of privacy control suppresses the relationship between ad personalization and perceived privacy violation.	**Not supported**
H5	Trust in retailers amplifies the relationship between the perception of privacy violation and the likelihood of a click-through.	**Confirmed**

Source: Own work.

5.2.11 Classification and regression tree

This type of decision tree is an interpretable machine learning model used for classification and regression named as Classification and Regression Tree (CART) (Sharma, 2019). It is also seen as a predictive technique which enables us to foresee the end result by using sets of if-else questions. We rely on this specific method as it is the most commonly used one when trying to partition the data (Srivastava, 2014).

CART is very commonly used as there are various advantages from using it including that "they are able to capture the non-linearity in the data set" as well as that when using such trees, the need for data standardization is not necessary (Sharma, 2019). This is due to the fact that CART trees calculate only if-else between the data rather than any Euclidean distance or other measuring elements (Sharma, 2019). Although we are using a predictive classification model, the goal is not the prediction itself but rather focused on what drives people to click-through. In other words, the goal is to find "buckets" where the concentration of participants who are likely to click is the highest, by splitting one variable at a time.

To build the tree, we used a sample of 404 participants and filtered out the data to include only the ones which are either likely or unlikely to click-through, excluding the ones which were undecided. In the end, we were left with a sample of 374 participants. Before filtering, we also divided the participants into two groups. The ones who selected "Very Unlikely" and "Unlikely" as their answer were placed in the first group named "No" and the ones who selected "Very Likely" and "Likely" as their answer, were placed in the second group named "Yes".

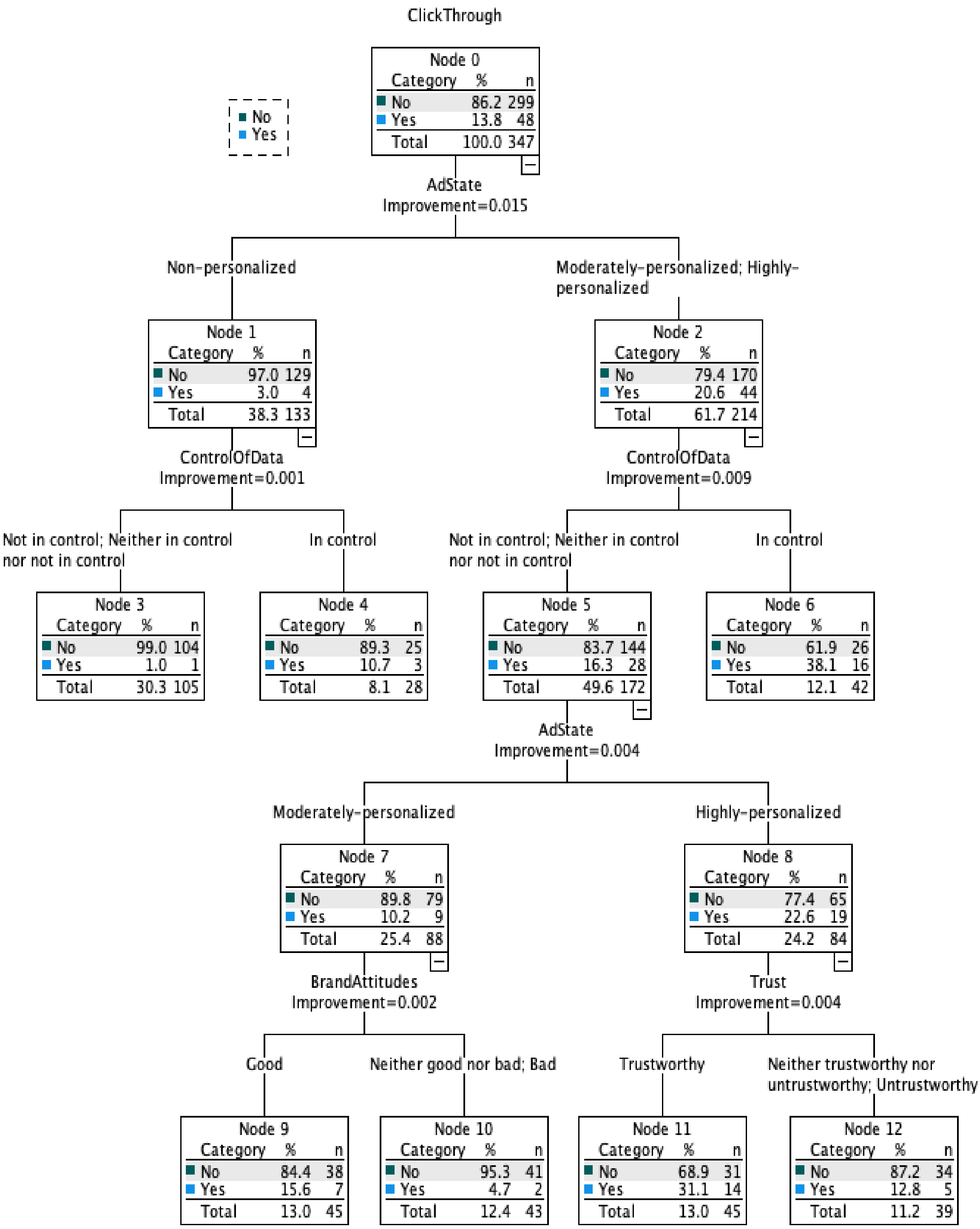
Further on, we included various variables in the analysis such as: Social Media use, brand attitudes, gender, country of origin, trustworthiness, perception of data control, perceptions of ad intrusiveness, ad relevancy and different ad states i.e., non-personalized, moderately – personalized and highly – personalized. To simplify, beforehand we classified all answers of participants into three groups. For example, for the feeling of control of their data they are grouped as "in control", neither in control nor not in control" and not in control; for brand attitudes the participants are grouped as "good", "neutral" and "bad"; for trust, they are grouped as "trustworthy", "neither trustworthy nor untrustworthy" and "untrustworthy"; for perceptions of privacy violations (i.e., ad intrusiveness) their answers are grouped as "intrusive", "neither intrusive nor nonintrusive" and "nonintrusive"; finally, for perceptions of ad relevancy they are grouped as "relevant", "neither relevant nor irrelevant" and "irrelevant".

Variables which are not part of the tree but were initially included in the analysis, are considered as less important compared to the ones seen on the figure when it comes to "influencers" of the willingness to click-through. The model itself automatically filters the most important variables and further makes it locally optimal. Below we have figure of how the tree looks like based on our sample (See Figure 28). Each square or bucket represents a node which has an if-else clause based on a specific variable, for example the ad state (i.e., non – personalized, moderately – personalized or highly – personalized).

Overall, there are three types of nodes: root nodes, internal nodes and leaf nodes. Root nodes normally do not have any parent nodes and depending on the question they generate two child nodes (Sharma, 2019). Similarly, the ones which are internal nodes also give two child nodes however, these nodes actually have a parent node. Finally, leaf nodes have a parent node as well however they do not have child nodes (Sharma, 2019). At any given node the split is the best possible split, to maximize the concentration of participants who are likely to click in one of the two buckets. For instance, whether the ad is personalized or not is the top variable to distinguish among participants who are more likely to click compared to ones who are not.

Furthermore, at each node "n" represents the number of participants in each node. For example, n in "yes" is the number of the people who are likely to click and n in "no" are the people who are unlikely to click on the ad. In our tree, the click-through bucket represents the root node.

Figure 28: Drivers of the willingness to click-through



Source: Own work.

As we already mentioned, the goal is to find all buckets where the concentration of participants who are likely to click is at the highest possible level. In order to do so, the CTR growing method was selected as CTR aims to maximize the homogeneity within the nodes (IBM, n.d.).

For the criteria, the maximum tree depth was set to automatic, which means five for CTR, and the minimum number of cases within the parent node was 60 while in the child node 25. Impurity is flagged whenever a node does not hold a homogeneous subset of cases (IBM, n.d.). On the contrary, a node in which all cases have an identical value for the dependent variable (i.e., it is homogenous) is also a node which indicates purity and needs no further splitting (IBM, n.d.). In order to measure impurity, we chose the default measure – Gini as this coefficient is most commonly used and it helps guide the model to reach the node with largest impurity and further split it (Tao, 2020). This measure reaches its minimum when all cases are placed within a single group and it is based on squared probabilities of belonging for each group of the dependent variable (IBM, n.d.).

The first two children of the root node are the non-personalized ad scenario on the left and the personalized ad scenario on the right (both moderately- and highly-personalized) making this the most important distinguishable variable in our sample, which was expected and shows that our experiment was successful. Looking at these two internal nodes or buckets, we can see that people are more likely to click-through if the advert they come upon to is personalized (Yes= 20.6%) versus when it is not personalized (Yes= 3.0%). These nodes further have children (two each), which in fact represent the second most important decisive variable: the feeling of control over personal data.

For the sake of analyzing the tree more efficiently and with a more organized flow, we will first look at the left side of the tree i.e., the non-personalized ad scenario bucket. The non-personalized bucket or internal node has two children: the left leaf contains the participants who are not in control as well as the ones who neither feel in control nor not in control of their data, and the right leaf contains the people who feel in control of their data. When we look at these leaves (buckets) we can notice that the concentration of people who are more likely to click-through is in fact higher in the second leaf. In other words, it is the bucket of participants which feel in control of their personal data (Yes=10.7% versus Yes=1.0%). As we already pointed out before, these nodes have a parent node however they do not have child nodes, making them “the end” of the left side of our tree.

Moving forward to the right side of the tree, we can see that the tree itself becomes more complex. This is due to the fact that there are various variables to be observed. As we previously mentioned, here we can identify the second most valuable variable when it comes to deciding whether to click-through or not – the feeling of control over personal data. Once again, the participants which feel in control of their data are placed in a different node (on the right) than the ones which are not in control and the ones which neither feel in control nor not in control of their data. In the former, participants are more likely to click-through than in the latter (Yes= 38.1% compared to Yes= 16.3%). It is interesting to observe that the right node is in fact a leaf which shows us that participants are indeed more likely to click-through when an ad is personalized (moderately – and highly – personalized), however these participants need to feel in control of their data in order to do so. Moreover, within the whole tree model, this is the leaf which has the highest concentration of people who are more likely to click-through (38.1%).

