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# Handelshøyskolen BI

## GRA 19703 Master Thesis

### Thesis Master of Science 100% - W

#### Predefinert informasjon

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#### Deltaker

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#### Informasjon fra deltaker

| | |
|---|---|
| **Tittel *:** | An examination of attribution of responsibility: Platform versus advertiser data collection practices and online behavioral advertising on social media |
| **Navn på veileder *:** | Matilda Dorotic |

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|---|---|---|---|
| **Inneholder besvarelsen konfidensielt materiale?:** | Nei | **Kan besvarelsen offentliggjøres?:** | Ja |

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**An examination of attribution of responsibility: Platform versus advertiser data collection practices and online behavioral advertising on social media**

Supervisor:

**Matilda Dorotic**

Study program:

**Strategic Marketing Management**

# Summary

The purpose of this thesis is to understand how different data collection practices and usage of personal data in advertising affects consumers' experiences when using social media platforms. More specifically, the thesis sheds light on who is seen as responsible for a user's data when that data is used in highly personalized advertisement.

We present relevant literature focusing on the firm and consumers perspectives through the lens of Online Behavioral Advertising. These perspectives highlight the importance of privacy concern, intrusiveness and responsibility attribution according to our research questions. Additionally, we go through the literature on covert vs. overt data collection and intention to purchase (ITP).

Our research method was an experiment through a survey where groups were randomized into either covert/overt and either high personalized ad/low personalized ad display. We then proceeded to ask questions about how intrusive they found the ad, their privacy concern, their ITP and how they would distribute responsibility of data collection (cookies).

None of our hypotheses were fully supported, however, we did find significant differences between groups. Intrusiveness was highest amongst people being exposed to highly personalized ads, people who held the SoMe platform more responsible had a significant linear regression with privacy concern.

Through our research, we found the social media platform was assigned more responsibility by consumers for the use of cookies. Self-regulation of social media platforms and advertisers does not seem like a viable option to ensure consumers privacy and trust at this point in time, as most consumers lack education about online advertising and data collection. Instead, regulation from the government is needed to keep consumers from being exploited for their personal data.

# Acknowledgements

This thesis concludes two incredibly testing and educational years during our MSc program at BI Norwegian Business School. Due to Covid-19 our learning experience had to drastically change to accommodate restrictions. Even so, the course of these studies have been highly engaging and we feel well prepared for the future.

We have found this thesis to be both very rewarding and challenging, as we had to immerse ourselves in new educational territory. The guidance our supervisor Matilda Dorotic provided us, made this seemingly impossible task possible for us. Matilda's constructive feedback and patience inspired us and ensured we were motivated to keep going.

We would also like to thank all the people who took the time out of their day to respond to our survey, as well as our pre-testers for helping us construct and improve the survey. Without these people, we would not be able to write this thesis.

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# 1.0 Introduction

## 1.1 The purpose of this thesis

This master thesis seeks to understand how different data collection practices and usage of personal data in advertising affects consumers' experiences when using social media platforms. More specifically, the thesis sheds light on who is seen as responsible for a user's data when that data is used in highly personalized advertisement.

## 1.2 Background

The practice of personalization has taken on a new life on the internet, where recent advancements in data collection technology increases the capabilities of personalization to new heights (Libai et al., 2020). This has lead to a massive increase in the use of Online Behavioral Advertising (hereby OBA), which use the information created by a consumer's behavior online (cookies) in order to target that consumer with more personalized advertisements (Boerman, Kruikemeier & Zuiderveen Borgesius, 2017).

Social media (hereby SoMe) is also ubiquitously integrated in our lives. From 2020 to 2025, the number of people worldwide who use social media is expected to grow from 3.6 billion to 4.4 billion (Beveridge, 2022). SoMe are an expected part of our online personas. Social media platforms are designed to get people to engage and to willingly share parts of themselves and their lives. This makes these platforms an ideal place to use OBA, which many advertiser brands already do, evidenced by the fact that there were 10 million monthly active advertisers on Facebook in the third quarter of 2020 (Statista, 2022). These advertisers are able to use the data that the social media platform collects using cookies, for their own personalized advertisements. Ad spending on social media is projected to reach over $173 billion in 2022 (Beveridge, 2022).

OBA is made possible through the use of "cookies." Cookies are small text files that are put on users' devices  to facilitate the functionality of a website (first-party, session or functional cookies) or to collect profile information for targeted advertising (third-party or tracking cookies) (Smit, et al., 2014). Websites that use cookies are required by law to disclose this with a privacy notice for the consumer.

Research has revealed that 70% of consumers are aware of OBA, but have a poor understanding of what exactly a third party cookie is and how OBA works (Ham, 2017). Even among consumers who claimed to have previous knowledge of cookies, only 15.5% could actually demonstrate basic knowledge and only 11% correctly understood them after receiving instruction (Ham, 2017).

The use of cookies has been a heavily debated subject since they were introduced, because they rely on collecting, storing and using personal data. Despite this, cookies are used by 40,7% of all websites (World Wide Web Technology Surveys, 2022) use them. Many software companies have announced that they will be phasing out third-party cookies, with the biggest company being Google (BBC News, 2021). The reason stated for this change is both to increase user privacy, but also to introduce other data systems, usually produced by the company themselves.

The tech giant Google has vowed to get rid of third-party cookies on their Chrome browser by 2022 (Roth, 2022). Google plan to replace the third-party tracking systems with their own, called FLoC (or Federated Learning of Cohorts) (Roth, 2022). This system created cohorts out of users based on how they were browsing on the internet. FLoC was criticized for posing additional privacy risks (Electric Frontier Foundation, 2021) by making it very easy for advertisers to gain specific information about the users, potentially resulting in discriminatory targeted ads (Roth, 2022). Following the backlash against FLoC, Google has replaced it with a different interest-based system, “Topics”. “Topics” works by assigning a user five interests based off of your web activity over the last week. These interests are stored only for three weeks on entirely internal servers not tied to anyone but the user themselves, not even Google (Roth, 2022).

In October 2019, Europe’s highest court decided that users in the EU must actively consent to all analytics cookies when they log on to a website. This means that any website that tracks users before or without consent is breaking the General Data Protection Regulation (GDPR, 2016).

The technology behind OBA is rooted in artificial intelligence (AI), which requires access to real-time data in order to make inferences. What data is being collected and analyzed has resulted in many controversies in recent years. Facebook and Cambridge Analytica had a scandal in 2018 where data was used to form political profiles of users that could be persuaded, and further introduced propaganda slowly, then more aggressively as the users interacted more with the content. IBM photo-scraping controversy in 2019, where millions of users' faces were used to train AI facial recognition technology without the users' permission (Analyticsinsight.net, 2021). This technology could be used to create surveillance systems, which many people feel could violate their privacy. These examples show the importance of privacy concerns which is key for our thesis. Facebook got taken to court over their data usage, and a lot of people were invested in the case. This showcases how consumers are invested in seeing firms take responsibility for what data they choose to collect and how they use that data.

### 1.3 The aim of the research

Research questions:
*Where do consumers feel the responsibility of data protection lies between platforms and advertisers?*
*Does receiving a privacy notice about cookie collection affect this?*
*What are the effects of feelings of intrusiveness and privacy concerns on responsibility attribution and ITP?*
*How is ITP towards the advertiser's product affected by data collection practices and privacy concerns?*

SoMe advertising is only expected to grow in usage, and it is important to gain understanding about how the advertisers are affected by the platform they choose to advertise on. At the same time, we want to shed light on how the advertisers personal data usage in ads can affect the SoMe platform which provides them with this data. We want to see if the consumer's reaction to data collection and data usage is negative enough to reflect poorly on the firm's profitability. In which case the market could regulate itself to follow consumer demand rather than require governments to intervene and protect consumers. In other words, we want to see if there is a need for more regulation in data collection and data use practices from the consumer's perspective.

In this thesis we will first present the literature on online behavioral advertising, then different aspects of how this advertising affects firms and consumers. Furthermore present our hypotheses and conceptual model for our research, followed by the research process and. Finally, we will present our results, as well as discuss our findings and implications.

# 2.0 Literature review

### 2.1 Online Behavioral Advertising

Online Behavioral Advertising (OBA) is a tool that uses “cookies” that save consumers' online activities to match their behavior with needs (in terms of products). This creates a specialized marketing opportunity where a company can be more cost-effective and target their customers directly (Boerman et al., 2017). In turn the consumers receive offers of products that are more tailored towards their needs and wants. There are both benefits and challenges for firms when using OBA, as well as benefits and concerns for consumers.

### 2.2 The benefits of OBA for firms

Firms use OBA for a variety of reasons. By leveraging individual customer information, they can offer consumers curated products and services (Kumar et al., 2019; Libai et al., 2020). These types of personalized advertisements are often perceived as being more relevant by the consumer than non-personalized advertisements. This is thought to lead to a more positive evaluation of the ad, and consequently to higher purchase intentions (Goldfarb and Tucker, 2009; Van Doorn and Hoeksta, 2013). Additionally, the increased amount of consumer information that the data collection practices of OBA provide can be used to gain higher customer retention and make it easier to predict lifetime value (Kumar, et al., 2019; Libai et al., 2020).

### *2.2.1 Benefits for firms using OBA on SoMe platforms*

The social networks of social media platforms can be incorporated in OBAs for further personalization and fit of the ads. Gai and Klesse (2019) found through multiple experiments that when trying to increase the click-through rate of online articles, recommending articles using the user-based framing rather than item-based increased the click-through rate when those users were perceived as similar. In other words, social tendencies that affect us in the offline world, can affect us online as well.

Another example that further highlights the importance of social dynamics on social media platforms, is how social labels are still present and influential on social media. Behaviorally targeted ads can function as a social label even when it contains no explicit labeling information, as long as the label is perceived as plausible (Summers, Smith & Reczek, 2016). Consumers make adjustments to their self-perceptions to match the implied label, and these self-perceptions then impact behavior like including purchase intentions for the advertised product (Summers et al., 2016).

