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The Trade-off Between Privacy and Personalization:

Consumers' Willingness to Pay on Social Media Platforms

Master thesis, 2024

Master of Science in Business Administration

University of Stavanger Business School

Specialization: Strategic Marketing and Analytics

Acknowledgments

This thesis represents the completion of our Master of Science in Business Administration, specializing in Strategic Marketing and Analytics. It has been a fun and challenging process. We have applied what we have learned during our studies while also incorporating new approaches and gaining new knowledge throughout our project.

We would like to thank our supervisor, Dr. Avishek Lahiri, for his patience and guidance during this writing process. Your feedback has been an important contribution to the final result of our master's thesis. We would also like to thank everyone who participated in our survey, as these responses were crucial for our study. Lastly, we would like to thank our friends and family for their support during this process.

Abstract

This study examines the dynamics of Privacy, Personalization, and user behavior within social media platforms. Utilizing a Discrete Choice Experiment (DCE) methodology and statistical analysis, the research investigates users' willingness to pay (WTP) for privacy features amid the allure of personalized digital experiences. Focused on the Norwegian market, it inspects demographic influences and regulatory frameworks shaping user preferences. The findings emphasize the pivotal role of privacy concerns in user decision-making, explaining the subtle interplay between transparency, user preferences, and platform design. Ultimately, this research provides valuable insights for platform developers, policymakers, and users navigating social media platforms.

Table of Content

1. Introduction

In the digital era, platforms have become integral to modern life, shaping how we communicate, shop, and interact. Platforms can be defined as products or services that unite groups of users in two-sided networks (Eisenmann et al., 2006). A central aspect of these platforms is their dual process of value creation and value appropriation, where platforms leverage user data to enhance user experiences, drive innovation, and generate revenue (Zhang et al., 2021). However, this practice raises critical questions about user privacy and the ethical use of data.

Value creation is crucial for a platform's success (Hein et al., 2019). The platform works as a mediator for users and complementors, such as app developers and advertisers, to meet and exchange value that benefits both sides of the platform (Evans, 2012). An increase in users or complementors will increase the value for present users or complementors, as the network expands and enhances the possibility to connect and generate value on the platform. This is called the same-side network effect. Moreover, an increase in users will lead to more complementors, and vice versa. This is the cross-side network effect. It is however important to highlight that the same-side and cross-side network effect may be both positive and negative, depending on which perspective and participant you consider it from. Generally, network effects can be explained as the value a new user or complementor adds to the other users or complementors present in the network (Shapiro & Varian, 1999). Network effects have a crucial effect on the perceived value of a product, service, or platform among its users (Gregory et al., 2021).

Furthermore, digital platforms are founded on software complemented by modular services. (Tiwana et al., 2010; Tilson et al. 2010). Each modular service can be described as a software subsystem that aims to increase the platform functionality and enhance the value of the products for its users (Baldwin & Woodard, 2009). Facilitation of development tools provided by the platform owner enables complementors to develop complementary solutions that are of value for both the platform owner as well as the complementors, leading to the co-creation of value for all sides of a platform (Hein et al., 2019; Ghazawneh & Henfridsson, 2013; Nambisan et al., 2019). Examples of modular services include software development kits (SDKs) provided by the platform owner, and additional enhancements for complementors utilizing application programming interfaces (APIs) and other standardized interfaces to integrate new modules. (Hein et al. 2020; Ghazawneh & Henfridsson, 2013; Hein et al., 2019).

These modular services, such as SDKs and APIs, enable innovation based on large scales of user data, playing a pivotal role in the mobile app economy. Advertisers and data brokers, for instance, leverage SDKs to gather user information, tailoring app recommendations based on the acquired data. This initially means that all apps with the same SDK, which could be hundreds of thousands, will have access to the same user data collected through several different apps. However, users often remain oblivious to the presence and operations of SDKs, raising concerns about data privacy in the vast mobile app landscape. (Morrison, 2020)

The value creation of a platform is linked to the platform's ability to appropriate value. The concept of value appropriation emphasizes the mechanisms by which platform owners capture value from the platform ecosystem. This process involves extracting various benefits, such as revenue, data, and user engagement, generated through interactions facilitated by the platform (Lan et al., 2019).

Data sharing is crucial for various fields in the digital age, from scientific research (Devriendt et al., 2021) to targeted advertising (Swant, 2019). However, a growing reluctance to share personal information is emerging (Swant, 2019; FRA, 2020). Users are concerned about privacy violations and platforms' potential data misuse (Hsu et al., 2022). This lack of trust is exacerbated by a lack of transparency in data collection practices (Swant, 2019).

On the other hand, sharing data can unlock benefits like personalized experiences and targeted advertising relevant to user needs (Chandra et al., 2022; Busch-Casler & Radić, 2022). Additionally, users with higher engagement motivations and those older who have been using the platform longer tend to be more comfortable sharing information (Hsu et al., 2022). Legal frameworks like the GDPR empower users with control over their data, but cultural norms and national variations in user behavior also play a role (FRA, 2020). This creates a complex situation where users must weigh the potential benefits of personalization against privacy concerns.