While on the right side we have a leaf node, on the right side we have an internal node. This means that even though within the internal node we have the participants who are not in control as well as the ones who neither feel in control nor not in control of their data, we can still see there are some variables which influence the decision to click-through. This specific node is a parent to two child (internal) nodes which are in fact the moderately – personalized ad scenario on the left and the highly – personalized ad scenario on the right. Interestingly enough, we can observe that the right node (Yes= 22.6%) has a higher concentration of participants who are more likely to click-through compared to the left node (Yes= 10.2%). We would anticipate that the percentage of participants who would click-through would be in fact located within the left node (moderately – personalized ad scenario), rather than the right one, as it is assumed that these participants in fact do not feel in control of their data therefore a highly personalized ad might rise privacy concerns. However, this does not seem to be the case within our sample.

In fact, when we compare and contrast these two internal nodes, we can see that they are both personalized ad scenarios, however they both have different variables acting as child nodes. If we would observe the left side for a moment, we would notice that the variable brand attitude plays the role of a “determinant” when it comes to the intention to click-through on a moderately – personalized advertisement.

In particular, the moderately personalized node is the parent of two leaf nodes: on the left placed are the participants with a good attitude towards Samsung as a brand and on the right placed are the participants with a neither good nor bad and bad attitude towards the brand. The participants within the left leaf node are said to be more willing to click-through (Yes= 15.6%) than the ones within the right node (Yes= 4.7%). Moreover, this means that when these participants do not feel in control (or are not quite sure whether they feel or do not feel in control) of their data and when there is a moderately personalized ad, they are more likely to click-through if they view the brand itself with a positive attitude.

Finally, the right internal node or in other words the highly – personalized bucket is actually the parent of two leaves generated from a new variable: trust. In particular, participants which find the brand as trustworthy are classified within the left leaf and participants which do not find the brand as trustworthy or simply do not feel either way, are classified within the right leaf. It is apparent that the leaf which holds the participants which find the brand as trustworthy also holds highest concentration of people who are more likely to click-through compared to the other leaf (Yes= 31.1% in contrast to Yes= 11.2%). What can be derived from this is that if the participants do not feel in control of their data (or are not quite determined on how they feel when it comes to the control of their data) and are faced with a highly – personalized advert, the key driver which will lead them to carry out a click-through is the positive perception of trust. This leaf comes as second in terms of highest concentration of participants who are more likely-to click-through within the whole tree model.

6 DISCUSSION AND IMPLICATIONS

6.1 Theoretical Implications

Over the past two decades, the effects of certain drivers over the consumer's perception of personalized advertisements and the intention to click-through have been widely examined. In a somewhat paired manner, perceptions of trust, privacy control, privacy violations and ad relevance have been measured (e.g., Xu et al., 2012; Bleier & Eisenbeiss, 2015a, 2015b; Jung, 2017). Nevertheless, to our knowledge there is no available research which investigates all these drivers at once. To advance the theoretical understanding of the relationship between personalized advertisements and the likelihood of a click-through, this study tested what is the actual relationship while also observing its influencers: perceptions of ad relevance, privacy violation, privacy control and trust. Moreover, its unique contribution was to provide a view on the prevailing drivers of the willingness to click-through on an advert.

Specifically, this study measured the effectiveness of an advert through the likelihood of a click-through of the participants on Facebook. Looking at the ad scenarios, we can see that the willingness to click – through is higher when the participants are exposed to a moderately personalized ad which is also comparable to the findings of Keyzer, Dens and Pelzmacher (2015), or a highly personalized ad, rather than a non-personalized ad. Moreover, the study results were similar to what was reported in Pavlou and Stewart (2000), Tam and Ho (2005), Kalyanaraman and Sundar (2006), Noar, Benac, and Harris (2007), Arora et al. (2008) and finally, Walrave et al. (2018), suggesting that personalization does in fact improve the overall effectiveness of an ad.

In addition, we can observe that the likelihood of a click-through was higher in the highly – personalized ad scenario rather than in the moderately – personalized one. All the same, such interpretations need to be taken with caution as there was no statistically significant difference proven during the analysis. To give some background for future research, the scenarios were differentiated as the former would be when ad is created based on previous online private conversations with a colleague and the latter in a situation when an ad is created based on previous online browsing behaviour.

Conventional wisdom is that if an ad is perceived as more relevant, there will be an increase in the viewer’s attention and a decrease in the need to avoid the ad. To escape from the cluttered advert environment, marketers leverage consumer information to create tailored messages (Jung, 2017). Xia and Bechwati (2008) emphasize that personalized advertisements are perceived as more relevant compared to the non-personalized ones. Moreover, as a consequence they also receive a better and a more positive response (Anand & Shachar, 2009; Noar, Harrington & Aldrich, 2009). This research parallels such findings by showing that better perception of ad relevance does in fact influence the existing relationship between personalized ads and click-throughs in a positive way. Moreover, it could be also looked at as a transitive relation: personalized ads are perceived as more relevant and relevant ads lead to a higher willingness to click-through, therefore by transitivity, personalized adverts lead to a higher willingness to click-through.

Whilst better perceptions of ad relevance incentivize the individual to click-through, perceptions of privacy violations reduce the willingness to click-through. Privacy advocates share the very same concerns when it comes to using personal data to create personalized ads: highly personalized ads might increase the sense of vulnerability among consumers which consequently lowers the consumer adoption (Aguirre et al., 2015). This study finds that the more the participants found the ad to be personalized, the more their perceptions of privacy violation grew, and their click-through intentions decreased. Once again, the latter results were not proven to be statistically significant, however they are able to be linked with the ones of Aguirre et al., (2015), where a decrease in the click-through rate is noticed when highly personalized messages were delivered. We can argue that feelings of vulnerability stem the decrease in click-throughs.

Certainly, what might also fuel both perceptions of privacy violation and skepticism towards the ad itself is displaying information in the advert which was not explicitly provided by the viewer (consumer). In this study, information to which was not given explicit consent can be found in the highly personalized ad scenario where the advert is created based on previous online private conversations. The results of our study are similar to the ones of Perez and Steinhart (2014) where they find that the moderate level of personalization yields better results than highly personalized ads when perceptions of privacy violations are present. Even though we cannot support this empirically with our testing as the differences were not statistically significant, the analysis of the means themselves show encouraging results.

Furthermore, there is evidence which shows two sides of the same coin: one supporting the existence of the so called “privacy paradox” (e.g., Norberg et al., 2007; Acquisti & Grossklags, 2005) and the other opposing it (e.g., Blank et al., 2014; Lutz & Strathoff, 2014). To provide a somewhat feasible explanation why there are such conflicting findings within the existing literature, the current research created a small simulation. To bear in mind, there are various limitations which prevented us to properly challenge the paradox and we certainly cannot claim nor deny its existence based on these findings, but we do believe that the results can be used as a base for further research.

To determine if there are traces of paradoxical dichotomy between the feelings of privacy and the actual behavior within a personalized setting, we look at the data of the respondents who were actually exposed to a personalized ad in our study. In particular, we observe the respondents who claimed that they do in fact feel uncomfortable having their data used or shared without their permission. Such feelings can indicate that the privacy to these participants is in fact quite valuable, however when they were asked if they would like to click on the advert to receive information 19% of them responded positively. This number is not at all a dismissible one and can indicate that these people are acting somewhat contradictory to what they state and/or feel, as the highly personalized advert held information to which there was no given explicit consent. Such behavior can be regarded as paradoxical, as it clearly shows a disconnect between the consumer's privacy attitude and their actual behaviour (Martin & Murphy, 2016; Barth & Jong, 2017).

To enhance the effectiveness of the online ads, retailers might reach towards techniques which employ personal data on a larger scale and beyond its primary purpose. However, leveraging consumer data beyond its original purpose has proven to be a delicate matter, considering that it is a predominant trigger for feelings of privacy violation (Foxman & Kilcoyne, 1993; Malhotra, Kim & Agarwal, 2004). Xu et al. (2012) find that the perception of the privacy being violated can in fact be reduced through the perception of privacy control, as this is the focal mechanism through which data controlling actions influence the level of perceived privacy violation. Based on our results, we cannot confirm whether this is true or not as our results have not proved to be statistically significant. Nevertheless, not being able to prove this statistically does not mean that we should omit the finding that people who feel in control of their personal data also found the ad to be less intrusive. On the contrary, this indicates the necessity for additional examination which will better explain how privacy control impacts the relationship between personalization and the perceptions of privacy violation.

Our study also provides a better understanding of the psychological responses such as perceptions of trust and of privacy violation as these constructs mediate the impact of the viewer's behavioural responses such as click-throughs. Even though these constructs are individual, we find that they are very much inter-linked. Altogether, our results advocate that trust act as a mediator which has a significant impact. In particular, our findings that when the participants perceive the brand as trustworthy their willingness to click-through is also higher, reinforce previous research results. For instance, Bleier and Eisenbeiss (2015a) discover that retailers can improve their click-through rates if they are found as trustworthy.

By contrast, adverts from less trusted retailers elicit increased perceptions of privacy violations. These findings are in line with the one of Bleier and Eisenbeiss (2015a, 2015b) where absence of trust positively impacts the perceptions of privacy violations when consumers were exposed to an advert. Our reasoning is, because there is no presence of trust, consumers might fail to view the encountered personalized adverts as more useful which consequently incentivizes perceptions of privacy violations. These results provide clear practical implications and valuable contributions for the literature. Besides these findings, the study also maps a matrix to determine if brand attitude and trust go "hand in hand". The results were as anticipated as the respondents which had a positive brand attitude also found the brand as trustworthy (94%). Contrariwise, the respondents which had a negative brand attitude, found the brand as untrustworthy (60%). These findings are not to be lightly disregarded, since we mark a positive correlation.

Whilst our study reinforces the current knowledge about perceptions of ad relevance, privacy violation, privacy control and trust influencing the behavioural responses of consumers, there are certain limitations to be tackled which facilitate boulevards for future research.

6.2 Managerial Implications

In addition to contributing to a theoretical sense, this research also bears practical implications. Typically, it is required for marketing to strongly rely on consumer data (e.g., Wedel & Kannan, 2016) as multiple areas from it are able to embrace consumer data to an unparalleled degree (Goldfarb & Tucker, 2019).

To get both affirmation and insights which would help lay out the ground where companies in reality stand when it comes to usage of consumer data and personalized marketing communications, we carried out several interviews. The results imply that there are no major differences between distinct industries when it comes to consumer data collection and analysis. All selected companies choose to both rely on and leverage data when it comes to decision-making for marketing and communication purposes. From generating innovative ideas for products to sending personalized messages to potential target audiences, the value of consumer data is widely appreciated.