### *2.2.3 Gap in research in the use of OBA and effect on consumers*

The theoretical background of OBA research is highly fragmented (Boerman, et al., 2017). Many studies look at OBA in terms of acceptance or rejection of the advertising message. At the same time, while some research on targeted ads on SoMe platforms exists, a lot of it focuses on Facebook (Aguirre et al., 2015). We found no studies that look at social media platforms and advertisers at the same time.

## 2.3 Challenge for firms: responsibility

OBA only works if the firm is able to collect and use information about the consumers they plan to advertise to. A common strategy for firms using OBA is to collect as much information as possible, in the case that it can be used at a later point. Data can be intentionally provided by consumers, however, they may have different degrees of understanding of the process in which they are participating.

When there is a lack of certainty in the information exchange, the other party is relegated to faith that the exchange will cause no harm now or in the future (Walker, 2016). In other words, the consumer does not know how this information will be used and by whom. This would indicate that the responsibility of that data and how it is used lies with the firms that use consumers data to provide services.

If multiple actors are present, the one arousing the most negative affect or whose behavior confirms unfavorable expectations tend to receive the most responsibility (Alicke, 2000). However, the process of responsibility attribution is fallible and prone to cognitive biases (Shaver, 1985).

#### *2.3.1 Research gap*

We have found no articles researching responsibility attribution regarding either SoMe platforms of SoMe advertisers regarding data collection and data use.

### 2.4 Challenge for firms: intrusiveness

We define intrusiveness based on various studies (Boerman et al., 2017; van Doorn & Hoekstra, 2013; Goldfarb & Tucker, 2011). An ad will be considered intrusive if it includes inferred information not explicitly given by the consumer, or information that a consumer considered "sensitive", such as economic information or information relating to marital status. This definition of intrusive ads is not to be confused with invasive ads, such as pop-ups, even though this term is often used to describe these as well.

The perceived intrusiveness of an advertisement is shown to have an effect on advertisement effectiveness, in that an intrusive ad will be more negatively evaluated by the consumer (Goldfarb & Tucker, 2011; van Doorn & Hoesktra, 2013). This negative evaluation will in turn lead to decreased intention to purchase and affective behavior.

Situations involving novel technologies often lead to ambiguous situations, meaning situations that are hard to judge and in which people do not really know how to behave (Langer & König, 2018). In these situations, people might have queasy feelings that are hard to describe or express (Langer & König, 2018). For lack of a better description, people tend to refer to ambiguous situations, or ones they have difficulty judging, or that evoke uneasy feelings as "creepy" (Langer & König, 2018).

### *2.4.1 Research gap*

Van Doorn and Hoekstra (2013) examines the trade off between intrusiveness of personal data used and tailoring the ad to the customer's needs. However, there are still many aspects of this trade off we do not know.

We wish to highlight the difference between a highly intrusive ad and a less intrusive ad in terms of how they affect consumers' ITP and responsibility attribution towards the advertiser/platform. The aspect of intrusive ads that we want to use is an ad using personal data provided by the consumer to the SoMe platform.

## 2.5 Benefit for the consumer: Increased personalization

A recent survey of Millenials found that 72% of them wanted to see more ads personalized to their interests and activities (Westcott et al., 2021, referenced in Grigorios et al., 2022). When the consumer feels an ad fits them well, these ads are evaluated more positively and can lead to higher purchase intentions from the consumer. Achieving high fit ads is a lot easier using OBA strategies, as real time personalization can help create a lot of well-fitted advertisements for all kinds of different consumers (Kumar et al., 2019; Libai et al., 2020).

Personalization and intrusiveness are closely linked, as including more personal data can lead to the consumer perceiving the ad fits them better, but at the same time the ad can be perceived more intrusive.

## 2.6 Consumer concern: Privacy

The cost of personalization comes in the form of data exchange, which many consumers express concerns about (Grewal et al., 2021). Even if most consumers state that they want to see more personalized advertisements, only 40% stated that they would provide more information in order to receive targeted advertising. (Westcott et al., 2021, referenced in Grigorios et al., 2022).

The aspects of the data capture process might lead to feelings of threat against consumers' personal control and them feeling exploited (Puntoni et al., 2021). Data collection is becoming harder to avoid. In addition, consumers may not realize how data is aggregated and there is a lack of regulation, transparency, and accountability, which could make consumers feel exploited (Puntoni et al., 2021).

One of the main current threats of OBA, is the consumer perception that clicking personalized online ads involves risks regarding their personal information (Ozcelik & Karnali 2019). When online shopping became commercialized, there was credit card fraud, delivery problems and unexpected shipping costs associated with purchases online. Today, these perceived risks shifted towards privacy violations and identity theft (Ozcelik & Karnali 2019).

Consumers' stated behavioral intentions online and how they actually act are quite different (Kokolakis, 2017). A concept often referred to as the Privacy Paradox refers to this dichotomy between a person's intentions to protect their online privacy and how they actually behave in the online space. We tend to give away a lot more information than the stated intention (Kokolakis, 2017). New technology is also much more advanced and capable of discerning information from context clues or similar ways.

Traces of a consumer's presence and actions are left behind in almost any aspect of the internet (Kunaivski, 2010). These "information shadows" can be used in ways we have no way of foreseeing and could unwittingly allow for others to find out information you did not intentionally share (Kunaivski, 2010). For example, a study by Oh et al. (2016) on facial recognition algorithms found that blurring or hiding a person's face is not enough to hide their identity. Today's systems are so advanced that they can use the context of the picture to identify the person in it.

### *2.6.1 Research gap*

Privacy concern seems like a crucial aspect of responsibility distribution when discussing data protection. Because a person with high privacy concerns would perceive, in theory, a website that shows highly personalized ads as more intrusive. We would like to examine how this person would distribute responsibility towards the website collecting the information and/or the advertiser purchasing the information.

### 2.7 Tensions of OBA between consumers and firms

OBA strategies are often centered around collecting as much information as possible, as this allows for more customization and personalization. However, there is an imbalance in this information exchange between firms and consumers (Walker, 2016). It is possible to learn valuable information by "eavesdropping" in this way, however, this may come at the cost of the rapport between the two parties involved (Puccicinelli & Tickle-Degnen, 2004). Consumers may start to feel uncomfortable and "watched", which as previously stated mitigates the benefits of using OBA (Goldfarb & Tucker, 2009).

Given the vast variety of uses for technology like OBA, ethics should be considered when deploying it (Hermann, 2021). Currently, firms are mostly focused on the short-term implications of online data collection. Surrendering information to technology is a long-term ethical problem for individuals and society as a whole.

### 2.8 Covert and overt data collection

One way of giving consumers more power in the data exchange between consumer and firm, is to inform them about the data collection practices, and allow them to choose whether they want to participate or not (Oh et al., 2016).

Informing consumers that data collection has taken place leads to them finding personalized ads more useful, improving their behavioral intentions (Tam & Ho, 2006). Not informing customers leads to the opposite effect.

The terms used for whether a consumer receives a data collection notice or not, are overt and covert data collection. *Overt* data collection refers to data collection where consumers are explicitly made aware that their data is being collected. Contrastingly, engaging in *covert* data collection means collecting consumer data without their knowledge (Grigorios et al., 2022).

A brands' transparency around data collection and consumers' control over the collection process, decreases the consumer's perceived vulnerability and increases firm performance (Martin, Borah & Palmetier, 2017). Overt data collection also reduces the negative effect of data breach (Martin, et al., 2017). However, the consumer needs to feel in control over the data collection process for these effects to take place (Martin, et al., 2017). A study by Grigorios et al., (2022) supports the positive effect of overt data collection, as consumers were more favorable towards an advertiser's products after receiving the personalized advert based on overt information collection.

Low transparency (covert data collection) and low control leads to a more negative effect on firm performance following a data breach (Martin et al., 2017). The reason why firms choose covert data collection, can be explained by the privacy paradox. Compared to overt data collection, covert data collection increases perceived ad intrusiveness, which elicit privacy concerns and negative cognitive responses in consumers (Grigorios et al., 2022).

Contrary to some of the other studies on the positive effects of overt data collection, Brough et al. (2022) that overt data collection could lead to more negative responses than covert. Due to "the bulletproof glass effect", people might feel more vulnerable when encountered with bulletproof glass despite the protection it provides. This makes people feel less secure and less inclined to purchase from websites with overt data collection (cookie collection notices). The notices may decrease trust (Brough et al., 2022), and in turn, we believe it can increase responsibility assigned to the platform issuing the notice.

### *2.8.1 Gap in overt and covert data collection research*

There is research both on the positive effects of overt data collection and the negative. There seems to be a lot of factors at play for consumers in determining whether the explicit announcement of data collection leads to positive outcomes for the advertiser or not. We have found no studies of overt and covert data collection where both a social media platform and an advertiser are present. We want to know whether overt data collection will lead to the advertiser getting less responsibility than the platform in a case where the consumer sees an intrusive advertisement containing a lot of personal data. According to the “bulletproof glass” theory, the platform will get more responsibility because people will feel vulnerable and less trusting towards the agent collecting the data (Brough, et al, 2022). Contrary, other studies suggest the overt data collection can lead to improved behavioral intentions and intention to purchase (Tam and Ho, 2006; Grigiorios et al, 2022). We would like to find out which effect seems to be true in our setting. We propose a scenario where a social media platform collects data, but a third party advertiser actually uses it for an intrusive ad. Who gets assigned the responsibility for the use of the data in this case?

## 2.9 Intention to purchase

A highly customized ad can be a double edge sword since it promotes a higher intention to purchase (ITP), but at the same time increases perceived intrusiveness levels which in itself reduces ITP (Van Doorn & Hoekstra, 2013). In other words, personalization and customization can lead to increased ad effectiveness, or it can lead to the target consumer feeling uncomfortable, which mitigates the beneficial effects (Goldfarb & Tucker, 2009; Boerman, et al., 2017).