Athey et al. (2017) found that users are generally unwilling to pay to protect their privacy, raising economic considerations for users and companies heavily reliant on data collection to train their platforms models, to offer personalized content to their users. However, as mentioned earlier, network effects are the value a new user adds to current users in the network, potentially creating a tension between WTP to protect their privacy and desire to interconnect with others.

Moreover, the cross-market network linkage significant to ad-supported platforms indicates that users will likely have to bear an increased financial burden for personal privacy in the future (Bhargava et al., 2019). The introduction of a subscription fee by Meta, charging users 13 euros a month in Europe who opt to prevent Facebook and Instagram from collecting their data, adds a layer of complexity to the privacy debate (Gulbrandsen et al., 2023). This move has sparked a moral discussion about placing personal privacy behind a paywall, especially considering privacy isa fundamental human right in the EU (Martens & Zhao, 2021), initially leading to the question: Do we have to pay to retain our human rights?

Our study aims to address the following research questions:

Research question 1: What is the extent of users' WTP for the trade-off between privacy and personalization when it comes to users' social media platform usage?

Research question 2: How do factors such as, platforms' transparency regarding their usage of the data they collect shape their WTP for privacy features on social media platforms?

The purpose of the study is to analyze users' willingness to pay (WTP) for Privacy and Personalization features on social media platforms, primarily focusing on the Norwegian market. While our analysis is centered around social media platforms generally used in the region, including popular platforms such as Snapchat, Facebook, Instagram, and X (formerly known as Twitter), our research aims to delve into the complex trade-off between users' desire for Privacy and the allure of Personalized product offerings.

Understanding how users navigate this trade-off is paramount for platform developers, policymakers, and users in an era marked by increasing data privacy and surveillance concerns. Our study employs a discrete choice experiment (DCE) to gather insights into users' preferences and WTP regarding privacy features on social media platforms. The DCE methodology enables us to simulate real-world decision-making scenarios and estimate the economic value users place on various attributes related to Privacy and Personalization within social media platforms. We can systematically explore the factors influencing users' decision-making in this domain by presenting participants with hypothetical choice sets containing different combinations of privacy and personalization features.

As the Norwegian market serves as our primary research context, we aim to understand how users in this region perceive and value privacy features in the context of their social media usage. Because of the EU's implementation of GDPR general data protection regulation, Norway is an interesting place to explore how people feel about their privacy features. Although Norway is not explicitly part of the EU, it is still required by law to follow the regulations through the EEA agreement (Utenriksdepartementet, 2021). By studying user attitudes towards these features, we can better understand how people feel about protecting their data.

By examining the interplay between cultural norms, regulatory frameworks, and individual preferences, we can gain valuable insights into the factors shaping user behavior in the Norwegian market. Furthermore, by exploring these research questions, we seek to contribute to a deeper understanding of user behavior and preferences regarding Privacy and Personalization on social media platforms. Our research can potentially inform platform developers, policymakers, and users about the trade-offs inherent in data sharing and personalized product offerings. Moreover, shedding light on user attitudes towards privacy features, can pave the way for developing more user-centric and privacy-respecting digital services.

Our research addresses an interesting aspect of the digital age: the trade-off between Privacy and Personalization and users' WTP on social media platforms. With the increasing concerns about data privacy and the growing demand for personalized experiences, understanding how users navigate this trade-off is important for academics and practitioners in the digital world. Furthermore, our study sheds light on user preferences and WTP in the context of Privacy and Personalization, offering valuable insights for platform design, policymaking, and user education.

In this introductory chapter, we provide the background and motivation for our research, outlining the growing importance of understanding user preferences and behavior on social media platforms. We present our research questions and provide an overview of our methodology, including key concepts such as network effects, value creation, privacy regulations, and user WTP.

Our literature review delves into the fundamental concepts underpinning our research. We explore the dynamics of network effects in social media and their implications for platform growth and user behavior. Additionally, we examine the mechanisms of value creation and appropriation within social media ecosystems, considering the roles of platform owners, complementors, and users. Furthermore, we review existing privacy frameworks and regulations, highlighting the evolving landscape of data protection in the digital age. Finally, we analyze prior research on user preferences and WTP in digital contexts, providing a theoretical foundation for our study.

The methodology chapter details our research methodology, beginning with an introduction to the DCE approach. We outline our survey design and data collection procedures, emphasizing the importance of capturing diverse perspectives from social media users. Additionally, we explain our statistical analysis techniques, including multinomial regression models and logistic regression, which form the basis of our empirical analysis.

For our results chapter, we present our study's empirical findings. We start by describing the demographic characteristics of our respondents, providing insights into the composition of our sample. Next, we analyze multinomial regression models, examining the factors influencing user preferences for Privacy and Personalization on social media platforms. Additionally, we employ logistic regression to test and evaluate the effect on WTP, shedding light on the relationship between user characteristics and willingness to pay.