The results of this study suggest that social media networks are not only used on a day-to-day basis, but in fact several times a day (97%). In particular, respondents spend most of the time on social network sites such as Instagram, Facebook and YouTube which is also an indication that these are likely the most popular networks. To this end, we need to highlight that even though our sample is relatively balanced when it comes to gender split, there is a particularly saturated age group, that is the one of vicenarians (85% are between the age of 20 to 29). These findings reinforce previous research such as the one of Chu (2011), where it was found that social media are certainly the most used communication channels among young people. Companies should certainly evaluate their standing within the social media world as these networks are probably the best way to reach and communicate with both potential and existing target groups. Moreover, it was proven that social network sites ideally enable companies to do this with an unprecedented speed and saving cost efficiency (e.g., Trusov, Bucklin & Pauwels 2009; Wen, Tan & Chang 2009; Saxena & Khanna 2013).

However, companies should try and put more emphasis on delivering adverts to the right consumers. If done otherwise, consumers might be overwhelmed and stuck within an advertising clutter which would trigger a necessity to avoid the ad. The results of the study show that consumers are faced with this clutter far more frequently than necessary: 79% of them notice more than five social media advertisements in a time frame of two weeks. Undoubtedly, delivering one-on-one marketing communications helps reduce the ad clutter. In particular, this is done by generating ads based on individuals' preferences and personalized according to his/her needs. One of the main findings from this research suggests that such adverts are not just perceived as more relevant for the individual, but also reflect in a higher click-through intention.

Conventional wisdom is that the aim of a personalized advertisement is to reach the right audience by leveraging consumer data and avoid unnecessary costs of wrongly delivered messages. In order for this to result in effectiveness, the companies need to adhere to certain rules and avoid triggering feelings of privacy violation. The most straightforward implication for managers is that once their companies start using consumer data for creating personalized online adverts, they should clearly communicate it to their consumers. In other words, when an ad is being created, it should not be displaying information which was not explicitly provided by the consumer. By taking such additional steps, they prevent consumers from experiencing "loss of privacy".

Furthermore, the study also points out the significance of continuously observing and upholding privacy expectations in terms of data storage. That is, companies should clearly disclose how they store the collected data in order to diminish privacy concerns and provide more confidence among their consumers. Overall, we find that consumers are aware of the ways companies track their online activities and that they are familiar with the data collection techniques. However, a large number of them are not so much aware of how this shared data is actually being stored and if they can go back after data disclosure to make a request which would delete it. If such misalignments exist between the company and their consumers' privacy expectations, then it is best to take actions which would alleviate them. For instance, enabling the consumers to pick from different options on how the data will be employed, avoids the negative consequences that appear when their information is used for personalized ads without previously granted permission on data disclosure.

Although legislative changes may encourage consumers to consent more deliberately to privacy policies (Wright & Xie, 2019), if companies were to take advantage of this, they would probably benefit from it in the short-run. However, companies which encourage consumers to actively participate how their personal data will be handled and employed create more benefits for themselves in the long-run. A company which is probably one of the best examples when it comes to thinking long-term is Amazon. This company completely discloses its privacy policies and facilitates consumers with straight-forward instructions on how they can either opt-out from having delivered personalized adverts or boost their user experience with both personalized adverts and recommendations (Amazon, n.d.).

In a mere transparent manner, Amazon provides consumers with the right to control how their personal data is gathered and used by simply submitting a preference: "*Show me interest-based ads provided by Amazon*" or *"Do not show me interest-based ads provided by Amazon"* (Amazon, n.d.). By being transparent, the company gains the ability to use consumer data more efficiently and effectively, which consequently builds up a positive brand attitude as well as feelings of trust towards the company among its consumers (Rothaar, 2018). These factors certainly bear positive implications for both small, medium and large companies.

Such example from the real world is also in line with our findings which show that the consumer's reaction towards a personalized advert is mediated through brand attitude and trust. Most of the survey-questionnaire respondents who have a positive (good) attitude towards the brand placed on the simulated online advert, they also find it as trustworthy (94%) and the ones who have a negative (bad) attitude towards the same, exact brand, also find the brand as untrustworthy (60%).

Moreover, our findings further indicate that companies which are found as untrustworthy should bear in mind the level of message personalization as their ads will be probably perceived as intrusive. Contrariwise, the results imply clear differences in the perceptions of ad intrusiveness when the brand is found to be trustworthy. Regards needs to be shown for the fact that perceptions of trust normally vary from consumer to consumer, thus, companies need to assess general perceptions of trust in comparison with their competitors via market research (Bleier & Eisenbeiss, 2015a). All of the aforementioned factors are somewhat interconnected and influence each other. These findings provide clear guidelines where transparency and informativeness are key to having efficient marketing communication strategies.

The center of attention in the discussions about consumer data in a marketing context are about proper collection and usage of data, in order to create more engaging ads. However, to our knowledge, very few studies have explored the actual "influencers" of the willingness to click-through. Distinguishing the prevailing drivers of this peculiar willingness is probably one of the major and most unique contributions of this paper in terms of managerial implications. To profoundly understand them, we built a classification tree based on different variables which we identify to have influenced the willingness to click-through.

For instance, if we would go level by level, we can find that the top distinguishable variable among participants who are more likely to click-through compared to the ones who are not is the advert's state. In particular, our results suggest that personalized ads yield better results in contrast to non-personalized ones. This is a clear indication for managers to lean towards leveraging personalized ads within their communication. However, if we would look at the whole branch, they should bear in mind that this variable is best when escorted by perceptions of control. Meaning, their consumers need to feel in control in order to actually click-through.

We can say that personalized ads and the feeling of control do incentivize the willingness to click-through among viewers and given the fact that within the whole tree model, this is the leaf which has the highest concentration of people who are more likely to click-through (38.1%) is an interesting finding for marketing managers alone. However, we also identify factors which might influence the people who feel otherwise. For these consumers, we propose for managers to "play around" with the levels of ad personalization. For instance, delivering a highly personalized ad to the participants who do not feel in control of their data or are not quite determined on how they feel when it comes to this control, is one way to attract these consumers and initiate their willingness to click-through. However, for this to work, trustworthiness is crucial. Trust is the key driver which would lead these consumers to carry out a click-through when feelings of control are absent. This leaf comes as second in terms of highest concentration of participants who are more likely-to click-through within the whole tree model (31.1%).

Delivering moderately personalized ads is another way of reaching these consumers who do not feel in control or are not quite determined on how they feel when it comes to the control of their data. Contrarily to the highly personalized ads where trust was key, our findings suggest what is important when serving moderately personalized ads is actually the perception of positive brand attitude. This perception is the driver of the willingness to click-through. If we contrast and compare, both of these ads are personalized however, managers should always differentiate and acknowledge that the personalization depth is influenced by the perceptions of brand attitude and feelings of control.

It is most certainly of great worth for managers to understand what drives people to click-through. Moreover, to pinpoint when and who will click-through enables them to target their audience more efficiently and effectively. This study provides them with a better understanding of the consumers' inner psychological stimuli which fuel their click-through intentions. In particular, we identify perceptions of control, trust and brand attitude as well as the level of ad personalization to be the incentives which drive the willingness to click-through. However, in a real-life setting, a marketing department would benefit more from a large-scale predictive model.

The model itself would not predict the willingness to click through, but the actual clicking-through. However, in this case, questionnaire-survey data would not be enough due to biases in the way it is collected. For instance, people might assert they are willing to click-through, although they wouldn't have clicked in a real-life setting. The required data in order for this model to be accurate is knowing when someone actually clicks on the ad. The itself data could be collected from a random experiment, where people at random are sent the ad and it would include demographics, device data, browser data, etc., and whether or not the person clicked on the ad.

Furthermore, a Machine Learning model such as CART would then be trained to predict who will click on an advertisement. The resulting model could further be used on other people in order to predict which are most likely to click through and to which should the advert be sent to. This targeting approach would save a significant amount of money typically invested in social media advertising campaigns, as it would avoid sending the ad to people that are very unlikely to click on it. In that case, CART remains an accurate and interpretable method that could be used, however, from a cost-saving standpoint, it would be worth giving up some interpretability by using more accurate Machine Learning algorithms.

Optimal Classification Trees, Random Forests, Gradient Boosted Trees or Deep Neural Networks can provide better accuracy results, thus help to better serve potential customers personalized advertisements and consequently bring in the same amount of revenue with lower campaign costs. One caveat is that such model would require a significantly larger dataset to reach good accuracy results.

6.3 Limitations and Future Research

Although we highlight theoretical and managerial implications, of course, there are also several limitations to our research.

For instance, the main limitation of the study comes in terms of measuring the click-throughs to the given advertisement. We assume that the click-through intentions in this research parallel the click-through rate, yet actual respondent behaviour and consequently results might differ in a real-world setting. Particularly, the analyses within the study account only for consumer response in terms of their intentions rather than their actual click-throughs. Moreover, the average click-through intentions (which we consider to be the actual rates) amounted to 11.9%, whilst in the real world, the actual average click-through rate is 0.90% on Facebook (Irvine, 2020), indicating somewhat of a discrepancy. This leaves the doors open for companies which have the capability to carry out the experiment in a real setting and measure the actual click-through rate.

Furthermore, in our research we employ a scenario-based approach. When it comes to the serving of the different types of adverts, the respondents were given a simulation which resembles reality i.e., non-, moderately- and highly-personalized advert scenario. This exhibits as a limitation as the advertisement itself was not actually real, thus some of the respondents might have not kept the given scenario in mind when answering the questions. Moreover, imagining oneself in a situation is not the same as being in the real situation. A field experiment with actual personalized ads might yield different results as it will not measure a self-reported behaviour. Certainly, this study can serve as a future reference and a base on how the adverts can be put together in terms of personalization depth. If such experiment were to be done by companies, they could also use real consumer data which would help them navigate properly when it comes to the advertisements' personalization and use their network to distribute the created adverts on a larger scale.

Occasionally, a consumer might also misjudge a personalized advertisement for a non-personalized and vice-versa. Once again, due to the nature of the quantitative experiment, i.e., not using an actual ad, we were not able to address this differentiation properly. Ergo, an experiment with an actual advertisement could be carried out in line with Li & Liu (2017).

The generalizability of our results also might be limited due to the fact that our survey-questionnaire respondents are mainly among the age of 20 to 29. Our sample involves particularly this age group due to the fact that our survey distribution network is actually within that age range. This means that the results are probably only relevant and applicable for companies whose target audience is among the age of 20 to 29. If this experiment were to be done on a scale where the participants' age is equally distributed, then the results would be widely applicable and thus not so limited.