ITP can be negatively affected by including privacy notices (Brough et al., 2022), also caused by a decrease in trust. However, an *absence* of privacy notice can also lead to a decline in purchase interest (Brough et al., 2022).

### *2.9.1 Gap related to ITP*

An area that needs more exploring is the effect privacy notices have on consumer behavior (Brough et al., 2022). As privacy notices become the new norm, the negative effect on ITP may change and an absence of a privacy notice could have a greater effect on ITP.

# 3.0 Hypotheses and conceptual model

The purpose of our thesis seeks to understand how different data collection practices and usage of personal data in advertising affects consumers' experiences when using social media platforms, specifically who is seen as responsible for a user's data when that data is used in highly personalized advertisement.

### 3.1 Hypotheses

For our first hypothesis we are clarifying if the "bulletproof glass" effect is consistent and that the responsibility will be put on the platform rather than the advertiser when using overt data collection.

*H1:* The advertiser will be assigned less responsibility than the platform for the use of personal data when overt data collection takes place, even if the consumer sees a high personalized from the advertiser

Some studies find covert data collection practices can lead to negative emotions, higher privacy and higher perceived intrusiveness (Martin et al., 2017; Grigorios et al., 2022). We believe it could also affect ITP through privacy concerns as a moderator.

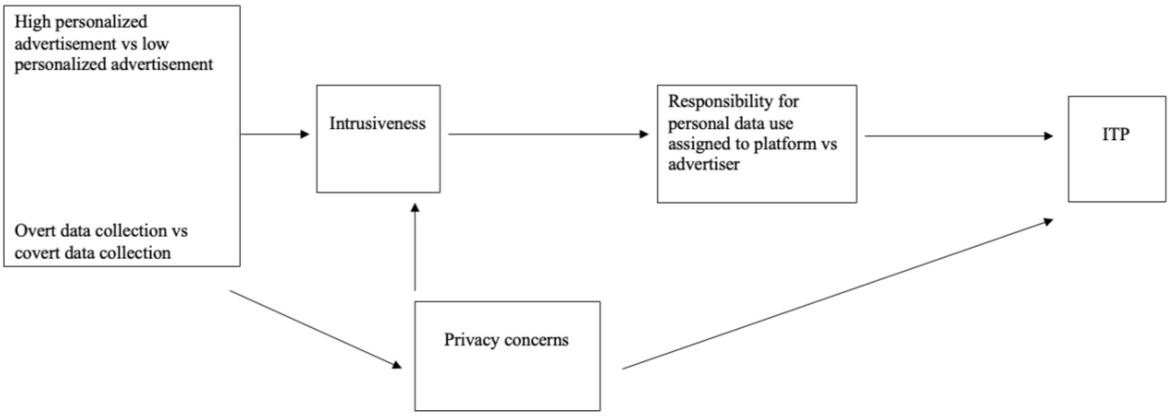
*H2:* Covert data collection by the platform leads to higher privacy concerns and lower ITP towards the advertiser's product.

Our final hypothesis examines the connection between high personalized advertisements, privacy concerns, intrusiveness and responsibility towards advertiser. By "high personalized" we are referring to an ad that contains a lot of personal information, and is expected to be perceived as intrusive. We distinguish between "intrusiveness" and "high/low personalized ad" because they are related concepts, but not entirely equivalent.

We believe the advertiser will receive more negative effects if the consumer sees a highly personalized ad from them. This is supported by Alicke (2000) stating that if multiple actors are present, the one arousing the most negative affect or whose behavior confirms unfavorable expectations tend to receive the most responsibility.

*H3:* High personalized advertisement leads to higher privacy concerns, intrusiveness, and responsibility towards advertiser

## 3.2 Conceptual model



# 4.0 Research process

## 4.1 Methodology

In order to compare the different groups with statistical analysis, a quantitative approach is most appropriate (Malholtra, 2020). We chose a 2x2 fractional factorial experimental design (Malholtra, 2020) with IVs overt/covert (see figure 1 and 2) and High personalized ad/low personalized ad (see figure 3 and 4). This will allow us to test both IVs' effect on the DV (responsibility attribution) separately, as well as possible interaction effects between the IVs.

The chosen method for our experiment is a survey. The survey is characterized as a structured questionnaire which is given to a sample of a population and designed to gather specific information from these respondents (Malholtra, 2020). We use a structured-direct survey for our data collection with fixed-alternative questions (Malholtra, 2020). Questions related to attitudes were measured using a 5-point likert scale with values from “strongly disagree” to “strongly agree”.

## 4.2 Measures and scales used

The attitudes of the respondents were measured using a Likert scale including values from 1-5, where 1 equals “strongly disagree”, 3 equals “neutral” and 5 equals “strongly agree”.
We used Cronbach’s alpha to check for our chosen scales’ reliability. Cronbach’s alpha should be over 0,6 because this experiment deals with experimental data where the respondent groups have been shown different things. The reliability should not be too close to 1 in order to keep the indicators from being too similar and therefore not capturing the entire concept one is trying to capture (Gipsrud, Olsson & Silkoset, 2016).

Some of our questions were reversed in our survey (noted by “R” in table) to prevent boredom and habit clicking. These were re-reversed to use in our analysis. Table 1 summarizes our measurements and reliability measured through Cronbach’s alpha. Table 2 shows our scales.

| Measurement (hypothesis) | Items | Measure | Cronbach's alpha |
|---|---|---|---|
| Responsibility | Q26 | Nominal: Forced choice | . |
| Responsibility of platform | Q25_4 | 1-5 Likert scale | . |
| Responsibility of advertiser | Q25_5 | 1-5 Likert scale | . |
| Intrusiveness | Q13_1, Q13_2, Q13_3, Q13_4, Q15_1, Q15_2, Q_15_3 | 1-5 Likert scale | .885 |
| Privacy concern | Q16_2, Q16_3 (R), Q16_4, Q_16_5, Q16_6 (R). Q16_1 (R) was removed due to low correlation to the rest. | 1-5 Likert scale | .729 |
| ITP | Q15_4, Q15_5 | 1-5 likert scale | .911 |

(Table 1: Summary of measurements and reliability)

| Question | Items | Measurement | Scale referenced |
|---|---|---|---|
| Q13- Answer the following questions on your opinion about the ad from "Kuletskjorter.no".<br><br>Q15 - Answer the following questions on | Q13_1 - The ad gave me a nasty feeling<br>Q13_2 - The ad was threatening<br>Q13_3 - The advertiser "Kuletskjorter.no" knows too much about me | Creepiness<br><br>Intrusiveness | Langer and König (2018)<br><br>van Doorn and Hoekstra (2013) |

| | | | |
|---|---|---|---|
| your opinion about the ad from “Kuletskjorter.no”. | Q13_4 - The ad made me feel unsafe<br><br>Q15_1 - This ad is disturbing<br>Q15_2 - This ad is irritating<br>Q15_3 - This ad is annoying | | |
| Q15 - Answer the following questions on your opinion about the ad from “Kuletskjorter.no”. | Q15_4 - The likelihood of purchasing this product is large<br>Q15_5 - The probability that I would consider buying the product is large | ITP | van Doorn and Hoekstra (2013) |
| Q16 - These questions are regarding personal data on the internet. | Q16_1 - I have control of my own personal data<br>Q16_2 - I am worried that my personal data will be shared with various companies online<br>Q16_3 - Websites I visit use and keep my personal data in a safe way<br>Q16_4 - Platforms monitor my online communication<br>Q16_5 - Various companies monitor my my online communication<br>Q16_6 - I am *not* worried about my personal data when I visit platforms on the internet. | Privacy concern | Masur (2018) |
| Q25 - Answer these questions related to cookies and personal data on the internet. | Q25_1 - The use of cookies is “Kuletskjorter.no’s” responsibility<br>Q25_2 - The use of cookies is “Frogbook’s” responsibility<br>Q25_3 - The use of cookies is “Kim” responsibility<br>Q25_4 - If personal data is lost, “Frogbook” should be punished<br>Q25_5 - If personal data is lost, “Kuletskjorter.no” should be punished | Responsibility | Inspiration from Fazio, Kroner and Forth (1997). |

| | | | |
|---|---|---|---|
| | Q25_6 - It is “Kim’s” responsibility to protect their own data | | |
| Q26 - Who do you view as most responsible for your personal data online? | A1: The user “Kim”, or yourself<br>A2: Social media platforms, such as “Frogbook”<br>A3: The advertiser on the platform, such as “Kuletskjorter.no” | Responsibility | Inspiration from Fazio, Kroner and Forth (1997). |

(Table 2: Scales used for our survey)

## 4.3 The Survey

### *4.3.1 Software and construction*

To create and distribute our survey, we used Qualtrics XM. The program allows for different types of media, making it possible for us to represent the scenario with a combination of text and graphics. The survey language was Norwegian, in order to maximize the amount of people we could reach to respond.

The survey is presented as a look into the user experience on a new social media platform “Frogbook”, in order to not reveal too much about the experiment. Some general questions about “Frogbook” were included to not make it obvious what we were testing for. some questions were reversed.

We used scenarios in order to present the respondents with a situation close to the real life experiences one may have using the internet and social media. An approximation of a social media website was created and presented using graphics. A combination of text and graphics were used to present the IV’s covert/overt and high/low personalization (Figure 1, 2, 3 and 4).

He, Kim and Gustafsson (2021) propose that a transgressing brand’s marketplace power and the customer-brand relationship power can affect consumers’ attitude towards the brand. In order for these factors to not affect the relationships we want to measure, we created fictional brands (platform and advertiser) in the experiment.

### *4.3.2 Sampling and distribution*

Our target population for the survey was adults in Norway who use or have previously used social media. We believe this group to be more familiar with the concepts we are researching, like OBA, covert/overt data collection and personalized ads.