In the discussion section, we discuss and interpret our findings in the context of existing theoretical frameworks. We explore the practical implications of our research for social media platforms, policymakers, and marketers, highlighting the importance of balancing user preferences with regulatory requirements. Additionally, we reflect on our study's methodological implications and constraints, identifying opportunities for future research and improvements in methodology.

Our summary chapter synthesizes the key findings and contributions of our research, reaffirming the significance of our study in advancing knowledge in the field of digital economics. We reflect on the broader implications of our findings and provide recommendations for future research directions, concluding with a reflection on the overall significance of our research.

Our key findings summarized are:

1. User Preferences: Our study reveals that users exhibit a WTP for Privacy over Personalization on social media platforms, highlighting the significance of privacy concerns in user decision-making.
2. Role of Transparency: Higher Platform Transparency leads to a higher level of user trust in platforms. Possibly reducing the likelihood of users choosing Privacy features. However, this effect is moderated by users' strong preferences for these features, indicating the complexity of transparency's influence on user behavior. This highlights the nuanced interplay between transparency, user preferences, and platform features in shaping user behavior on social media platforms.
3. Demographic Influences: Age and income significantly influence preferences, with middle-aged users showing a higher preference for Privacy and lower-income users exhibiting a lower WTP. This underscores the importance of considering demographic factors in platform design and policymaking.

2. Theory

2.1. Network Effects

Platforms can be defined as products or services that unite groups of users in two-sided networks. Platforms offer infrastructure and regulations that facilitate transactions between these two groups. (Eisenmann et al., 2006). Platforms are characterized by high connectivity, meaning that they depend on the number of users and complementors present on the platform to ensure a valid value proposition. Value proposition refers to the benefit a certain product or service offers its users. For social media platforms, this translates to the advantage of connecting and sharing content in the forms of pictures, messages, videos, and so on with other users, alongside linking users with complementors like advertisers and app developers, who co-create value to the users through offering their services through the platform. (Dutta & Segev, 1999; Caillaud & Jullien, 2003)

Network effects can be defined as the value a new user or complementor adds to the other users or complementors present in the network (Shapiro & Varian, 1999). Furthermore, it is understood to have a crucial effect on the perceived value of a product, service, or platform among its users. (Gregory et al., 2021). Same-side network effects for users, therefore, refer to the value a new user adds to present users on the platform. For complementors, the same-side network effects refer to the increased possibility to build new features on existing features provided by other complementors. It may however lead to increased competition, which for some complementors may be viewed as negative for their revenue and possibility for co-value creation.

In contrast, cross-network effects refer to how the value of one market side grows with the expanding number of participants on the opposite side (Schilling, 2002). When the number of platform users increases, the adoption and use of a product or platform results in the expansion of offerings for complementary products and services (Jullien & Sand-Zantman, 2021). The increased presence and offerings from complementors, lead to higher revenue for the platform itself and better offerings to the platform users. The presence of these complementors might also make the platform more attractive to potential users, leading to an increase in new sign-ups (Eisenmann et al., 2006). However, an increase in complementors may not necessarily lead to an increase in users. Advertisers for instance, in a high presence, might deter the users. The cross-side network effect may therefore be both positive and negative. An illustration of network effects is presented in Figure 1.

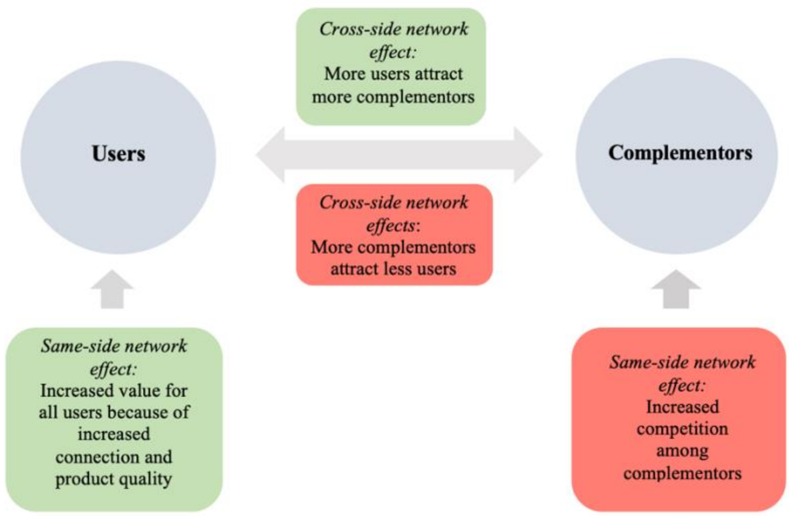


Figure 1: Network effects

With the increased use of technological tools to acquire customer data, and AI's role in creating user value, a new category of network effect has emerged, data network effects.