While through our distribution network we managed to have respondents from 33 different countries, making it a relatively diverse sample, it would be even better if the number of respondents was equally (or at least comparably) distributed among the countries. For instance, most of our respondents' country of origin are Slovenia and North Macedonia, while from the other countries we do not have even what could be considered as a comparable number. In other words, we do not have a large enough number of respondents which could be considered as representatives of the whole (or at least a part) population. This makes us feel uncertain if the outcome would be any different than ours in the case of a bigger sample, once again making the generalizability of our results limited. Nevertheless, we do believe that our findings could still be referred to for future research, however, researchers might consider focusing on consumers only in one country or having the experiment on a larger scale, including more of a decent number of respondents coming from multiple countries.

As already pointed out, the survey-questionnaire included three different scenarios, however, the main focus of the research was not the depth of the personalization itself but rather the distinction between non-personalized and personalized ads. Intrigued by the availability of data and what results could we find apart from this "main focus", we carried out an in-depth analysis. This analysis allowed us to observe and spot the differences between the personalization states i.e., moderately- and highly- personalized. As already laid out in the results and findings chapter, these results did not prove to be statistically significant, however, the findings do indicate that there are indeed differences among the levels, certainly depending on the other factors included.

To this end, future work might investigate the personalization depth in connection to other factors (such as privacy controls, violations or trust), in line with Bleier & Eisenbeiss (2015a). Moreover, through our interviews we find that companies are enthusiastic about experimenting with the levels of personalization and are open to the idea to have it done in the near future. If a company were to experiment with this in the real world, one way it could be done is through a randomized test. In other words, consumers would be randomly assigned to a level of personalized advert while the company observes to which one, they respond better.

When it comes to the privacy paradox, our results seem to be leaning towards its existence. However, even within the existing literature there are so many conflicting results (e.g., Acquisti & Grossklags, 2005; Norberg et al., 2007; Blank et al., 2014; Lutz & Strathoff, 2014) which show a clear indication of the need for further, in-depth research. One very important limitation of our research in terms of investigating the existence of the paradox is the sole form of our experiment. In particular, our experiment takes form of a survey-questionnaire which in reality does not allow us to observe the actual behavior of the respondent(s). While we do generate some results, due to the ambiguous nature of the paradox itself we cannot really conclude how reliable and relevant they are. Future research could observe the paradoxical behavior of the respondents in a form different than a survey-questionnaire. For example, with an experiment where the actual behaviour of the participants is observed, rather than the self-reported one.

One of the ways how companies nowadays are trying to diminish and prevent privacy concerns among their consumers is by using transparent practices. In particular, they aim to inform their consumers how the served advert has been created and why are they seeing it. While we examined the general perceptions of ad transparency among the participants, the actual ad transparency was not tested. That is so because of the limitation that the given advert was not actually real but was rather a simulation which resembles reality. Even though the ad scenarios themselves were suggesting with which data the advert was created, it did not provide the actual information in a more transparent manner where they were able to click and learn by themselves. Therefore, further research could use this study as a start point and then address ad transparency more thoroughly along with the other aforementioned factors. Similarly to Facebook's ad transparency practice, the experiment itself could be done by generating an advert which also includes "space" to which consumers can be referred to, if they were open to learn how the ad was created. Then, companies compare the results to the consumers who do not have this option to gain more information on the advert and measure if ad transparency affects consumers perception of privacy violations and privacy concerns.

Another limitation which certainly exists in this study can be found in the conceptual model. That is, we only concentrate on exploring the effects of perceived privacy control over the relationship of personalization and privacy violation, however, this moderator can influence other relationships which are present in the model. This would be also the case for trust, whereas this research we only focused on its effects over the relationship between perceived privacy violations and click-throughs. An idea which could help build further research is that these variables could be studied in a more complexed manner: exploring their influence on some other relationships within the model.

Further, we also experienced shortcomings during our research with two of our hypotheses. We were prevented to accept hypothesis H3 as the results found in H3b were not proven to be statistically significant. Particularly, we were not able to prove that the perceptions of privacy violations and click-throughs have a negative relationship. This comes despite the fact that we could still note that the willingness to click-through is higher when the participants find the ad to be nonintrusive than when the participants find the ad to be intrusive. Due to the encouraging results, we believe that tone of our limitations preventing us to statistically confirm this might've been the sample size. Future research could certainly address this complexity and use our study as a reference in doing so.

The second hypothesis which could not be confirmed due to the inability to deliver statistically significant results is H4. In particular, we were not able to confirm whether increased perception of privacy control negatively impacts the relationship between personalization and perceived privacy violation. Generally, there is surprisingly, very little research to which we could refer to when measuring this. Despite this being a limitation, once again we were able to generate encouraging results which makes us believe that perceptions of privacy control do impact this relationship. These findings are definitely proposing fruitful directions for future investigation.

An important part of our empirical research analysis is the classification and regression tree (CART). We have already highlighted its implications for managers, and we believe these findings are grounds for further research. The method itself is widely used in academia and companies as it possesses the unique advantage of both being very interpretable and showing good accuracy results on real-world data. However, the method also presents shortcomings. In particular, one of the limitations of the CART classification trees is the fact that they are built with a top-down, greedy approach. This conveys that each split is locally optimal and are built without taking other future splits into consideration. In other words, the tree as a whole might not be exactly globally optimal.

For instance, the first split is locally optimal: if we could only partition the consumer data based on one variable, the first split (i.e., in our case whether or not the ad is personalized) is the best possible split to maximize the concentration of people willing to click-through in one of the children nodes. Once this first split has been made, the model runs recursively on the left child node, then on the right child node independently. Similarly, it runs on the children of the left child node and on the children of the right child node and so on and so forth. However, it is possible that a different combination of splits would have provided better results overall, i.e., the possibility to isolate a higher concentration of people willing to click through. This takes us back to the fact that the tree is locally optimal, and its splits are made independently rather than all at once.

Further research can be certainly done by leveraging state-of-the-art, mixed integer optimization. In order to do so, companies and researchers could refer themselves to the novel method developed by Bertsimas and Dunn (2017) called Optimal Trees. This method allows to build the whole tree at once with more precision, making it a globally optimal. Moreover, using an Optimal Classification Tree instead of a CART classification tree certainly enables higher confidence in the tree as a whole. In addition, it would help find even higher concentrations of people willing to click-through with less splits.

CONCLUSION

Companies use advanced personalization techniques that leverage behavioural consumer data at an extent that this data has become the pillar of successful marketing communication strategies. Greater personalization positively influences ad effectiveness, but consumers may experience discomfort when targeted with such advertisements. The main purpose of this research was to develop knowledge about data-driven marketing communication strategies within companies and to identify the attitudes of consumers towards personalized advertisements as well as the reactions that consequently appear, i.e., perceptions of ad relevance, privacy violation and trust as crucial drivers that influence their click-through intentions.

With the help of both theoretical framework and empirical findings we hope to guide marketing managers how to be more effective when structuring their marketing communication strategies. In particular, this study sheds light on personalized advertising by including all prevailing positive as well as negative drivers that might influence the ad effectiveness, in particular the click-through intention. We feel sure that our purpose has been fulfilled by analyzing in-depth our empirical findings and contrasting them with the existing theoretical literature.

The **main research question** addressed through our thesis was: *What is the relationship between personalization and the likelihood of a click-through and is this relationship mediated by perceived ad relevance and privacy violation, while moderated by privacy control and trust?*

Overall, the empirical findings suggest that there is a positive relationship between personalization and click-throughs and that this relationship is influenced by various factors. In particular, this study finds that perceptions of ad relevance positively impact this relationship. Regrettably, the gathered sample data did not suggest the existence of statistically significant traces which enables us to confirm that perceptions of privacy violations influence the relationship between personalization and click-throughs. Nevertheless, we found encouraging results which indicate that these factors in reality most likely influence this relationship.

Furthermore, the **supporting research questions** of our thesis were: *Do increased perceptions of privacy control negatively impact the relationship between personalization and perceived privacy violation?* further, *Can trust in the retailer positively impact the relationship between perceptions of privacy violation and the likelihood of a click-through*?

and *Among levels of personalization, ad relevance, trust, brand attitude, perceived privacy violation and control which are the prevailing drivers that lead an individual to click-through?*

Due to the inability to generate statistically significant results, the first supporting research question still remains unanswered. However, we were still able to generate stimulating results which makes us believe that perceptions of privacy control do impact this relationship. The findings of this experiment are definitely proposing intriguing directions for future investigation.

Altogether, our results advocate that trust acts as a mediator which has a significant impact since when the participants perceive the brand as trustworthy their willingness to click-through is also higher. By contrast, adverts from less trusted retailers elicit increased perceptions of privacy violations. Our reasoning is, because there is no presence of trust, consumers might fail to view the encountered personalized adverts as more useful which consequently incentivizes perceptions of privacy violations. These results provide clear practical implications and valuable contributions for the literature.

Distinguishing the prevailing drivers of the willingness to click-through is probably one of the major and most unique contributions of this paper in terms of managerial implications. We identify perceptions of control, trust and brand attitude as well as the level of ad personalization to be the prevailing incentives which drive this peculiar willingness. It is most certainly of great value for companies to understand the consumers' inner psychological stimuli and pinpoint when and who will click-through. This enables them to target their audience more efficiently and more effectively.

Whilst our study reinforces the current knowledge about perceptions of ad relevance, privacy violation, privacy control and trust influencing the behavioral responses of consumers when exposed to personalized adverts, there are certain limitations to be tackled which facilitate boulevards for future research.

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APPENDICES

Appendix 1: Povzetek (Summary in Slovene)

Velik tehnološki razvoj v 21. stoletju je močno zaznamoval trženjsko komuniciranje. Načini ustvarjanja in izvajanja strategij trženjskega komuniciranja so se s prihodom novih orodij in tehnik močno razvili in tako tržnikom ponudili učinkovitejšo interakcijo s ciljno publiko (Jayaram, Manrai & Manrai, 2015). Sodobne tehnike in komunikacijski kanali podjetjem omogočajo pridobivanje podrobnih podatkov o potrošnikih in njihovem spletnem vedenju, kar posledično omogoča mnogo novih priložnosti (Shanahan, Tran & Taylor, 2019). Podjetja, ki svoje odločitve sprejemajo na podlagi zbranih podatkov so s tem spremenile svojo strategijo trženjskega komuniciranja (Saura, 2020). Novi pogledi na trženjsko komuniciranje tako temeljijo na celostnem pristopu in s tem sinergiji sporočil preko vseh komunikacijskih kanalov s t.i. integriranim trženjskim komuniciranjem (ITK) (Palmatier & Sridhar 2017, str.162). S tem so se spremenili tudi izbrani kanali komuniciranja, saj je fokus prešel iz tradicionalnih medijev, kot sta na primer televizija ter radio, v nove digitalne kanale (Chaffey & Ellis-Chadwick, 2012, str. 11).