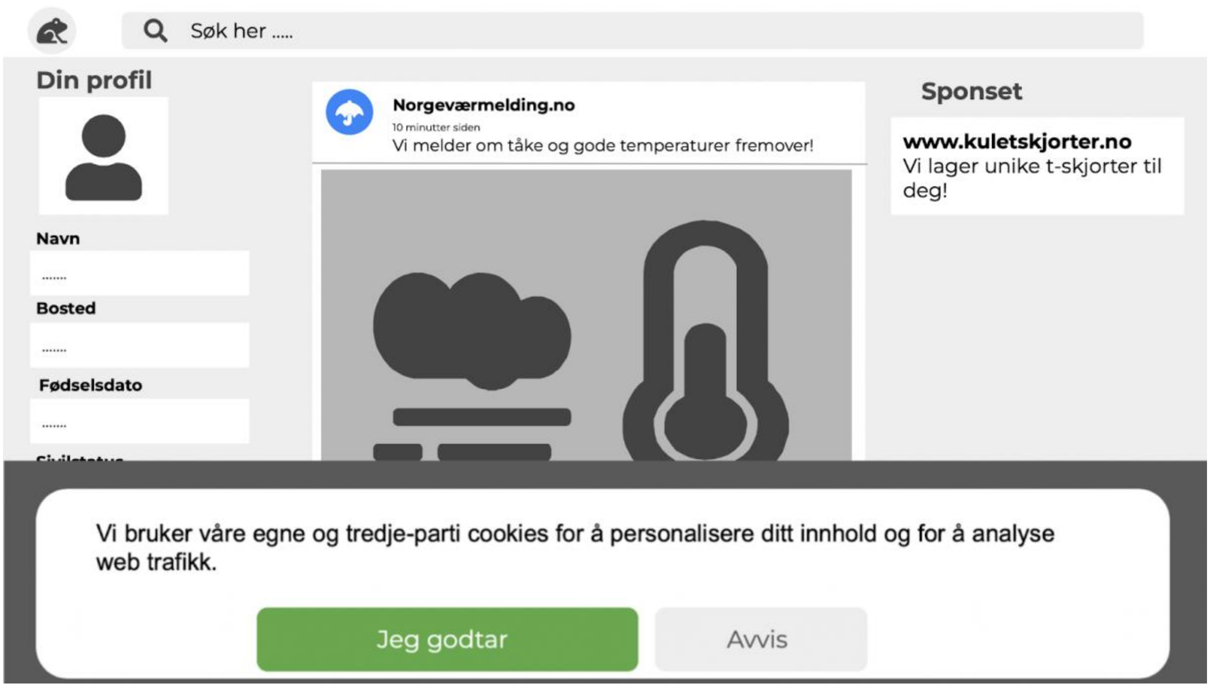
The survey was distributed using convenience sampling based on the people we had access to. This is a non probability technique, meaning we can not objectively evaluate the precision of the results of this survey, only say something about our particular sample (Malholtra, 2020). Convenience sampling was our chosen method due to the low cost and high yield this method has. However, this method comes with some potential sampling errors, such as self-selection (Malholtra, 2020).

### *4.3.3 Pilot study*

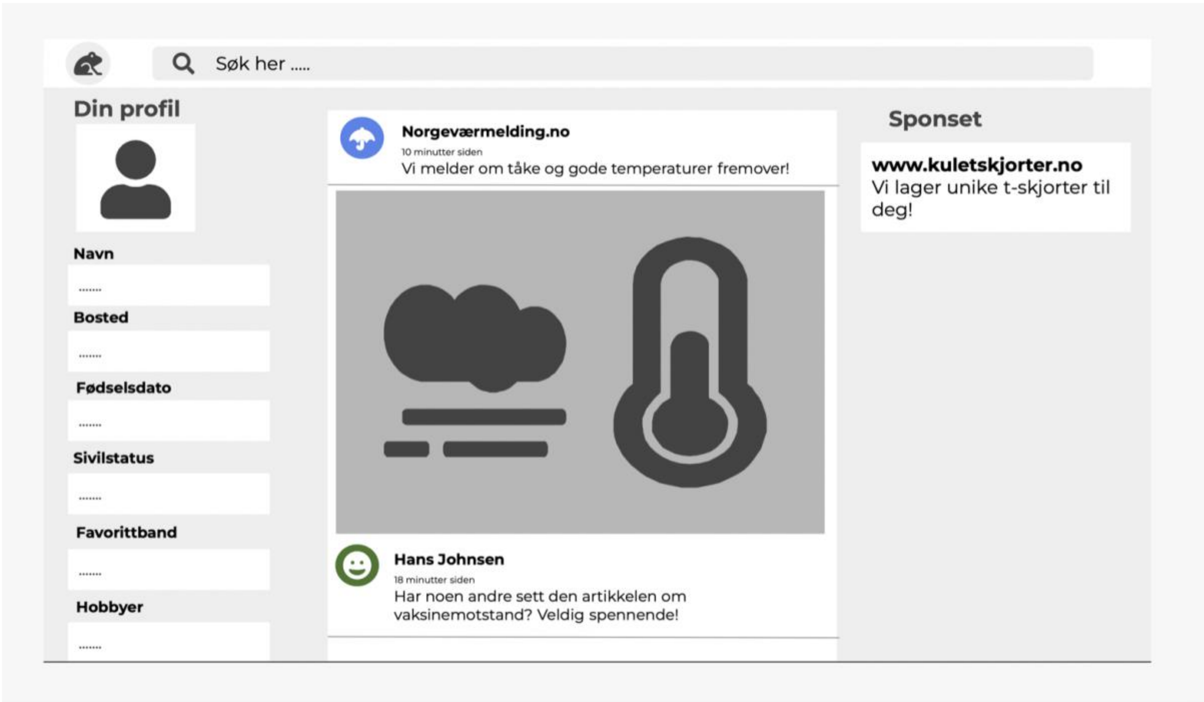
Following the completion of the survey questions, we ran a pilot study with a small number (6) of respondents. We asked them to take notes of anything they thought about during the survey process, and used their feedback to improve clarity of some of the question's wording afterwards.

### *4.3.4 Procedure*

The respondents were first told that they were to evaluate a new social media platform, called "Frogbook". They were told through text to imagine themselves as "Kim Hansen", a person joining this new platform after being recommended by friends. At this point, the first randomization took place, and the respondents were either shown an overt data collection screen in the form of a pop-up cookie collection notice (fig. 1), or the covert scenario which is just just the platform landing page (fig. 2).

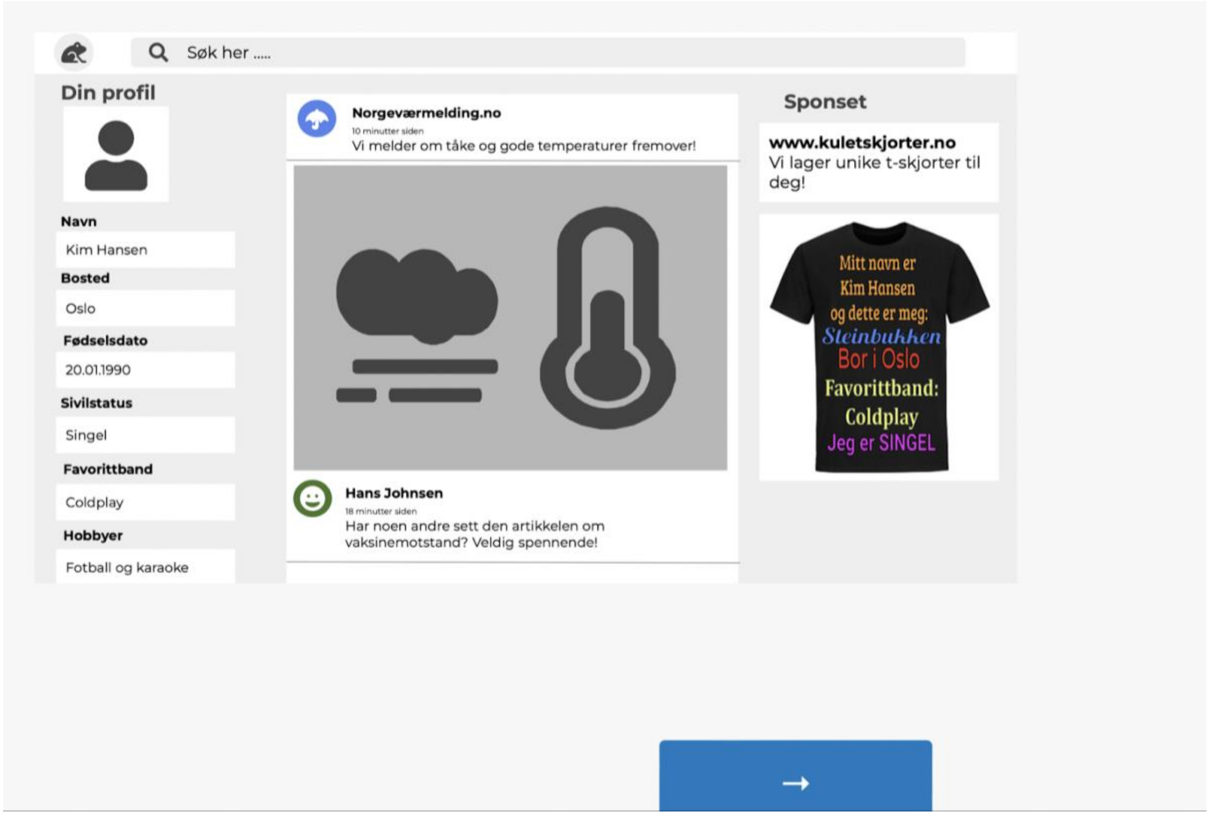



(Figure 1: Overt data collection screen)