Data network effects can be defined as the effect where a product's value increases due to increased product usage and the accumulation of data from users. For data network effects to be present, two conditions must be fulfilled. Firstly, the improvements from learning from one user should also be of equal benefit to other users. Secondly, the change in the product must influence the current value for the current customers. (Clough & Wu, 2022; Cennamo, 2020). AI within digital platforms plays a significant role in activating data network effects (Gregory et al., 2021). AI and machine learning have enabled firms to transform learning from their customer data into innovative and improved products. The increase in product quality attracts more customers, giving the firms access to even larger scales of customer data that they can train their models on and use for further research and development. (Hagiu & Wright, 2023a).

Social media significantly impacts users' day-to-day lives, shaping communication, individuals' decision-making, purchasing behavior, and even self-perception (Allen, 2019). This influence is fueled by network effects, a phenomenon where a platform's value increases with its user base (Stobierski, 2020b). However, while offering undeniable benefits to users, these network effects also present challenges in the form of reduced competition, echo chambers, and potential privacy concerns.

Global network effects refer to the network effect of users being able to connect and interact with a large variety of people globally, unlike locally, where the ability to connect is limited to a defined area (Hagiu & Wright, 2023b). The core strength of global network effects lies in the platform becoming more valuable as the total number of users grows. A social media platform where one can only connect with a handful of people can quickly be perceived as of little use. A larger user base increases the chances of connecting with friends, family, and like-minded individuals (Stobierski, 2020b). Additionally, a vast user base attracts businesses for advertising, potentially leading to a richer content experience for users.

On the other hand, the dominance established through global network effects can lead to negative outcomes. Smaller platforms may struggle to gain traction without a critical mass of users, stifling competition (Evans & Schmalensee, 2010). This could deprive users of innovative features or niche communities these smaller players offer. Additionally, managing a vast user base may prompt platforms to employ algorithms to maximize user engagement. These algorithms, which deliver content based on past user behavior and interaction, can lead to users becoming more polarized and potentially being sent down 'rabbit holes,' thereby raising concerns about user privacy and well-being (Jha & Verma, 2023; Singh, 2024).

Adversely, local network effects offer a more nuanced perspective, shaping behavior within online social networks, and are pivotal for platform adoption and growth (Katona et al., 2011). Local network effects exist within limited geographical areas, where a platform's value primarily depends on interactions between users within that specific area (Hagiu & Wright, 2023b). They are underscoring the value of connecting with specific user groups (Katona et al., 2011). A professional networking platform like LinkedIn gains immense value for a user when there are more people in their field on the platform. Similarly, a niche social media platform focused on dog lovers becomes more valuable to a dog owner as more dog owners join. Local network effects foster a sense of community and targeted interaction, allowing users to connect with those who share their interests and passions.
However, local network effects can also create echo chambers, where users primarily connect with those who share their views. This can limit exposure to diverse perspectives and potentially contribute to social polarization. Additionally, smaller communities within a platform might be more susceptible to manipulation or targeted misinformation campaigns. (Cinelli et al., 2021)

The pervasiveness of network effects creates tension with user privacy. Platforms often gather vast amounts of user data to personalize content and target advertising. While personalization can enhance the user experience by suggesting relevant content or connecting users with similar interests, it can also lead to a feeling of being constantly surveilled (Boudet et al., 2019; Rothschild et al., 2019). Users might be forced to choose between a more valuable platform experience (through data sharing) and a higher degree of privacy.

2.2. User Privacy

Personal data is any information that relates to an identified or identifiable living individual. Examples include names, addresses, emails, location data, and online browsing habits (European Commission, n.d.). Data privacy can be deduced as protecting and managing personal information in the context of evolving technologies and societal norms. It involves establishing clear guidelines for handling personal information transparently, managing its use appropriately, and addressing digital challenges such as privacy breaches, targeted ads, and data mining. (Sharma, 2019)

The European Union (EU) has established itself as a global leader in data privacy through its comprehensive legal framework. The General Data Protection Regulation (GDPR), implemented in 2018, represents a significant shift in how personal data is collected, processed, and protected within the EU (Quinn, 2021).

Before the GDPR, data privacy concerns were addressed through a patchwork of national laws across the EU member states. This fragmented approach created inconsistencies and challenges for businesses operating in multiple jurisdictions. Rapid technological advancements and increasing reliance on personal data for commercial purposes necessitated a more robust legal framework (Markopoulou et al., 2019).

The GDPR represents a fundamental shift in the balance of power between individuals and data controllers - organizations that determine the purposes and means of processing personal data (European Commission, 2016). The GDPR empowers users with key provisions such as:

Enhanced Transparency and Control: Individuals have the right to be informed about how their data is collected, used, and stored. They also have the right to access their data, rectify inaccuracies, and request erasure under certain conditions (*Article 8 - Protection of Personal Data*, 2023).