S prihodom digitalnih načinov trženjskih komunikacij se je obenem spremenil način ciljanja potrošnikov iz celotne populacije na posameznega potrošnika (Kim, Han in Shultz, 2004). Način prilagajanja in osredotočanja na individualnega potrošnika z oglasi, ki temeljijo na potrošnikovih preferencah, imenujemo personalizacija (Bleier & Eisenbeiss, 2015a; Keyzer, Dens & Pelzmacher, 2015). Personalizacija pozitivno vpliva na učinkovitost oglasnega sporočila, kot so potrdile številne študije (Pavlou and Stewart, 2000; Tam & Ho 2005; Kalyanaraman and Sundar 2006; Noar, Benac & Harris 2007; Sohl and Moyer 2007; Arora et al. 2008 in Walrave et al., 2018). Personalizirani oglasi se najbolj pogosto pojavljajo v obliki personaliziranih elektronskih sporočil, priporočenih izdelkov (Awad & Krishnan, 2006), oglasov na družbenih omrežjih (Keyzer, Dens & Pelzmacher, 2015), oglasnih pasicah in mobilnih oglasov (Bang & Wojdynski, 2016).

Personalizacija temelji na potrošnikovih osebnih podatkih, zato se morajo podjetja zavedati, da lahko poleg pozitivnih vplivov personaliziranih sporočil, ti podatki, v kolikor niso pravilno uporabljeni ali/in implementirani, sprožijo tudi negativen odziv (Aguirre, Mahr, Grewal, Ruyter & Wetzels, 2015). Potrošniki so venomer izpostavljeni kršitvam in vdorom v njihovo zasebnost, kar jim vzbuja občutek skrbi in ranljivosti (Smith in Cooper-Martin, 1997) in ko govorimo o ranljivosti potrošniških podatkov, se sklicujemo na potrošnikovo zasebnost in njegovo stopnjo strpnosti pri kršitvi te zasebnosti s škodljivimi praksami uporabe podatkov (Martin, Borah & Palmatier, 2017). Ranljivost potrošnikov in njihovih podatkov je regulirana tudi s strani zakonodaje. Brez sedanjih predpisov bi se namreč zasebnost sčasoma lahko zmanjšala in posledično potrošnikom povzročila veliko škodo (Rust, Kannan & Peng, 2002). Nedavna pomembna uredba, ki obravnava pomisleke glede zasebnosti potrošnikov, je Splošna uredba o varstvu podatkov (GDPR) (Evropska komisija, nd). K vse večjemu spoštovanju zasebnosti strmijo tudi podjetja, ki poskušajo svoje načine zbiranja in obdelave podatkov opraviti na bolj transparentne načine (Karwatzki, Dytynko, Trenz & Veit, 2017). Transparentnost pozitivno vpliva tudi na potrošnikove pomisleke glede zasebnosti, potrošnikovo zaupanje (Treiblmaier & Pollach, 2007; Karwatzki, Dytynko, Trenz & Veit, 2017) ter obenem potrošnikov občutek nadzora nad svojo zasebnostjo (Karwatzki, Dytynko, Trenz & Veit, 2017). Pomemben dejavnik personaliziranega oglaševanja je tudi relevantnost oglasa, saj meri, kako relevanten je izdelek/storitev za potrošnika in v kolikšni meri zadovoljuje njegove potrebe (Jung, 2017).

Potrošniki morajo velikokrat izbrati med zasebnostjo in ugodnostmi, ki jih prejmejo v zameno za deljenje osebnih podatkov (Norberg, Horne & Horne, 2007). Kljub dejstvu, da potrošniki izkazujejo zaskrbljenost glede osebnih podatkov, v večini primerov njihova dejanja s tem niso skladna (Kokolakis, 2017). Neskladje med željami glede zasebnosti in dejanskim vedenjem razkritja osebnih informacij imenujemo "paradoks zasebnosti" (Martin & Murphy, 2016; Barth & Jong, 2017).

Kot omenjeno, obstajajo različni faktorji, ki vplivajo na potrošnike pri odločitvi med njihovo zasebnostjo in razkritjem informacij za nekatere ugodnosti, kot je na primer personalizacija oglasov. V magistrskem delu smo raziskali naslednje vprašanje: *Kakšen je odnos med personalizacijo in verjetnostjo klika na oglas ter kako nanj vpliva zaznava relevantnosti oglasa in kršitve zasebnosti?* Glavnemu raziskovalnemu vprašanju smo dodali tudi podporna raziskovalna vprašanja in sicer: *Ali povišano zaznavanje nadzora zasebnosti negativno vpliva na odnos med personalizacijo in zaznavo kršitve zasebnosti? Ali zaupanje v prodajalca pozitivno vpliva na percepcijo kršitve zasebnosti in s tem verjetnosti klika na oglas?* in *Kateri dejavniki med stopnjami personalizacije, relevantnostjo oglasa, zaupanjem, odnosom do blagovne znamke, zaznavo kršitve zasebnosti in nadzora zasebnosti najbolj vplivajo na potrošnikov klik na oglas?*

Magistrsko delo je zasnovano na teoretičnem uvodu, napisanem na podlagi pregleda sekundarnih virov in kjer so predstavljeni ključni koncepti in z njimi povezane relevantne študije. V nadaljevanju pa je empirični del, ki je oblikovan na podlagi primarnih virov, zbranih s pomočjo kvalitativnih in kvantitativnih podatkov preko strukturiranega intervjuja ter vprašalnika.

Empirične ugotovitve so pokazale pozitiven odnos med personalizacijo in klikom na oglas, na katerega vpliva tudi vrsto drugih faktorjev. Z raziskavo smo ugotovili, da zaznava relevantnosti oglasa pozitivno vpliva na odnos med personalizacijo in klikom. Na žalost s pomočjo zbranega vzorca ne moremo statistično potrditi pomembnih povezav med dejavniki, preko katerih bi lahko potrdili, da zaznava kršitve zasebnosti vpliva na odnos med personalizacijo in klikom ter da povišano zaznavanje nadzora zasebnosti negativno vpliva na odnos med personalizacijo in kršitvijo zasebnosti. Kljub temu so rezultati vzpodbudni in nakazujejo na to, da ti faktorji po vsej verjetnosti vplivajo na odnosa. Obenem se s tem odpirajo vrata za nadaljnje raziskave.

Rezultati naše raziskave so obenem pokazali, da zaupanje nosi pomembno vlogo in ima velik vpliv na potrošnika, saj so tisti, ki blagovni znamki bolj zaupajo tudi bolj nagnjeni h kliku na oglas. V nasprotju s tem pa oglasi, ki prihajajo s strani blagovnih znamk, katerim potrošnik ne zaupa, izzovejo zaznavo kršitve zasebnosti. Iz tega lahko sklepamo, da v primeru odsotnosti zaupanja v blagovno znamko, potrošnik personaliziranega oglasa ne zazna kot bolj uporabnega in s tem ta v njem sproži občutek kršitve zasebnosti. Ti rezultati obenem podajajo jasne praktične implikacije in koristen prispevek k že obstoječi literaturi.

Praktična uporaba je mogoča predvsem na področju razlik med dejavniki, ki najbolj vplivajo na potrošnikov klik na oglas in so zagotovo ključene ugotovitve magistrskega dela. Te kažejo, da so zaznava nadzora, zaupanje, odnos do blagovne znamke in stopnja personalizacije oglasa tisti dejavniki, ki najbolj vplivajo na nagnjenost potrošnika h kliku oglasa. Boljše razumevanje potrošnikov na podlagi njihovih občutenj in dražljajev, ki vplivajo na klik na oglas je najbolj pomembno za podjetja, ki uporabljajo personalizacijo v sklopu svojega oglaševanja. S tem lahko bolj natančno določijo kdo in kdaj se bo odzval na njihov oglas. Posledično bo njihovo targetiranje ciljne skupine veliko bolj natančno ter učinkovito in tako oglaševalski cilji, kot tudi strategija bodo uspešnejši.

Naša raziskava dopolnjuje dosedanje študije o vplivih personalizacije na klik na oglas, personaliziranju oglasov in posledični zaznavi relevantnosti oglasa, kršitvi zasebnosti, zaznavi nadzora in zaupanju, in s tem največ prispeva k znanju o vedenju potrošnikov. Seveda pri tem ne smemo zapostaviti pomanjkljivosti študije, predvsem način testiranja potrošnikovega obnašanja kot takega in s tem klika na oglas, velikost in raznovrstnost samega vzorca ter obenem razlike med stopnjami personalizacije, ki odpirajo priložnosti za nadaljnje raziskave.

Appendix 2: Survey Questionnaire

Dear participant, we are a group of marketing students from the School of Economics and Business, University of Ljubljana. As part of our Master's thesis, we are doing research on consumer usage of social media and we would appreciate your participation. Please stay assured that your responses will stay completely anonymous and will be kept strictly confidential. The responses will not be shared with third parties and will only be used for the purpose of our master thesis. The survey is short and will take approximately 6-7 minutes. Thank you in advance for your time and help. Maja, Maja and Nejc :)

gdpr - Consent to collect personal data in the survey.

Survey is collecting personal data (GDPR):

By clicking "I agree", I hereby give my explicit consent for the processing of the personal data (age, gender, occupation and country), as collected in this survey questionnaire. The personal data will be processed solely for the purpose of carrying out the scientific research project. All personal data obtained with the survey will be stored under a research code (anonymization), thus fully protecting the identity of the participants, while only summary results (anonymized and presented in different statistical forms) will be publicly available.

Privacy policy and general terms are available on this link.

Please indicate whether you agree with collecting your personal information:

○ No, I do not agree with collecting my personal information

○ Yes, I agree with collecting my personal information

BLOCK 1

Q1 - How often do you use social media?

○ Several times a day

○ Once a day

○ Several times a week

○ Weekly

○ Not at all

Q2 - Which of the following social media platforms do you use most often?

More than one answers are possible

☐ Facebook

☐ Instagram

☐ TikTok

☐ LinkedIn

☐ Pinterest

☐ YouTube

☐ Other (please specify):

Q3 - What type of device(s) do you most often use to access social media platforms?

More than one answers are possible

☐ Desktop

☐ Mobile

☐ Tablet

☐ Other (please specify):

Q4 - How many advertisements (paid messages where the brand is known) have you seen placed on social media platforms in the last two weeks?