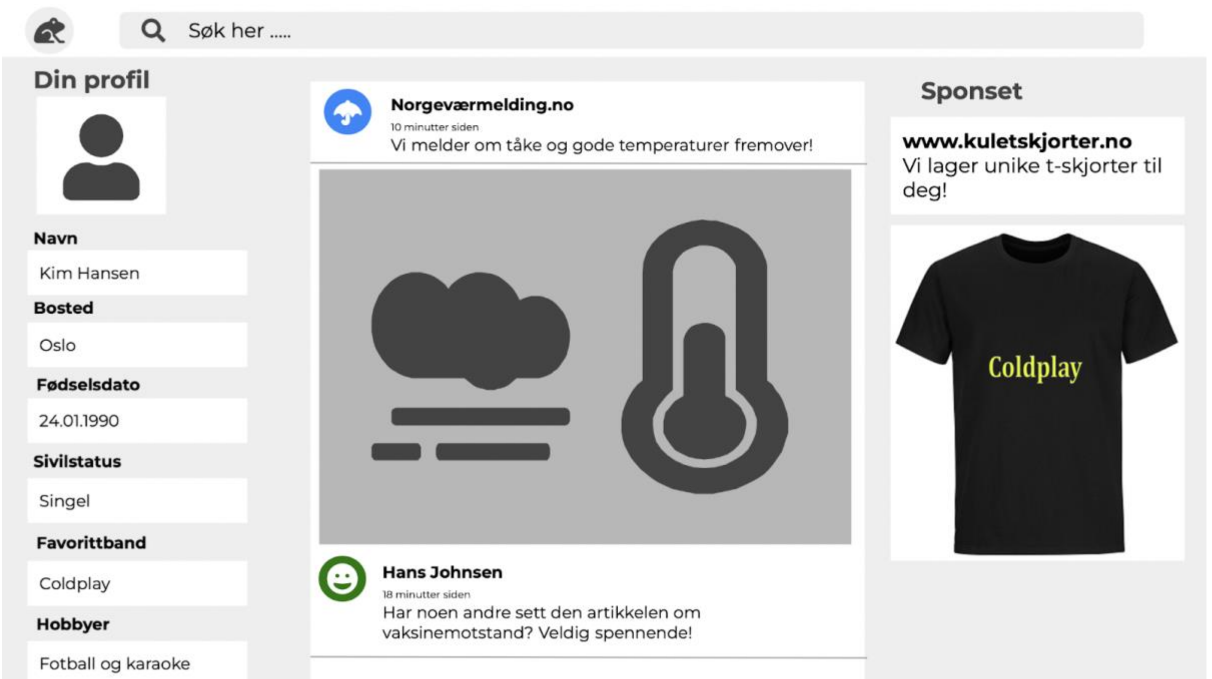



(Figure 2: Covert data collection screen)

After the first randomization, a second took place, dividing the respondents between seeing a high personalized or low personalized advertisement. The high personalized advertisement consists of the user's name, star sign, the city they live in, their favorite brand and their marital status (fig. 3). The low personalization advertisement shows only their favorite band's name (fig. 4).



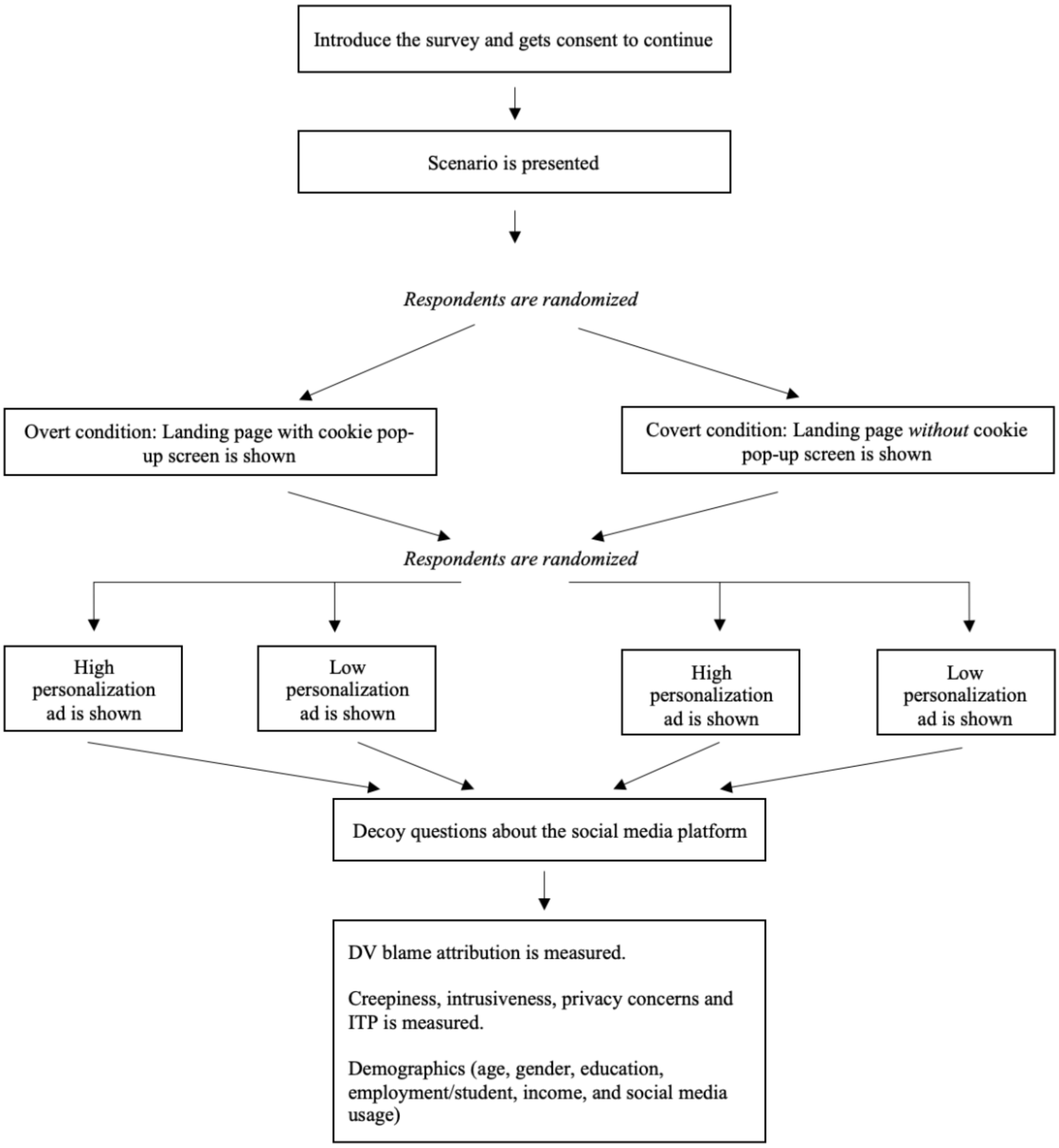

(Figure 3: High personalization ad screen)




(Figure 4: Low personalization ad screen)

After both the randomizations were concluded, the respondents were first asked some decoy questions about the SoMe platform they had seen. Following this, they were asked various questions to measure, intrusiveness, ITP, privacy concerns, responsibility attribution and demographic variables.

### 4.4 Survey flow




(Figure 5: Survey flow)

### 4.5 Ethical considerations

The respondent's data were anonymized, meaning there is no way for anyone to identify the respondents. This meant that an NSD approval was not necessary for our research. Every respondent was asked for their willing consent to participate before the survey, and were informed they could retract their consent at any point.

# 5.0 Results

Our objective for the experiment was to test for differences in attribution of responsibility towards the platform and advertiser under conditions of covert and overt data collection practices, and low personalization and high personalization advertisement on social media. We also wish to describe concepts related to these variables.

### 5.1 Statistical analyses

Our data was analyzed using IBM SPSS. Using SPSS, Cronbach's alpha-testing was performed to check the reliability of our measurement scales.

Anova tests were used to test our hypotheses for significant differences between groups.

A Pearson's correlation analysis was also executed to check for connection between our independent variables and other measured scales, such as demographics.

We have chosen to use an alpha level of [$\alpha = .10$] for our tests, meaning a significant result provides a 90 % confidence that difference between groups is due to variation alone.

## 5.2 Descriptive data

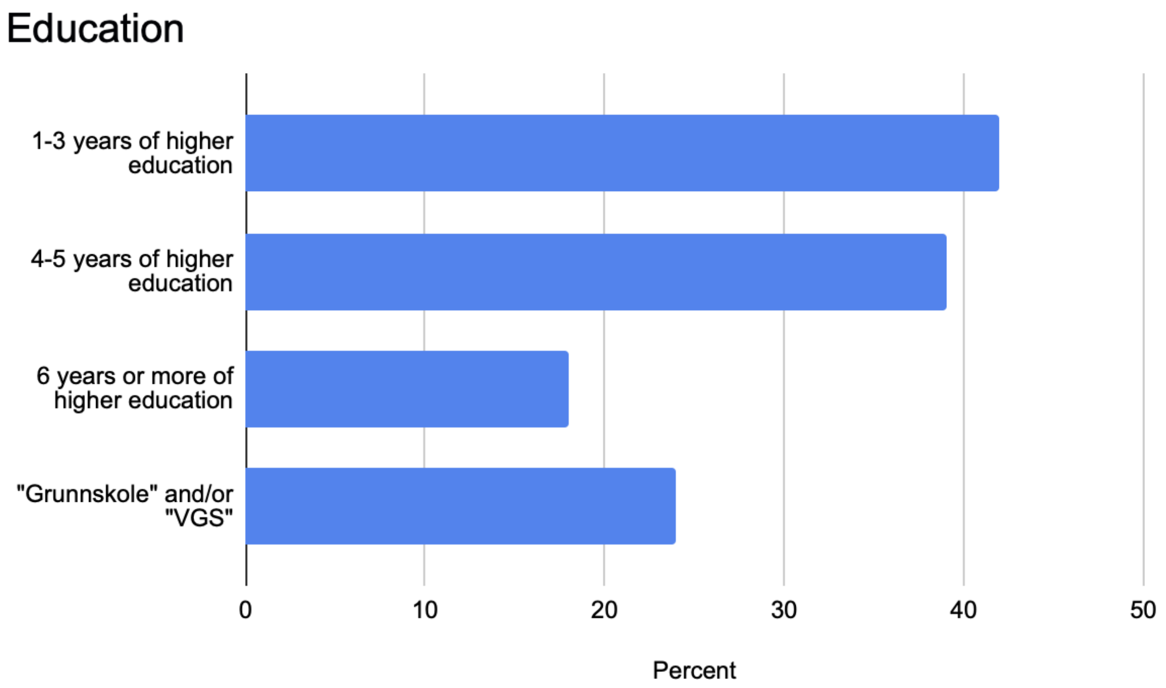
### *5.2.1 Demographics*

The survey was sent out to approximately 300 people. The data was cleaned, incomplete or invalid responses were removed. This left us with 125 responses to analyze and a response rate of approximately 42 %.