Lawful Basis for Processing: Data controllers must have a legal basis for processing personal data, such as Consent, contractual necessity, or legitimate interests. Under the GDPR, Consent must be freely given, specific, informed, and unambiguous (*Art. 6 GDPR – Lawfulness of Processing*, 2023; *Art. 7 GDPR – Conditions For Consent*, 2018)

The GDPR has undoubtedly significantly impacted data privacy practices within the EU and beyond. It has raised awareness of data rights and has spurred businesses to implement stricter data governance measures. However, challenges remain. The sheer volume of data collected, and the increasing sophistication of data collection techniques pose ongoing challenges for regulators and businesses alike (Quach et al., 2022). Additionally, ensuring consistent enforcement across the EU member states continues to be an area of focus (European Commission, 2020).

The EU's approach to data privacy continues to evolve. The European Commission is constantly evaluating the effectiveness of the GDPR and exploring potential updates to address emerging technologies and data processing practices. Furthermore, the Schrems II decision by the EU Court of Justice has cast doubt on the validity of data transfer mechanisms with third countries that do not offer an equivalent level of data protection as the EU (CJEU, 2020). These developments highlight the EU's commitment to remaining at the forefront of data privacy regulation and its determination to ensure individuals retain control over their data in the digital age.

2.2.1. User behavior: data sharing preferences

The digital age hinges on the constant exchange of personal information, with data sharing playing a critical role in various domains, from scientific advancement (Devriendt et al., 2021) to targeted advertising strategies (Swant, 2019). However, a growing reluctance to share personal data is becoming increasingly evident.

A report by the Advertising Research Foundation highlights a concerning trend: a decline in Americans' willingness to share personal data with companies. The survey revealed a significant decrease in respondents sharing basic information such as home address (41% to 31%) and spouse's name (41% to 33%) within a year (Swant, 2019). This shift in attitude signifies a burgeoning public wariness towards data collection practices employed by commercial entities.

Similar concerns resonate across the European Union. The Fundamental Rights Survey reports that 41% of respondents were unwilling to share personal data with private companies (FRA, 2020). This statistic underscores a significant distrust towards commercial entities in handling personal information. Furthermore, the survey emphasizes a strong correlation between the type of data and sharing propensity. Only 5% of respondents felt comfortable sharing sensitive information like facial images or fingerprints (FRA, 2020), indicating a heightened concern regarding collecting biometric data.

The reluctance to share personal information extends to social media platforms as well. A study by Hsu et al. (2022) investigated the factors influencing information-sharing behavior on these platforms. The research reveals a complex interplay of factors, including privacy concerns, platform evaluation, user motivation, and demographic characteristics such as age and tenure.

The research reveals a negative correlation between privacy concerns and information disclosure. Individuals apprehensive about online privacy are less likely to share information on social network sites (SNS). This apprehension stems from anxieties regarding potential data misuse, privacy violations, or lack of trust. Interestingly, the study suggests a moderating effect of system evaluation on information sharing. While directly, platform evaluation (perceived trustworthiness or effectiveness) might not significantly impact sharing behavior, it interacts with other factors (e.g., privacy concerns) to influence disclosure. For instance, at low levels of system evaluation, individuals with high privacy concerns are even less likely to share information.

These findings in Hsu et al.'s (2022) study align with the ARF report, pinpointing that a lack of transparency shows user apprehension when sharing personal data. According to the report, only 30% of respondents could understand the term "third-party," which is frequently used in privacy policies. This, in turn, highlights a critical gap in users' comprehension of data collection practices employed by companies. Furthermore, Donato, the ARF Chief Research Officer, emphasizes the need for clear communication regarding how and why data is collected. (Swant, 2019).

While concerns regarding data privacy are valid, there are also potential benefits to consider when sharing information with social media platforms. By allowing for the collection of personal data, users can unlock a more personalized experience. Social media platforms can leverage this data to curate content recommendations and suggest connections aligning with users' interests and social circles. This can translate to encountering news articles or updates that resonate more deeply or reconnecting with long-lost friends through the power of data-driven matchmaking. (Chandra et al., 2022; Page et al., 2022; Shmait et al., 2023)

However, targeted advertising, often perceived as intrusive, can hold value for users. Social media platforms can use personal data to expose individuals to products and services relevant to their needs and interests (Busch-Casler & Radić, 2022). This can be a time-saving and cost-effective advantage, as users encounter offerings that directly align with their preferences, eliminating the need to sift through irrelevant advertisements (Bleier & Eisenbeiss, 2015; Strycharz et al., 2019).

Furthermore, the research of Hsu et al. (2022) also highlights the role of user motivation as a key factor influencing information sharing. Users who strongly desire to engage with their online communities, share ideas, or actively participate on the platform demonstrate a greater propensity to disclose personal information. Additionally, the study identifies a curvilinear relationship between age and information sharing, with older users exhibiting a higher tendency to share. Similarly, users with longer website usage display a greater inclination to share.

Building trust and ensuring transparency are crucial steps towards fostering a more open data-sharing environment (Martin et al., 2017). The General Data Protection Regulation (GDPR) implemented in the European Union (FRA, 2020) is an example of a legal framework that empowers users with control over their data. This includes the right to access users' personal information that companies hold and the ability to withdraw consent for data sharing (FRA, 2020). Understanding these national and international efforts to safeguard privacy rights is essential in the ongoing conversation about data ownership and utilization.