○ None

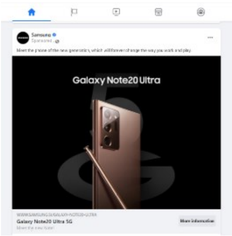
○ 1-5

○ More than 5

○ I don’t know

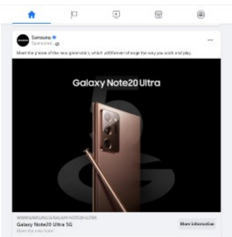
BLOCK 2

Q5_ 2 - Please carefully observe the following ad.



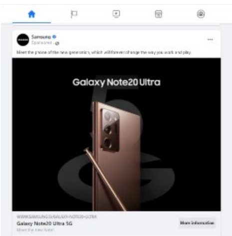
Assume that you are on your Facebook profile scrolling through your home page. At some point, you reach this advertisement and you have no previous private online messaging or browsing activities related to mobile phones, Samsung Galaxy Note20 Ultra or the brand itself.

Q5 - Please carefully observe the following ad.



Assume that you were visiting Samsung's webpage and browsing through mobile phones. Shortly afterwards, you log in onto your Facebook account and you encounter this advertisement on your homepage.

Q6 - Please carefully observe the following ad.



Assume that you were discussing with your colleague the new Samsung Galaxy Note20 Ultra phone in your private online messages. At this point, you have not browsed at all for this specific phone. Shortly afterwards, you are on your Facebook homepage and you encounter this advertisement.

BLOCK 3

Q7 - How likely is it that you would click on the ad that you have just seen?

○ Very unlikely

○ Not likely

○ Neutral

○ Likely

○ Very likely

Q8 - For each statement, please mark correspondingly your degree of agreement or disagreement:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I believe the ad I saw is not based on my preferences.	○	○	○	○	○	○	○
I believe the ad I saw is relevant for my needs.	○	○	○	○	○	○	○
I believe the ad I saw was created specifically for me.	○	○	○	○	○	○	○

BLOCK 4

Q9 - For each statement, please mark correspondingly your degree of agreement or disagreement:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am aware that the company Samsung has collected my data based on my previous online activities.	◯	◯	◯	◯	◯	◯	◯
I find this ad to be intrusive towards my privacy.	◯	◯	◯	◯	◯	◯	◯

BLOCK 5

Q10 - For each statement, please mark correspondingly your degree of agreement or disagreement:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I consider Samsung a trustworthy company.	◯	◯	◯	◯	◯	◯	◯

Please choose "Somewhat agree" as your answer.	◯	◯	◯	◯	◯	◯	◯

BLOCK 6

Q10_ 2 - For each statement, please mark correspondingly your degree of agreement or disagreement:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I am aware that companies have ways to track my online activities.	◯	◯	◯	◯	◯	◯	◯
I am aware of the techniques companies use to collect my data.	◯	◯	◯	◯	◯	◯	◯
I am uncomfortable when an ad is too close to my online activities.	◯	◯	◯	◯	◯	◯	◯

I am aware of how my shared data is being stored.	◯	◯	◯	◯	◯	◯	◯
I am uncomfortable having my data used and/or shared without my permission.	◯	◯	◯	◯	◯	◯	◯
I feel in control of my data.	◯	◯	◯	◯	◯	◯	◯
I feel informed beforehand that my data will be collected by the company.	◯	◯	◯	◯	◯	◯	◯
I can pick from different options on how my data will be used by the company.	◯	◯	◯	◯	◯	◯	◯
I can always go back and request/delete myself the collected data.	◯	◯	◯	◯	◯	◯	◯

BLOCK 7

Q11 - My overall attitudes towards Samsung as a brand are:

	1	2	3	4	5	
Bad	○	○	○	○	○	Good

Q12 - What is your gender:

○ Male

○ Female

○ Other (Please specify) :

○ I prefer not to answer.

Q13 - Please specify your age:

○ <19

○ 20-29

○ 30-39

○ 40-49

○ >50

○ I prefer not to answer.

Q14 - Which country do you come from?

Afghanistan

Albania

Algeria

Andorra

Angola

Antigua and Barbuda

Argentina

Armenia

Australia

Austria

Azerbaijan

Bahamas

Bahrain

Bangladesh

Barbados

Belarus

Belgium

Belize

Benin

Bhutan

Bolivia

Bosnia and Herzegovina

Botswana

Brazil

Brunei

Bulgaria

Burkina Faso

Burundi

Cabo Verde

Cambodia

Cameroon

Canada

Central African Republic

Chad

Chile

China

Colombia

Comoros

Congo

Costa Rica

Croatia

Cuba

Cyprus

Czech Republic (Czechia)

Côte d’Ivoire

Denmark

Djibouti

Dominica

Dominican Republic

DR Congo

Ecuador

Egypt

El Salvador

Equatorial Guinea

Eritrea

Estonia

Eswatini

Ethiopia

Fiji

Finland

France

Gabon

Gambia

Georgia

Germany

Ghana

Greece

Grenada

Guatemala

Guinea

Guinea-Bissau

Guyana

Haiti

Holy See

Honduras

Hungary

Iceland

India

Indonesia

Iran

Iraq

Ireland

Israel

Italy

Jamaica

Japan

Jordan

Kazakhstan

Kenya

Kiribati

Kuwait

Kyrgyzstan

Laos

Latvia

Lebanon

Lesotho

Liberia

Libya

Liechtenstein

Lithuania

Luxembourg

Madagascar

Malawi

Malaysia

Maldives

Mali

Malta

Marshall Islands

Mauritania

Mauritius

Mexico

Micronesia

Moldova

Monaco

Mongolia

Montenegro

Morocco

Mozambique

Myanmar

Namibia

Nauru

Nepal

Netherlands

New Zealand

Nicaragua

Niger

Nigeria

North Korea

North Macedonia

Norway

Oman

Pakistan

Palau

Panama

Papua New Guinea

Paraguay

Peru

Philippines

Poland

Portugal

Qatar

Romania

Russia

Rwanda

Saint Kitts

Nevis

Saint Lucia

Samoa

San Marino

Sao Tome

Principe

Saudi Arabia

Senegal

Serbia

Seychelles

Sierra Leone

Singapore

Slovakia

Slovenia

Solomon Islands

Somalia

South Africa

South Korea

South Sudan

Spain

Sri Lanka

St. Vincent

Grenadines

State of Palestine

Sudan

Suriname

Sweden

Switzerland

Syria

Tajikistan

Tanzania

Thailand

Timor-Leste

Togo

Tonga

Trinidad and Tobago

Tunisia

Turkey

Turkmenistan

Tuvalu

Uganda

Ukraine

United Arab Emirates

United Kingdom

United States

Uruguay

Uzbekistan

Vanuatu

Venezuela

Vietnam

Yemen

Zambia

Zimbabwe

Q15 - What type of community do you live in?

○ Large city

○ Suburb near a large city

○ Small city or town

○ Rural area

Q16 - What is the highest degree or level of school you have completed? If currently enrolled, highest degree received.

○ Less than a high school diploma

○ High school degree or equivalent

○ Bachelor’s degree (e.g., BA, BS)

○ Master’s degree

○ Other (Please specify):

○ I prefer not to answer.

Q17 - Please state your current occupation:

Multiple answers are possible

☐ Student

☐ Employed (full-time)

☐ Employed (part-time)

☐ Unemployed

☐ Retired

☐ Other (Please specify):

☐ I prefer not to answer.

Appendix 3: Interview transcripts

Company #1

We are a group of marketing students from the School of Economics and Business, University of Ljubljana, currently doing research on personalized advertising and consumer privacy. This research is part of our Master's thesis where our main purpose is to develop knowledge about marketing communication strategies and ad personalization techniques. We assure you that your and your company's identity will stay completely anonymous throughout the entire process. Your responses will not be shared with any third-parties and will only be used for the purpose of our master thesis.

Thank you for taking the time to have this interview with us.

GENERAL INFORMATION

Industry type: *Sports equipment (bikes)*

Company size (no. of employees): *15*

Company's age: *27 years*

Contact's position and department in the company: *CMO, marketing department*

Date and time of the interview: 2.10.2020

QUESTIONS:

1. **Does the company gather consumer data? (Consumer data is the information that includes all personal, behavioural and demographic data.)**

Yes, our company leans towards gathering consumer data as nowadays we think consumer data is key. Apart from the types of data you already mentioned, we also gather data about our consumers' online purchases.

2. **Which department in your company is responsible for gathering the consumer data?**

In our company the marketing department is responsible for collecting the aforementioned data. Considering that we are still a very small company, our department currently consists out of two people.

3. **Which channels does the company use to gather the consumers' data? Which ones are used more frequently than others? (For example: Social media, website, e-commerce, etc.)**

Since we are present in both brick-and-mortar stores and online, I must admit for our physical store we are not that data-driven. I would say that this is kind of a drawback for our business as it is not as convenient (it is much harder to be data-driven when owning a physical store) and does not allow us to anticipate what the consumers visiting our store would like. We do have types of forms that can be filled out but, this requires much more time and energy from both our employees and customers. However, when it comes to our online presence, we most certainly try to rely our marketing decision-making on consumer data as much as possible. Mostly, we use our website and e-commerce as primary channels to gather consumer data. However, we have presence on social media as well (e.g., Facebook) therefore we are able to collect data there as well.

4. **Which types of consumer data does the company gather? (Demographic, social, behavioural, etc.)**

The data collection depends on the purpose. What we mean by this is that for example, data such as name, surname, email, phone number and delivery address is mainly when a customer carries out a purchase. Of course, some of this data is also used for marketing purposes e.g., sending newsletters and promotions. On top of this, we also collect behaviour data generated through our website.

5. **Which tools does the company normally make use of in order to analyse the gathered data? Which ones are used more frequently than others? (Google Analytics, CRM platform, etc.)**

Our primary tool for data analysis is Google Analytics, mainly due to our e-commerce business nature.

6. **Is the company marketing decision-making driven by consumer data? Which decisions are mainly driven by consumer data?**

Some of our decisions for our online marketing communication are data-driven, however, not all. We are definitely striving to improve this and rely on consumer data as much as possible in the future.

7. **Is the company using ad personalization as part of your marketing communication?**

Yes, we use personalized ads to target more specifically individuals with our available sports equipment.

8. **Which personalization techniques does your company use in your marketing communication?**

More often we use display advertising.

9. **In your opinion, what are the benefits of personalized ads compared to non-personalized?**

I think that personalized ads are much better as they enable us to target the right audience and drive traffic to our online store more effectively.

10. **Has the company ever tested how different levels of personalization affect your customers?**

No, we have never tested, however we certainly hope to do so in the near future.