| Demographic characteristics of the sample | | |
|---|---|---|
| Characteristics | | Percentage |
| Gender | Male | 50,4 |
| | Female | 47,2 |
| | Other/Do not know/ Do not want to say | 0,8 |
| Age | 18-24 | 11,2 |
| | 25-34 | 61,6 |
| | 35-44 | 2,4 |
| | 45-60 | 19,2 |
| | 61-74 | 2,4 |
| | 75+ | 1,6 |

(Table 3: Demographics)

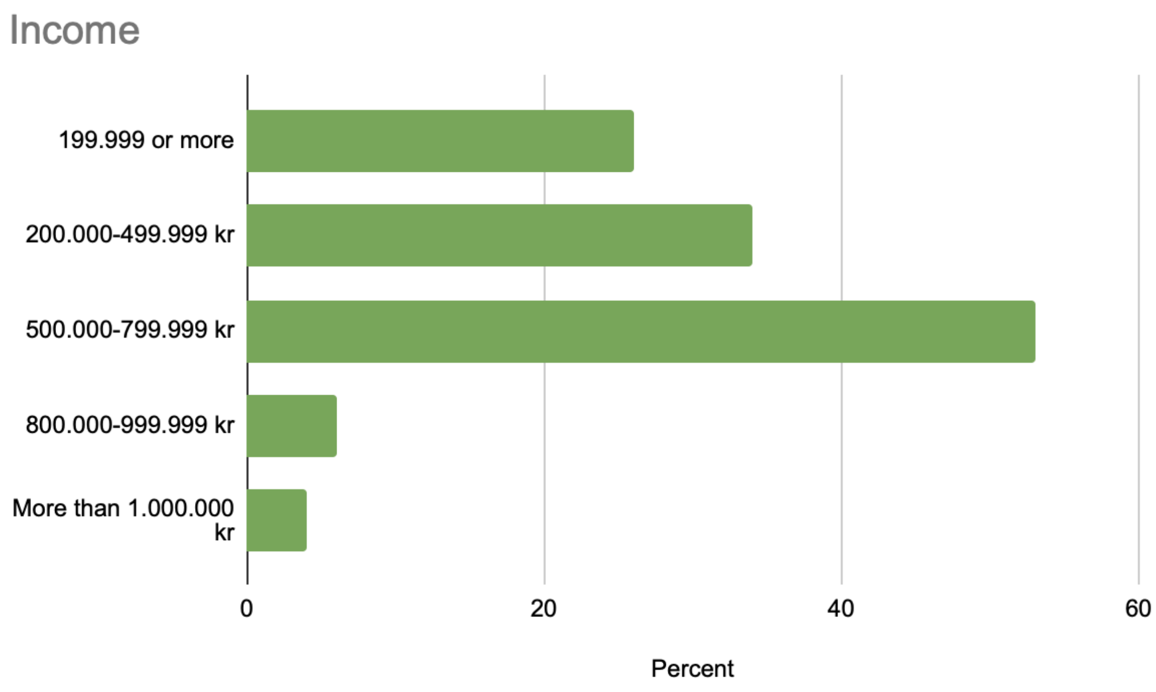
47,2 % of our respondents are female, 50,4 % are male. The majority (61,6 %) of our respondents are between 25-34 years old, 19,2 % are between 45-60, 11,2 % are between 18-24. Not highly represented are the age ranges 35-44 (2,4 %), 61-74 (2,4 %) and 75+ (1,6 %).




(Figure 6: Education)

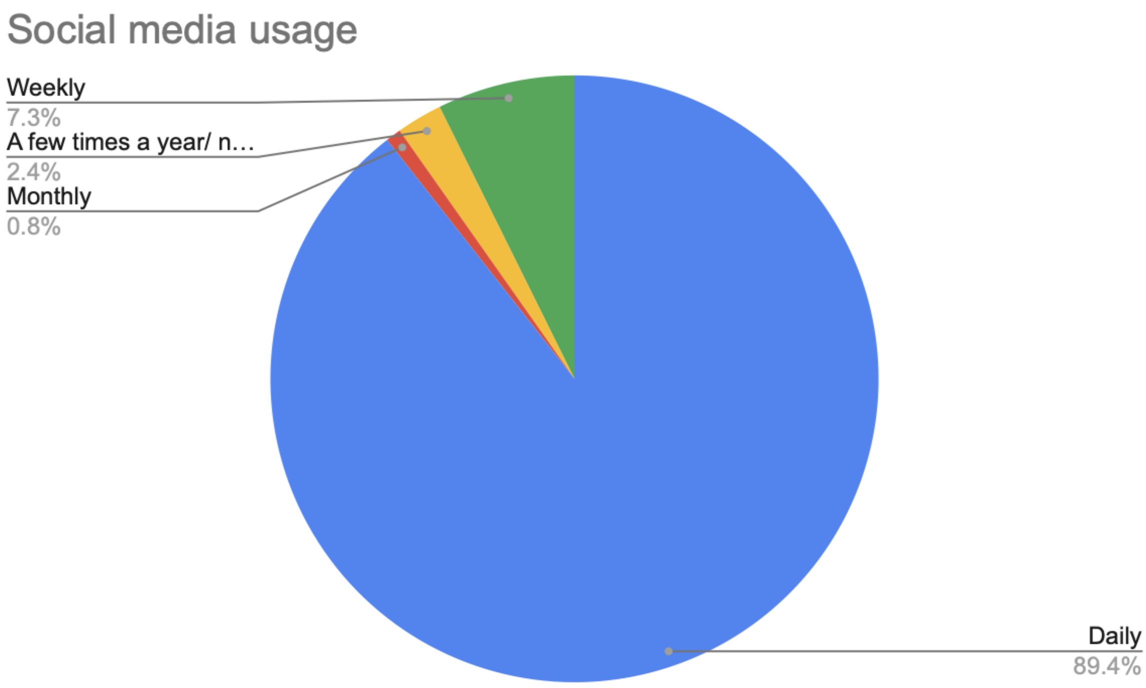
Most of our respondents are highly educated. 33,6 % of the respondents had an education level of 1-3 years of higher education, 31,2 % reported an education level of 4-5 years of higher education and 14,4 % reported an education level of over 6 years of higher education. 19,2 % of the respondents reported no years of higher education.

Most of the respondents work full time (78,8 %), and 17,6 % are full time students. 8,8 % of the respondents work part time and 3,2 % were unemployed/other.




(Figure 7: Income)

20,8 % reported a yearly income of less than 199.999 NOK. Most of the respondents (42,4 %) had a yearly income of between 500.000-799.999 NOK. 27,2 % reported earning between 200.000-499.999 NOK yearly. 4,8 % reported a yearly income between 800.000-999.999 NOK and the remaining 3,2 % reported a yearly income of over 1.000.000 NOK.

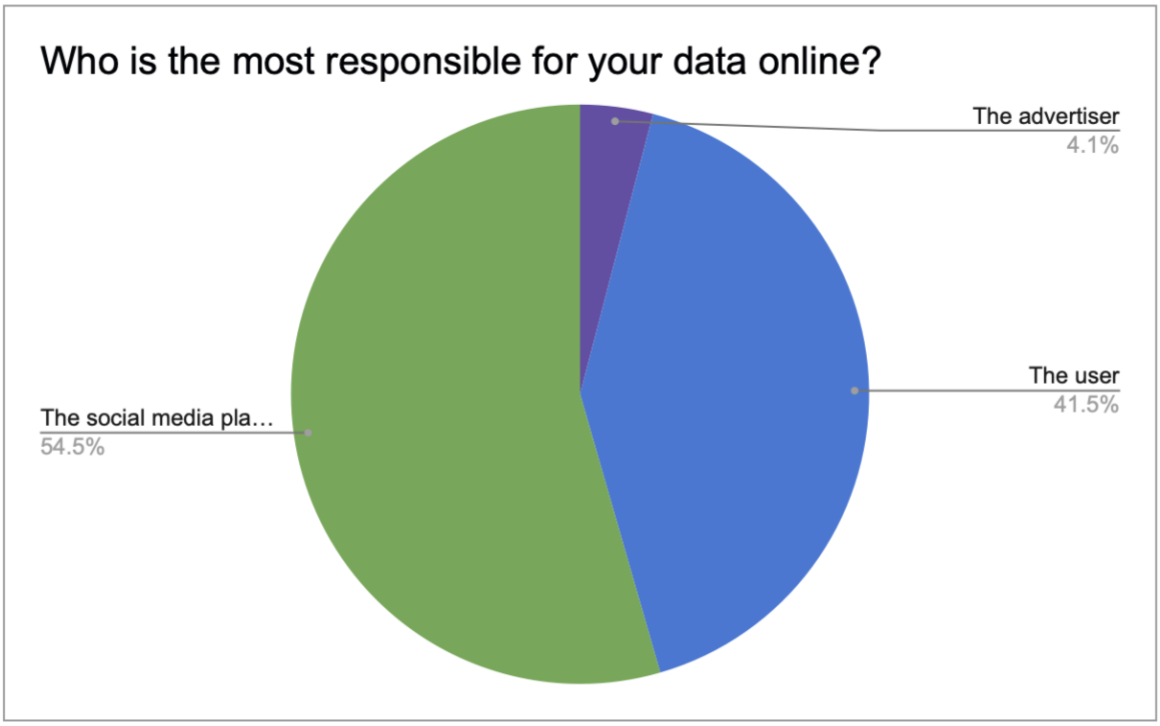



(Figure 8: SoMe usage)

When asked about their social media usage, 89,4 % of the respondents said they use SoMe on a daily basis.