The Fundamental Rights Survey underscores the existence of significant national variations in user behavior. For instance, the percentage of individuals who neglect to read online terms and conditions differs considerably between countries. While 47% of users in Belgium and Cyprus skip these terms, only 22% in Estonia do the same (FRA, 2020). These discrepancies highlight the influence of cultural norms and legal frameworks on data privacy practices.

2.3. Value creation: Personalization

Social media platforms have become essential in modern life, transforming how we connect, communicate, and collaborate (Chugh et al., 2020). By connecting billions of users, these platforms have transformed how we learn, teach, and exchange information (Perez et al., 2023).

Social media platforms create value in several ways. They have become essential information-gathering, dissemination, and collaborative learning tools. Platforms like Facebook, X (formerly Twitter), and Instagram facilitate online social and professional connections, enhancing virtual communication and document exchange (Perez et al., 2023).

In addition, Social media platforms offer opportunities for recognition and exposure, access to others' work, engagement with diverse audiences, and establishing connections with funders and industry partners (Research Impact Academy, 2024).

Beyond information sharing, social media platforms excel in entertainment. Personalization plays a crucial role in enhancing the value created by social media platforms. Personalization means tailoring experiences and interactions across channels based on individual preferences and behaviors to enhance engagement and satisfaction. This personalization goes beyond just the user interface. Social media platforms leverage algorithms to curate content recommendations, suggesting posts, articles, and videos likely to resonate with each user's interests and past behavior. This targeted approach keeps users engaged by presenting a personalized feed of relevant and captivating content. (Salesforce, n.d.)

In other words, social media platforms are crafted to foster user engagement, enriching their entertainment appeal. Functions like likes, shares, comments, and reposts empower users to interact with content, fostering a lively and engaging entertainment atmosphere. Moreover, these platforms entertain community cultivation. Users can connect with like-minded individuals, join groups, engage in discussions, and partake in virtual events, turning social interactions into entertainment in their own right. (Perez et al., 2023)

Another example of personalization is trait-based personalization. Trait-based personalization of social media messages has been found to increase engagement when posts address specific persuasive susceptibilities. This type of personalization tailors advertisements to psychographic profiles using users' digital trace data (Winter et al., 2021). Additionally, user profiling is significant as it allows for extracting information and insights from user profiles. This data can then personalize the user experience, enhancing user engagement and satisfaction (Gilbert et al., 2023).

2.4. Value appropriation: Revenue Model

Industry platforms, or platform ecosystems, consist of large networks of firms connected through a common technological infrastructure. These platforms include two main types of firms: platform owners, the entity or organization that owns and operates the central platform, and complementors, companies or entities that offer goods or services that complement the platform product (Lan et al., 2019). Examples of complementors are third-party apps and Services, Influencers and Content Creators, and E-commerce Platforms. Social media platforms, for instance, rely heavily on content creators and advertisers who utilize their platforms to reach audiences (McFarlane, 2022).

A key concept for platform success is value appropriation, the process by which the platform owner captures value from the ecosystem. It involves extracting benefits such as revenue, data, or user engagement from the platform's interactions. (Lan et al., 2019)

According to McFarlane (2022), social media platforms primarily generate revenue through advertising. When users use a social media platform, they are essentially the product. The transaction occurs when the platform successfully rents users' attention to advertisers. Advertisers recognize the efficiency of reaching millions of potential customers through platforms. Using an advertiser-supported model (rather than charging individual users), social media companies can attract as many users as possible, making it a win-win situation for both the platform and the advertisers.

However, there is a need for a balance between the value appropriation and the platform's overall vitality. When platform owners heavily depend on complementors market segments for revenue, it can reduce complementary participation within the ecosystem. Complementors may be less motivated to join or innovate within the platform if they perceive the owners disproportionately benefit from their efforts. Ultimately harming the platform's user engagement and attractiveness to advertisers (Lan et al., 2019).

Some platforms use revenue-sharing. Revenue-sharing mechanisms can help mitigate the tension. Revenue sharing involves distributing a portion of the platforms generated revenue amongst complementors within the ecosystem. This practice has become common in the mobile ecosystem as platform leadership transitions from network operators to mobile operating system providers. Digital platforms divide the money earned from platform-related activities between the owner and other contributors (such as app developers, content creators, or influencers). When a platform generates revenue (e.g., through advertising, subscriptions, or in-app purchases), it allocates a percentage of that revenue to various stakeholders. The specific terms of revenue sharing vary based on the platform's policies and agreements. (Oh et al., 2015)

2.5. WTP

Understanding individual preferences and decision-making is crucial for optimal resource allocation in economics. This is where willingness to pay (WTP) comes into play. This concept provides valuable insights into how individuals' values change in their current state, offering a more nuanced perspective beyond market prices.