Company #2

We are a group of marketing students from the School of Economics and Business, University of Ljubljana, currently doing research on personalized advertising and consumer privacy. This research is part of our Master's thesis where our main purpose is to develop knowledge about marketing communication strategies and ad personalization techniques. We assure you that your and your company's identity will stay completely anonymous throughout the entire process. Your responses will not be shared with any third-parties and will only be used for the purpose of our master thesis.

Thank you for taking the time to have this interview with us.

GENERAL INFORMATION

Industry type: *Beverage*

Company size (no. of employees): 600 and around 85,000 worldwide

Company's age: *195 years*

Contact's position and department in the company: brand manager, marketing *department*

Date and time of the interview: 28.9.2020

QUESTIONS:

1. **Does the company gather consumer data? (Consumer data is the information that includes all personal, behavioural and demographic data.)**

Yes, mostly we gather behavioural data from our website.

2. **Which department in your company is responsible for gathering the consumer data?**

In Slovenia, the R&D belongs to the marketing department, however on a global level these two are separate, meaning there is a separate department for research and development and a separate one for marketing.

3. **Which channels does the company use to gather the consumers' data? Which ones are used more frequently than others? (For example: Social media, website, e-commerce, etc.)**

We mostly gather the data via our website, while the rest of the data is also collected through the social media, such as Facebook and Instagram where we are present.

4. **Which types of consumer data does the company gather? (Demographic, social, behavioural, etc.)**

Essentially our department gathers and turns into insights all data you mentioned, including demographic, social and behavioural.

5. **Which tools does the company normally make use of in order to analyse the gathered data? Which ones are used more frequently than others? (Google Analytics, CRM platform, etc.)**

While we analyze the collected data primarily with the help of Google Analytics, we also get some data driven insights of the company's strategy from the global department, such as which group should we target etc.

6. **Is the company marketing decision-making driven by consumer data? Which decisions are mainly driven by consumer data?**

Certainly we aim to be a data-driven company within all sectors, however, I would say that the marketing decisions are strongly driven by consumer data.

7. **Is the company using ad personalization as part of your marketing communication?**

Of course, we study our target group in detail and the commercials are specially targeted accordingly.

8. **Which personalization techniques does your company use in your marketing communication?**

Display advertising, social media advertising, email advertising.

9. **In your opinion, what are the benefits of personalized ads compared to non-personalized?**

I strongly believe that personalized advertising has a way better effect than the traditional. As a company that has had such a long advertising history and we have definitely used all of the available media channels to deliver our adverts in the past, we can really see that the personalized ones perform better and are more measurable than for example our tv ads.

10. **Has the company ever tested how different levels of personalization affect your customers?**

Unfortunately, we haven't tested that yet. We are curious about the results and I can say with confidence that this is a "thing" on our marketing agenda that we want to test next.

Company #3

We are a group of marketing students from the School of Economics and Business, University of Ljubljana, currently doing research on personalized advertising and consumer privacy. This research is part of our Master's thesis where our main purpose is to develop knowledge about marketing communication strategies and ad personalization techniques. We assure you that your and your company's identity will stay completely anonymous throughout the entire process. Your responses will not be shared with any third-parties and will only be used for the purpose of our master thesis.

Thank you for taking the time to have this interview with us.

GENERAL INFORMATION

Industry type: *Financial services*

Company size (no. of employees): 20

Company's age: *6 years*

Contact's position and department in the company: Marketing project manager, Marketing

Date and time of the interview: 9th October 2020

QUESTIONS:

1. **Does the company gather consumer data? (Consumer data is the information that includes all personal, behavioural and demographic data.)**

Yes, since our whole business is within an mobile app, consumer data is definitely crucial for our development and existence. All of the stated types of data are collected through our app.

2. **Which department in your company is responsible for gathering the consumer data?**

Development and partially Marketing.

3. **Which channels does the company use to gather the consumers' data? Which ones are used more frequently than others? (For example: Social media, website, e-commerce, etc.)**

The majority of the data is collected through out mobile app, as mentioned before, but we do also collect it via our website.

4. **Which types of consumer data does the company gather**? (**Demographic, social, behavioural, etc.)**

Demographic and behavioural data.

5. **Which tools does the company normally make use of in order to analyse the gathered data? Which ones are used more frequently than others?** (Google Analytics, CRM platform, etc.)

Google Analytics is definitely one of the tools we use to analyze the gathered consumer data. We also have internally developed systems which enable us to do data analysis. Now that I think of it, we also use Hotjar to analyze our collected data.

6. **Is the company marketing decision-making driven by consumer data? Which decisions are mainly driven by consumer data?**

Usually yes. Based on the date we decide which campaigns to run, which goals to pursue and finally, which customers to target.

7. **Is the company using ad personalization as part of your marketing communication?**

Yes, we do use personalized advertisements as part of our marketing communications.

8. **Which personalization techniques does your company use in your marketing communication?**

Not sure what is official classification, but we personalize our ad messages and CTA based on target audience of this specific ad.

9. **In your opinion, what are the benefits of personalized ads compared to non-personalized?**

In my opinion, personalized ads are more efficient and bring better results.

10. **Has the company ever tested how different levels of personalization affect your customers?**

Not yet, but due to our fast development we will for sure need to in the near future.

Company #4

We are a group of marketing students from the School of Economics and Business, University of Ljubljana, currently doing research on personalized advertising and consumer privacy. This research is part of our Master's thesis where our main purpose is to develop knowledge about marketing communication strategies and ad personalization techniques. We assure you that your and your company's identity will stay completely anonymous throughout the entire process. Your responses will not be shared with any third-parties and will only be used for the purpose of our master thesis.

Thank you for taking the time to have this interview with us.

GENERAL INFORMATION

Industry type: *Retail*

Company size (no. of employees): *20*

Company's age: *21 years*

Contact's position and department in the company: *CMO, marketing department*

Date and time of the interview:

QUESTIONS:

1. **Does the company gather consumer data?** (Consumer data is the information that includes all personal, behavioural and demographic data.)

Yes, of course we do.

2. **Which department in your company is responsible for gathering the consumer data?**

This responsibility is mostly in hands of the marketing department.

3. **Which channels does the company use to gather the consumers' data? Which ones are used more frequently than others? (For example: Social media, website, e-commerce, etc.)**

Consumer data is always gathered on, or through, the website. Reason is that the customer has to accept our GDPR statement before we allow ourselves to store such data. We motivate and ask customers to register as our members and so submit their personal data through various social media platforms, online advertising and physical shops. In the later, there are still some "Post-it" stickers in physical shops, where sellers write down the numbers of customers, but we try to minimize and eventually ban that.

4. **Which types of consumer data does the company gather? (Demographic, social, behavioural, etc.)**

We collect data necessary to execute online orders (name, surname, address, email, phone number), additional demographic data (birth), behavioural (sport lifestyle preferences, past orders, abandoned shopping cart) and all other behavioural data that can be seen on Google Analytics by standard.

5. **Which tools does the company normally make use of in order to analyse the gathered data? Which ones are used more frequently than others? (Google Analytics, CRM platform, etc.)**

Google Analytics, Google Data Studio and Odoo (ERP and CRM system). Most often we use Google Analytics, because it is simple and covers a broad spectre of data.

6. **Is the company marketing decision-making driven by consumer data? Which decisions are mainly driven by consumer data?**

Yes. Speaking from e-commerce perspective, we communicate and promote items are most bought or viewed on our website. We use personal data to see, which geographical areas are spending more money and which ones less. That's how we can also adjust the content being promoted in different geographical areas. For example, trail running outfits are more favourable in mountain regions, whereas city running outfits are more favourable in the cities.

7. **Is the company using ad personalization as part of your marketing communication?**

We used to have it, then we stopped because we haven’t been running it efficiently, due to some technical difficulties. We will start again to use it this for this year’s Black Friday.

8. Which personalization techniques does your company use in your marketing communication?

We will start using abandoned shopping cart emails and remarketing display advertising with recently viewed items.

9. In your opinion, what are the benefits of personalized ads compared to non-personalized?

Personalized ads “hunt” the consumer with a product or a service that he/she has already expressed interest in. In this way consumers don't lose time searching for the solution, because the solution comes straight to them. The more often the consumer sees the product, the more likely he/she is to convert. Often consumers can be irritated by non-personalized and general ads, and might start to ignore them. However, personalized ads are just the opposite. It is like having a direct sales rep communication by an individual consumer, just that the sales rep doesn’t even know about it.

10. Has the company ever tested how different levels of personalization affect your customers?

No, but I am looking forward to that in the near future.

Company #5

We are a group of marketing students from the School of Economics and Business, University of Ljubljana, currently doing research on personalized advertising and consumer privacy. This research is part of our Master’s thesis where our main purpose is to develop knowledge about marketing communication strategies and ad personalization techniques. We assure you that your and your company’s identity will stay completely anonymous throughout the entire process. Your responses will not be shared with any third-parties and will only be used for the purpose of our master thesis.

Thank you for taking the time to have this interview with us.

GENERAL INFORMATION

Industry type: e-commerce

Company size (no. of employees): 4

Company's age: 10

Contact’s position and department in the company: CEO

Date and time of the interview: 27.9.2020

QUESTIONS:

1. **Does the company gather consumer data? (Consumer data is the information that includes all personal, behavioural and demographic data.)**

Yes.

2. **Which department in your company is responsible for gathering the consumer data?**

We don’t have specific department for that, however the person in charge of marketing is handling this part.

3. **Which channels does the company use to gather the consumers’ data? Which ones are used more frequently than others? (For example: Social media, website, e-commerce, etc.)**

The company gathers the data mostly over our e-commerce. This is where most of our data comes from. On top we also collect it from social media and email.

4. **Which types of consumer data does the company gather? (Demographic, social, behavioural, etc.)**

Yes, all of what you have listed. Over our e-commerce we get a lot of information regarding customers orders, as well as their behaviour as they browse through the page.

5. **Which tools does the company normally make use of in order to analyse the gathered data? Which ones are used more frequently than others? (Google Analytics, CRM platform, etc.)**

For marketing purposes, we mostly use insights from Google Analytics, while we also use CRM but that is however more for the business clientelle.

6. **Is the company marketing decision-making driven by consumer data? Which decisions are mainly driven by consumer data?**

Yes. Based on the collected and analyse data we focus on developing our new products, work on the user experience (UX) of our e-commerce, work on improving our marketing campaigns and decide which products we would recommend to specific segments etc.

7. **Is the company using ad personalization as part of your marketing communication?**

Yes, we have been using it for quite a while, probably from the very start.