### *5.2.2 Responsibility: nominal variable*

Only 4,1 % of the total respondents responded that the advertiser was the most responsible for their personal data online. 54,5 % responded that the most responsible was the social media platform, in this case “Frogbook”. The remaining 41,5 % responded that it was the user themselves responsibility.




(Figure 9: Nominal responsibility)

## 5.3 Correlation analysis

We use Pearson’s correlation coefficient to measure a linear connection between two variables. The correlation analysis provides a correlation coefficient between -1 and 1. This number is a quantitative expression of the reliability of our measures (Gripsrud, Olsson & Silkoset, 2016). Values between 0-.3 equal a low to no correlation between variables, values between .3-.6 equal a correlation of medium strength, and values between .6-1 equal a strong correlational connection between our variables (Gripsrud, et al., 2016).

We use correlation analysis to test the reliability of our measurements. We find multiple statistically significant correlations, however all at low values. The strongest correlation is between intrusiveness of the advertisement and privacy concerns (r=.342). The table shows correlations between our measures.

| Correlations | | Intrusiveness | Privacy concerns | ITP | Advertiser is responsible | Platform is responsible |
|---|---|---|---|---|---|---|
| Intrusiveness | Pearson Corr. | 1 | | | | |
| Privacy concerns | Pearson Corr. | .342** | 1 | | | |
| ITP | Pearson Corr. | -.256** | -0.162 | 1 | | |
| Advertiser is responsible | Pearson Corr. | -.242** | -0.014 | 0.042 | 1 | |
| Platform is responsible | Pearson Corr. | 0.041 | .316** | -0.009 | .184* | 1 |
| **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | |
| *. Correlation is significant at the 0.05 level (2-tailed). | | | | | | |

(Table 4: Correlations)

### 5.4 ANOVA: Hypotheses testing

ANOVA stands for analysis of variance. We used one-way ANOVA to determine whether there were statistically significant differences between our experimental groups. Following the two randomizations, four groups were created:

Group 1 = Covert data collection + Low personalization, hereby C+L
Group 2 = Covert data collection + High personalization, hereby C+H
Group 3 = Overt data collection + Low personalization, hereby O+L
Group 4 = Overt data collection + High personalization, hereby O+H

| Descriptives | Group | N | Mean | Std. Deviation |
|---|---|---|---|---|
| The use of cookies is “Frogbook's” responsibility | 1: C+L | 53 | 4.090 | 1.005 |
| | 2: C+H | 19 | 4.110 | 0.737 |
| | 3: O+L | 30 | 4.270 | 0.640 |
| | 4: O+H | 21 | 4.620 | 0.590 |
| | Total | 123 | 4.230 | 0.838 |
| The use of cookies is “Kuletskjorter.no's” responsibility | 1: C+L | 53 | 3.600 | 1.230 |
| | 2: C+H | 19 | 3.320 | 1.057 |
| | 3: O+L | 30 | 3.230 | 1.331 |
| | 4: O+H | 21 | 2.950 | 1.431 |
| | Total | 123 | 3.360 | 1.275 |
| ITP | 1: C+L | 53 | 1.623 | 1.037 |
| | 2: C+H | 19 | 1.895 | 1.162 |
| | 3: O+L | 30 | 1.667 | 0.903 |
| | 4: O+H | 21 | 1.095 | 0.256 |
| | Total | 123 | 1.585 | 0.960 |
| Privacy Concerns | 1: C+L | 53 | 3.793 | 0.772 |
| | 2: C+H | 19 | 3.832 | 0.626 |
| | 3: O+L | 30 | 3.667 | 0.627 |
| | 4: O+H | 21 | 3.733 | 0.655 |
| | Total | 123 | 3.758 | 0.692 |
| Intrusiveness | 1: C+L | 53 | 3.124 | 0.839 |
| | 2: C+H | 19 | 3.970 | 0.889 |
| | 3: O+L | 30 | 3.195 | 1.162 |
| | 4: O+H | 21 | 3.946 | 0.864 |
| | Total | 123 | 3.412 | 1.003 |

(Table 5: Group comparisons)

| ANOVA | | Sum of Squares | df | F | Sig. |
|---|---|---|---|---|---|
| The use of cookies is “Frogbook's” responsibility | Between Groups | 4.489 | 3 | 2.195 | .092 |
| | Within Groups | 81.137 | 119 | | |
| | Total | 85.626 | 122 | | |
| The use of cookies is “Kuletskjorter.no's” responsibility | Between Groups | 7.157 | 3 | 1.485 | .222 |
| | Within Groups | 191.104 | 119 | | |
| | Total | 198.260 | 122 | | |
| ITP | Between Groups | 7.135 | 3 | 2.690 | .049 |
| | Within Groups | 105.218 | 119 | | |
| | Total | 112.354 | 122 | | |
| Privacy Concerns | Between Groups | 0.429 | 3 | 0.293 | .830 |
| | Within Groups | 57.991 | 119 | | |
| | Total | 58.420 | 122 | | |
| Intrusiveness | Between Groups | 17.699 | 3 | 6.691 | <.001 |
| | Within Groups | 104.921 | 119 | | |
| | Total | 122.621 | 122 | | |

(Table 6: ANOVA)

***Hypothesis 1:***

The advertiser will be assigned less responsibility than the platform for the use of cookies when overt data collection takes place, even if the consumer sees an intrusive ad from the advertiser.

*The use of cookies is platform's responsibility:*

The difference in means between the groups is *almost* significant at 90% confidence interval $F(3, 119) = 2.195$, $p = .092$. Group 4: O+H has the highest mean ($M = 4.63$, $SD = .59$) of the four groups, however all agree that the platform should be assigned responsibility as the overall mean is 4.23 ($SD = .838$).

*The use of cookies is advertiser's responsibility:*

Group 4: O+H , which assigned the most responsibility towards the platform, signed the least responsibility towards the advertiser ($M = 2.95$, $SD = 1.431$). Group 1: C+L assigned the most responsibility towards the advertiser ($M = 3.60$, $SD = 1.230$). There is no significant difference between the groups $F(3, 119) = 1.485$, $p = .222$.

***Hypothesis 2:***

Covert data collection by the platform leads to higher privacy concerns and lower ITP towards the advertiser's product

*ITP:*

The general ITP for the proposed product was very low ($M = 1.585$, $SD = .960$). Group 2: C+H reported the highest intention to purchase at a mean of 1.86 ($SD = 1.162$). Group 4: O+H had the lowest ITP of all the groups ($M = 1.06$, $SD = 0.206$). The fact that the ITP was so low in general, may have affected proposed connections between variables. An initially more desirable product could elicit more nuanced responses. Even so, there was a significant difference between groups $F(3, 119) = 2.690$, $p = .049$.

*Privacy concerns:*

The overall mean of privacy concerns was 3.758 ($SD = .692$). There was not a significant difference between groups $F(3, 119) = .293$, $p = .830$.

The two covert groups, Group 1: C+L and Group 2: C+H, had the *highest* reported ITP compared to the overt groups. The difference in privacy concerns between the groups was not found to be significant. The hypothesis is therefore *not supported.*

***<u>Hypothesis 3:</u>***

High personalized advertisement leads to higher privacy concerns, intrusiveness and responsibility towards advertiser

*Intrusiveness:*

Significant difference between groups $F(3, 119) = 6.691$, $p = <.001$.

Group 2: C+H and Group 4: O+H had very similar means of respectively 3.960(SD = .890) and 3.946(SD = .864). Group 1 C+L (M = 3.124, SD = .840) and Group 3: O+L (M = 3.195, SD = 1.162) also had very similar means.

There is a significant difference between the groups for intrusiveness, and Group 2: C+H and Group 4: O+H scored higher than the groups that saw the low personalized ad. We already found that privacy concerns were not significantly different between the different groups. In terms of responsibility towards the advertiser, the difference between groups was not found to be significant, and the group with the highest mean was Group 1: C+L (M = 3.600, SD = 1.230).

We therefore do not find support for hypothesis 3. High personalized advertisements seem to lead to high intrusiveness, however, we found no significant link to privacy concerns and responsibility towards advertisers.

### 5.5 Regression analysis

We would also like to test how much effect above mentioned variables have on responsibility and ITP. Our full regression output is in Appendix 1.

Our first linear regression model shows that “Use of cookies is Frogbook’s responsibility” is the DV and means of  intrusiveness, privacy concerns and ITP is the IV’s. Here we find that privacy concerns have a significant effect ($p = <.001$) where the model explains 8,4% of the DV. Also for every point increase in “Use of cookies is Frogbook’s responsibility”, privacy concerns increase by .418.

The second linear regression model has the DV “Use of cookies is the advertiser “Kuletskjorter.no”’s responsibility”. Here we use the same IV’s as the first linear regression, and we get a significant variable ($p = .006$) within intrusiveness where the model explains 7,2% of the DV. For every point increase in DV we get a decrease of -.346 in intrusiveness.

Our third and last linear regression model we tested the effect of intrusiveness and privacy concerns on ITP, where we found that intrusiveness had a significant ($p = .017$) negative effect on ITP. This model explains 7,2% of the DV (ITP) and intrusiveness decrease by -.217 for every point increase in ITP.