WTP refers to the maximum amount a user is willing to sacrifice to acquire a good or service they currently do not possess (Stobierski, 2020a). Essentially, it represents the value an individual places on obtaining something desirable. WTP is a critical business metric, influencing strategies, revenue optimization, and customer satisfaction (Steigenberger et al., 2022). Schmidt and Bijmolt (2019) emphasize that understanding WTP allows businesses to set appropriate prices, balancing maximizing revenue with ensuring customer affordability. Charging too little can hurt profits, while overpricing can alienate customers. Studies have identified various determinants of WTP, including sociodemographic characteristics, perceived benefits, perceived barriers, and intrinsic motivations (Steigenberger et al., 2022). Businesses should consider these factors when estimating WTP for their products or services. For instance, segmenting customers based on their value perception can guide pricing decisions (Steigenberger et al., 2022). By aligning prices with customer WTP, businesses maximize revenue while maintaining competitiveness (Schmidt & Bijmolt, 2019).

Furthermore, WTP leads to better customer experiences; when prices match what customers are willing to pay, satisfaction increases, fostering loyal and repeat business (Frondel et al., 2021). WTP varies across demographics and contexts; high-WTP customers may receive premium offerings, while cost-sensitive segments get budget-friendly options. WTP insights guide product development, allowing businesses to invest based on customer value for specific features (Steigenberger et al., 2022). Understanding how much a customer is willing to pay for a product or service is crucial for optimal pricing strategies, product development, and overall customer satisfaction.

Social media platforms leverage personalization to tailor content to individual users, potentially increasing their willingness to pay (WTP) for the service. Belkacem et al. (2022) argue that personalized news feeds, driven by user preferences and behaviors, outperform non-personalized versions regarding prediction accuracy. This suggests that users find these feeds more valuable. Eg et al. (2023) further this point by highlighting how user interaction with curated content and their awareness of the algorithms behind it can influence their perceived value of the platform, ultimately impacting WTP.

However, concerns exist regarding the trade-off between personalization and privacy. Rahman (2023) and Marmor (2020) raise the issue of user control over data and privacy rights, suggesting these factors significantly influence WTP for personalized social media platforms.

The value users place on privacy in social media is a growing area of research. Rahman (2023) argues that privacy on these platforms is not just about protecting data like property and controlling how users present themselves online. This focus on self-presentation suggests that users value platforms that offer more control over their data, potentially influencing their willingness to pay (WTP). In addition, a study done by Athey et al. (2017) also concluded that users were in general, not willing to pay to protect their privacy. Nevertheless, research paints a complex picture of WTP for privacy. Schreiner and Hess (n.d.) explored a "Freemium" model where users could pay for privacy features. Their study found that some users were unwilling to pay, while others offered tiny amounts. This suggests that while privacy holds value, users might not be willing to pay much.

Rahman (2023) delves deeper into this complexity. They examine the balance between freedom of expression and privacy rights on social media. Additionally, they assess the legal frameworks and privacy policies that govern these platforms, questioning their effectiveness in protecting user privacy. This thinking suggests that user trust in the platform's privacy practices significantly impacts their WTP.

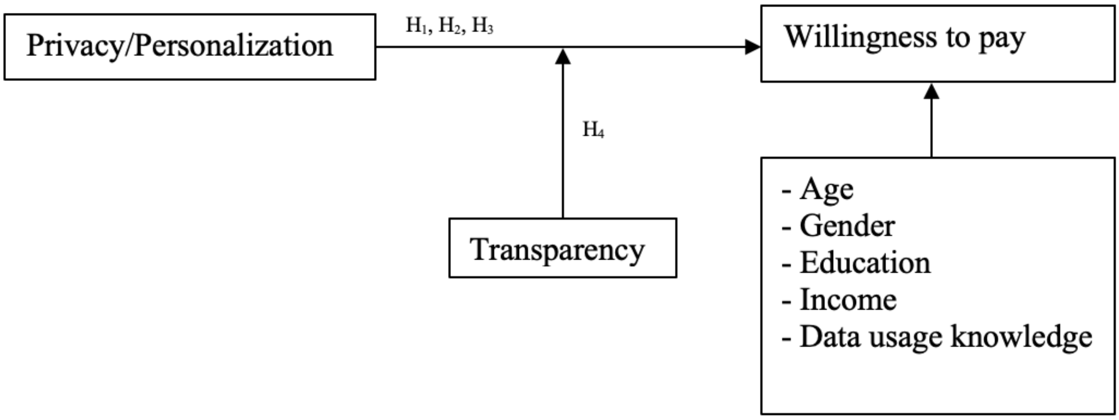
2.6. Hypothesis

As presented, these are our hypotheses. Based on our literature review and established theory, we believe the relationships of these hypotheses will be upheld.

H1: User preference for Privacy will be negatively related to WTP.
H2: User preference for Personalization will be positively correlated to WTP.
H3: Users that have a preference for privacy are WTP more than users that prefer personalization.
H4: The effect of user preference (privacy vs. personalization) on willingness to pay (WTP) is dependent on platform transparency.