8. **Which personalization techniques does your company use in your marketing communication?**

We focus our marketing campaigns on remarketing, which usually give better results. We also segment our customers – in terms of email marketing for example we divide them based on which products they are more interested in.

9. **In your opinion, what are the benefits of personalized ads compared to non-personalized?**

I believe they result in a more specific and better targeting of the ads. "Better" and more relevant ads, etc. At the end of the day, better profitability and better ROI for the company.

10. **Has the company ever tested how different levels of personalization affect your customers?**

No, not yet.

Company #6

We are a group of marketing students from the School of Economics and Business, University of Ljubljana, currently doing research on personalized advertising and consumer privacy. This research is part of our Master's thesis where our main purpose is to develop knowledge about marketing communication strategies and ad personalization techniques. We assure you that your and your company's identity will stay completely anonymous throughout the entire process. Your responses will not be shared with any third-parties and will only be used for the purpose of our master thesis.

Thank you for taking the time to have this interview with us.

GENERAL INFORMATION

Industry type: Spletna storitvena dejavnost zaposlitve

Company size (no. of employees): 6

Company's age: 10 let

Contact’s position and department in the company: specialistka za marketing

Date and time of the interview: 1. 10. 2020

QUESTIONS:

1. **Does the company gather consumer data**? (Consumer data is the information that includes all personal, behavioural and demographic data.)

Da, podjetje zbira podatke. Ime, priimek, e-mail. To so največkrat zbrani podatki, je pa vsekakor odvisno od primera do primera za kaj potrebujemo podatke. Poleg tega zbiramo tudi podatke o podjetjih s katerimi sodelujemo, kontaktne podatke teh oseb, maile.

2. **Which department in your company is responsible for gathering the consumer data**?

Za obdelavo podatkov in zbiranje teh podatkov sta v večini odgovora marketing in vodstvo.

3. **Which channels does the company use to gather the consumers’ data? Which ones are used more frequently than others?** (For example: Social media, website, e-commerce, etc.)

Uporabljajo se družbena omrežja, kot npr. Facebook, Linkedin, Instagram. Poleg tega se pa veliko stvari zbere tudi v Mailchimpu, ki ga uporabljamo za pošiljanje newslettrov. Podatke pa beležimo tudi v našem sistemu, kjer se osebe prijavijo v naše baze. Poleg naštetega pa znotraj CRM Sistema beležimo podatke o naših poslovnih partnerjih (ime, priimek, podjetje, telefonska številka, mail…)

4. **Which types of consumer data does the company gather**? (Demographic, social, behavioural, etc.)

Ime, priimek, mail, na družbenih omrežjih imamo tudi podatke o okvirni starosti, da lahko objavljamo targetirane objave. Poleg tega nas zanima tudi katero področje dela zanima posamezno osebo, da lahko targetiramo prosta delovna mesta. Za potrebe iskalnika pa beležimo tudi lokacijo, preko katere oseba dostopa do nas.

5. **Which tools does the company normally make use of in order to analyse the gathered data? Which ones are used more frequently than others?** (Google Analytics, CRM platform, etc.)

Dnevno uporabljamo google analytics, CRM platform (intrix), system, ki ga imamo razvitega za upravljanje z našo spletno stranjo. Poleg tega naša zunanja služba za marketing uporablja svoja orodja za pregled statistik, obiskov…

6. **Is the company marketing decision-making driven by consumer data? Which decisions are mainly driven by consumer data?**

Glede trženja se odločamo na podlagi tega, kaj želimo – povečati obisk, oglaševati našo blagovno znamko ali oglaševati nagradno igro. Običajno se odločamo na podlagi podatkov iz google analyticsa ter iz preteklih FB kampanj.

7. **Is the company using ad personalization as part of your marketing communication?**

Personalizirano pošiljamo dnevna obvestila ter občano newsletter. Delno se personalizira tudi oglase na družbenih omrežjih, vse ostalo je potem bolj splošno.

8. **Which personalization techniques does your company use in your marketing communication?**

Uporabljamo personalizacijo glede imena, glede na spol, starost, regijo.

9. **In your opinion, what are the benefits of personalized ads compared to non-personalized?**

Vsekakor je večji učinek, če se oglašuje personalizirano. Je pa res, da je to v našem poslu skoraj nemogoče, saj bi bilo to prevelik strošek in preveč oglasov.

10. **Has the company ever tested how different levels of personalization affect your customers?**

Testirali smo edino na newslettru, iz česar smo dobili zelo pozitivne odzive. Najverjetneje bomo s tovrstno personalizacijo tudi na daljevali, saj je večji odzivi strank ter večja odprtost samega sporočila.

Appendix 4: SPSS Outputs for Post Hoc Tests

Hypothesis 1:

Multiple Comparisons

Dependent Variable: Clickthrough
Tukey HSD

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
non-personalized	moderately personalized	-.45442*	.12350	<.001	-.7450	-.1639
	highly personalized	-.64185*	.12689	<.001	-.9403	-.3434
moderately personalized	non-personalized	.45442*	.12350	<.001	.1639	.7450
	highly personalized	-.18743	.12942	.317	-.4919	.1170
highly personalized	non-personalized	.64185*	.12689	<.001	.3434	.9403
	moderately personalized	.18743	.12942	.317	-.1170	.4919

*. The mean difference is significant at the 0.05 level.

Hypothesis 2a:

Multiple Comparisons

Dependent Variable: AdRelevance
Tukey HSD

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
non-personalized	moderately personalized	-.59048*	.19591	.008	-1.0513	-.1296
	highly personalized	-.43365	.20128	.080	-.9071	.0398
moderately personalized	non-personalized	.59048*	.19591	.008	.1296	1.0513
	highly personalized	.15683	.20529	.725	-.3261	.6398
highly personalized	non-personalized	.43365	.20128	.080	-.0398	.9071
	moderately personalized	-.15683	.20529	.725	-.6398	.3261

*. The mean difference is significant at the 0.05 level.

Hypothesis 2b:

Multiple Comparisons

Dependent Variable: Clickthrough
Tukey HSD

(I) AdRelevance1	(J) AdRelevance1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
irrelevant	neither relevant nor irrelevant	-.41328*	.15250	.019	-.7720	-.0545
	relevant	-.76549*	.10884	<.001	-1.0215	-.5095
neither relevant nor irrelevant	irrelevant	.41328*	.15250	.019	.0545	.7720
	relevant	-.35221	.15239	.055	-.7107	.0063
relevant	irrelevant	.76549*	.10884	<.001	.5095	1.0215
	neither relevant nor irrelevant	.35221	.15239	.055	-.0063	.7107

*. The mean difference is significant at the 0.05 level.

Hypothesis 3a:

Multiple Comparisons

Dependent Variable: AdIntrusiveness
Tukey HSD

(I) State	(J) State	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
non-personalized	moderately personalized	-.48556*	.19808	.039	-.9515	-.0196
	highly personalized	-.71774*	.20351	.001	-1.1965	-.2390
moderately personalized	non-personalized	.48556*	.19808	.039	.0196	.9515
	highly personalized	-.23218	.20757	.503	-.7205	.2561
highly personalized	non-personalized	.71774*	.20351	.001	.2390	1.1965
	moderately personalized	.23218	.20757	.503	-.2561	.7205

*. The mean difference is significant at the 0.05 level.

Hypothesis 3b:

Multiple Comparisons

Dependent Variable: Clickthrough
Tukey HSD

(I) Adintrusivness1	(J) Adintrusivness1	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
not intrusive	neither intrusive nor unintrusive	.16704	.17877	.619	-.2535	.5876
	intrusive	.08077	.13176	.813	-.2292	.3907
neither intrusive nor unintrusive	not intrusive	-.16704	.17877	.619	-.5876	.2535
	intrusive	-.08627	.15356	.840	-.4475	.2750
intrusive	not intrusive	-.08077	.13176	.813	-.3907	.2292
	neither intrusive nor unintrusive	.08627	.15356	.840	-.2750	.4475

Hypothesis 4:

Multiple Comparisons

Dependent Variable: NonpersonalizedIntrusivness
Tukey HSD

(I) NonpersonalizedControl	(J) NonpersonalizedControl	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
not in control	neither in control nor not in control	.37318	.37510	.581	-.5151	1.2615
	in control	-.13175	.38013	.936	-1.0320	.7685
neither in control nor not in control	not in control	-.37318	.37510	.581	-1.2615	.5151
	in control	-.50493	.46542	.525	-1.6071	.5973
in control	not in control	.13175	.38013	.936	-.7685	1.0320
	neither in control nor not in control	.50493	.46542	.525	-.5973	1.6071

Multiple Comparisons

Dependent Variable: Intrusiveness
Tukey HSD

(I) Control	(J) Control	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
not in control	neither in control nor not in control	.02242	.29285	.997	-.6680	.7128
	in control	.07647	.25971	.953	-.5358	.6887
neither in control nor not in control	not in control	-.02242	.29285	.997	-.7128	.6680
	in control	.05405	.35007	.987	-.7712	.8794
in control	not in control	-.07647	.25971	.953	-.6887	.5358
	neither in control nor not in control	-.05405	.35007	.987	-.8794	.7712

Hypothesis 5:

Multiple Comparisons

Dependent Variable: AdIntrusiveness
Tukey HSD

(I) Trust	(J) Trust	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
untrustworthy	neither trustworthy nor untrustworthy	.12931	.29292	.898	-.5598	.8184
	trustworthy	1.02033*	.27157	<.001	.3815	1.6592
neither trustworthy nor untrustworthy	untrustworthy	-.12931	.29292	.898	-.8184	.5598
	trustworthy	.89101*	.18320	<.001	.4600	1.3220
trustworthy	untrustworthy	-1.02033*	.27157	<.001	-1.6592	-.3815
	neither trustworthy nor untrustworthy	-.89101*	.18320	<.001	-1.3220	-.4600

*. The mean difference is significant at the 0.05 level.

Multiple Comparisons

Dependent Variable: Clickthrough
Tukey HSD

(I) Trust	(J) Trust	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
untrustworthy	neither trustworthy nor untrustworthy	-.06609	.18968	.935	-.5123	.3801
	trustworthy	-.44715*	.17585	.030	-.8608	-.0335
neither trustworthy nor untrustworthy	untrustworthy	.06609	.18968	.935	-.3801	.5123
	trustworthy	-.38106*	.11863	.004	-.6601	-.1020
trustworthy	untrustworthy	.44715*	.17585	.030	.0335	.8608
	neither trustworthy nor untrustworthy	.38106*	.11863	.004	.1020	.6601

*. The mean difference is significant at the 0.05 level.