# 6.0 Discussion

### 6.1 Main findings

Our research questions for this thesis were:
*Where do consumers feel the responsibility of data protection lies between platforms and advertisers? Does receiving a privacy notice about cookie collection affect this? What are the effects of feelings of intrusiveness and privacy concerns on responsibility attribution and ITP? How is ITP towards the advertiser’s product affected by data collection practices?*

We used ANOVA to test our hypotheses and regression analysis to look at the strength of our proposed connections. We did not find support for our three hypotheses, however, we did find significant findings. We did find that the group that had the highest mean for assigning responsibility towards the platform, and for intrusiveness, was the group that saw the high personalization advertisement and experienced overt data collection practices. This group also assigned the lowest level of responsibility towards the advertiser out of all the groups. Consumers feel the responsibility of data protection lies with the SoMe platform. This remains true regardless of what data collection practice was used by the platform, and which level of personalized advertisement the respondent saw.

The fact that overt data collection rather than covert increased intrusiveness and responsibility attribution the most could suggest the presence of the bulletproof glass effect (Brough et al., 2022), where the presence of a privacy notice leads to lower trust towards the platform than seeing no notice at all. In other words, a platform just informing people about their data collection practices risks a lot of negative consequences, and could in theory be better off not notifying people at all. However, the GDPR (2016) requires such a notice, so the alternative is to inform consumers in a better way (Brough et al., 2022).

Intrusiveness was also found to be significantly different between groups, and had the highest mean with the two groups that saw the high personalization ad. We also found that intrusiveness predicted lower ITP. The group with the highest ITP experienced covert data collection, and the group with the lowest ITP experienced overt data collection. The difference in means between the groups regarding ITP was found to be significant.

We found no significant differences between the groups regarding privacy concerns in our ANOVA, but did find in our regression analysis that higher privacy concerns lead to more responsibility being assigned towards the SoMe platform.

The descriptive analysis of the nominal question "who is most responsible for your data online?" 54,5% said the SoMe platform "Frogbook", 41,1% said they put the user as most responsible and only 4,1% said the advertiser "Kuletskjorter.no". Overall, the advertiser received very little responsibility for the collection of cookies. The differences between the groups were not found to be statistically significant in regards to assigning responsibility to the advertiser.

### 6.2 Implications for firms

Our research suggests that as an advertiser/third party using data from a platform, it seems you are fairly free from getting assigned responsibility for what the user's personal data is used for. This means there is no natural incentive for third parties and advertisers to act "ethically" when using data, rather there is an incentive to collect and use as much data as possible. The platform, on the other hand, will be held responsible in some cases, and has a natural incentive to be more mindful about how they collect data and how that data is used.

As mentioned before, it was decided that users in the EU must actively consent to all analytics cookies when they log on to a website (GDPR, 2016). The social media platforms are to only use overt data collection to comply with this. Our research shows that overt data collection could lead to some negative consequences towards the platform, like increased responsibility assigned for the use of cookies. To combat this, the firm should increase transparency consumer control around the data collection process (Martin et al., 2017). It is not enough to just put up a "we are using cookies" notification if you want to build trust among consumers.

The fact that platforms seem to end up with the responsibility for cookie use regardless of the advertisers ad practices, suggests that platforms would benefit from being selective when allowing third-party advertisers to use the platform's collected data. It could reflect negatively on the platform if the advertiser takes personalization a step too far.

### 6.3 Implications for consumers

Smith et al. (2014) raises the importance of education and understanding in cookie-use: "What does informed consent mean within a not-well-informed audience?" If consumers are to be able to feel and be more in control of their data online, educating them in how data collection works and how it can affect them is key.

One of the overall questions that emerges from our thesis' purpose is; should there be more regulation of the current data collection practices? Educating consumers through marketing and government initiatives could help them be more aware when browsing (Walker, 2016). Government regulations could also help consumers maintain certainty regarding their personal data online (Walker, 2016). There is an argument to be made that the market will regulate itself, by SoMe platforms and advertisers adhering to the consumers' demands about data collection practices. However, to be able to do this consumers need to be considerably more active in learning, as the systems for data collection are ever changing. Only 11% can correctly understand cookies even after receiving instructions (Ham, 2017), suggesting that there is a lot of room for improvement through learning. A solution to the tug of war between privacy concern and OBA proposed by Cui, Ghose and Halaburda (2021) is an idea of collecting only subsets of non-identifiable information that might be sensitive to the consumer, creating a win-win situation.

### 6.4 Limitations and suggestions for further research

The online survey method for collecting data has some limitations. We could only reach a limited number of respondents which can lead to skewed statistical results because of self-selection bias. In addition to this, convenience sampling was used to collect our respondents. Our sample suffered from unequal representation of age groups (few in the age groups 35-44, 61-74 and 75+). Our survey was distributed using the internet, so an online device became a requirement for answering. The survey was written in Norwegian in order to reach as many people as possible, but this could mean that the meaning of the questions or answers will be changed slightly because of the limitations of translation.

Factorial design requires more respondents than non-factorial, in order to fill all the cells. We did unfortunately not get enough respondents to be confident of our findings. We used randomization in two points of the experiment, which should, given a large enough sample, be equally distributed. However, our sample was not equally distributed, possibly due to an inadequate sample size.

We had to use an approximation of the situation (scenarios) we wanted to study due to restraints in budget and opportunity. With approximation, the scenario becomes some level of removed from reality, which could affect how people react to it. Even though we used fictional brands in our survey, we cannot guarantee that they did not remind respondents about existing brands. This could cause some associations tied to those brands to be transferred to our fictional ones.

For future research it would be interesting to see a similar experiment using different types of ads and/or different levels of personalization rather than just high level and low level. It would also be interesting to recreate the research with larger sample size to see if the effects are the same. There is also room for more research to examine the intricacies of the positive and negative effects of covert vs overt data collection, such as comparing the effects of differently worded data collection notices. There is a possibility that as the online environment and cookie collection practices changes, so could the effects of different privacy notices change. In addition, it would be beneficial to explore more about how the consumers find themselves responsible for their personal data online. We would also like to see more in-depth research about which measures of regulation seem appropriate for the consumers to be implemented on data collection practices.

# 7.0 Conclusion

The social media platform was assigned more responsibility for the use of cookies, regardless of data collection practices and whether a highly personalized advertisement was shown. This means the social media platform should consider how their third party advertisers actions could affect their own users' evaluation of them.

Consumers are in need of more education about data collection and data usage online. Gaining a more comprehensive understanding about how online advertising works, is the first step towards being able to advocate their own wishes to the firms regarding the use of their personal data.

Based on our research, self-regulation of social media platforms and advertisers does not seem like a viable option to ensure consumers privacy and trust at this point in time. Instead, regulation from the government is needed to keep consumers from being exploited for their personal data.

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# Appendix

## Appendix 1

### Linear regression model 1:

**Model Summary**[b]

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .326[a] | .106 | .084 | .802 |

a. Predictors: (Constant), avg_ITP, avg_privacyconcerns, mean of creepiness+intrusiveness

b. Dependent Variable: Bruken av cookies er FB sitt ansvar

**ANOVA**[a]

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 9.084 | 3 | 3.028 | 4.708 | .004[b] |
| | Residual | 76.542 | 119 | .643 | | |
| | Total | 85.626 | 122 | | | |

a. Dependent Variable: Bruken av cookies er FB sitt ansvar

b. Predictors: (Constant), avg_ITP, avg_privacyconcerns, mean of creepiness+intrusiveness

**Coefficients**[a]

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 2.817 | .471 | | 5.974 | <.001 |
| | mean of creepiness+intrusiveness | -.058 | .079 | -.070 | -.738 | .462 |
| | avg_privacyconcerns | .418 | .112 | .345 | 3.729 | <.001 |
| | avg_ITP | .025 | .079 | .029 | .323 | .747 |

a. Dependent Variable: Bruken av cookies er FB sitt ansvar

**Linear regression model 2:**

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | ,253[a] | ,064 | ,040 | 1,249 |

a. Predictors: (Constant), avg_ITP, avg_privacyconcerns, mean of creepiness+intrusiveness

**ANOVA**[a]

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 12,690 | 3 | 4,230 | 2,713 | ,048[b] |
| | Residual | 185,570 | 119 | 1,559 | | |
| | Total | 198,260 | 122 | | | |

a. Dependent Variable: Bruken av cookies er annonsøren KT sitt ansvar

b. Predictors: (Constant), avg_ITP, avg_privacyconcerns, mean of creepiness+intrusiveness

**Coefficients**[a]

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 4,043 | ,734 | | 5,507 | <,001 |
| | mean of creepiness+intrusiveness | -,346 | ,123 | -,272 | -2,812 | ,006 |
| | avg_privacyconcerns | ,140 | ,174 | ,076 | ,803 | ,423 |
| | avg_ITP | -,020 | ,122 | -,015 | -,167 | ,868 |

a. Dependent Variable: Bruken av cookies er annonsøren KT sitt ansvar

Linear regression model 3:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | ,268[a] | ,072 | ,056 | ,93219 |

a. Predictors: (Constant), avg_privacyconcerns, mean of creepiness+intrusiveness

**ANOVA**[a]

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 8,075 | 2 | 4,038 | 4,646 | ,011[b] |
| | Residual | 104,278 | 120 | ,869 | | |
| | Total | 112,354 | 122 | | | |

a. Dependent Variable: avg_ITP

b. Predictors: (Constant), avg_privacyconcerns, mean of creepiness+intrusiveness

**Coefficients**[a]

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 2,769 | ,486 | | 5,694 | <,001 |
| | mean of creepiness+intrusiveness | -,217 | ,090 | -,227 | -2,426 | ,017 |
| | avg_privacyconcerns | -,118 | ,130 | -,085 | -,907 | ,366 |

a. Dependent Variable: avg_ITP