> $H4_a$: Increased user perception of platform transparency leads to a decreased WTP for Privacy
>
> $H4_b$: Increased user perception of platform transparency leads to a decreased WTP for Personalization

2.7. Conceptual framework



3. Methodology

3.1. Empirical approach

For our research, we have chosen to practice a quantitative approach in the form of a discrete choice experiment (DCE). The method often estimates WTP for a unit change in each attribute projected (Mangham et al., 2009). Using a quantitative approach enabled us to create a survey, which ensured that we would get a large variety of data to analyze in a short amount of time, as opposed to using a qualitative approach such as an interview or focus group. Furthermore, when designing the DCE, we followed the steps of Mangham, Hanson, and McPake's (2009) method. The steps of the design are illustrated in Table 1 below.

Table 1: Steps design DCE (Mangham et al., 2009)

Steps	
Step 1	Identify the attributes relevant to the stated research questions
Step 2	Assign levels for each attribute
Step 3	Design the choice sets
Step 4	Generate and pre-test the questionnaire
Step 5	Analyze the data

3.2. Discrete choice experiment

A discrete choice experiment is a quantitative method used to determine individual preferences. It enables researchers to reveal how individuals assess specific product or service attributes by entailing respondents to state their preferred choice over sets of hypothetical alternatives (Mangham et al., 2009). As the participant can choose from several alternatives, it cannot be predicted which alternatives they will choose. However, the probability for each alternative can be measured (Lancsar & Savage, 2004). DCE has its theoretical foundation in random utility theory (RUT) and relies on the conjectures of economic rationality and the maximization of utility regarding choice behavior among users (McFadden, 1974). The RUT framework suggests that utility can be divided into a systematic and a stochastic component.

$$U_{in} = V_{in} + \varepsilon_{in}$$

The equation represents a model where U_{in} signifies the utility of individual i in scenario n. V_{in} denotes the systematic, also called observable, component contributing to this utility, while ε_{in} represents the random factor affecting the utility, also called the error term. It can be presumed that individuals would opt for alternative n if the utility gained from that choice surpasses the utility gained from any other option in the choice set (Louviere et al., 2010). Therefore, the likelihood of individual i selecting option i from a choice set is:

$$P(i|C_n) = P\left[(V_{in} + \varepsilon_{in}) > Max\left(V_{jn} + \varepsilon_{jn}\right)\right], for\ all\ j\ options\ in\ choice\ set\ C_n$$

The likelihood of choice is determined by comparing the utility of option i, represented by $V_{in} + \varepsilon_{in}$, to the maximum utility among all options j in the choice set, signified by $Max\left(V_{jn} + \varepsilon_{jn}\right)$, for all available options j. If the utility of option i is greater than the maximum utility of all other options in the choice set, then option i is chosen.

3.3. WTP

Our framework utilizes multinomial logit regression to estimate the influence of attributes (Privacy, Personalization, and Price) on an individual's willingness to pay. This approach relies on a key concept – the utility function.

The utility function, denoted as Uin, represents the level of satisfaction an individual i derives from choosing a specific alternative n (Gill, 2008). In this case, the alternatives are the different trade-offs between the varying levels of Privacy, Personalization, and Price. The higher the utility, the more likely an individual is to choose that option.

Utility Function:

$$U_{in} = 0_i + \beta_1 Price_{in} + \beta_2 Choice_{in} + \beta_3 Transparency + \beta_4\, Control\, Variables + \beta_5 Choice{:}Transparency + \varepsilon\_in$$

Where:

U_{in}: Utility of individual i for alternative n

0_i : Constant term specific to alternative n

β_1: Coefficient associated with Price. It captures the relationship between Price and utility

β_2: Privacy-Personalization Choice, $Choice_{in}$ denotes the choice made by the individual regarding the trade-off between privacy and personalization in the service. It is a binary variable with 1 indicating either Privacy or Personalization, depending on user preference and 0 indicating either no preference and the other variable that is not preferred.

β_3: Signifies the level of Transparency individuals perceive in the platform offering the service. (0 low level of perceived platform transparency, and 1 for high level of perceived transparency)

β_4: Represents other factors that may influence the utility, such as social demographics and knowledge about platform privacy and data usage (data usage knowledge).

> β_{4_1}: Gender: Refers to the respondents' gender identification (Male/Female)
>
> β_{4_2}: Data Usage Knowledge: Refers to respondents' perceived data usage knowledge level (1 for High to medium level of knowledge, 0 for rest.)
>
> β_{4_3}: Place of origin (1 for Norway, 0 for other)

β_5: Interaction term between the Choice and level of perceived Transparency

ε_{in}: Error term, assumed to be a random component influencing individual preferences beyond the captured attributes.

Regression Interpretation:

Multinomial logit regression uses this utility function to estimate the probability of an individual choosing a particular alternative i from a set of available options. By analyzing the estimated coefficients $\beta_1, \beta_2, \beta_3$, we can understand how individuals value each attribute and how these values translate into their WTP.

We considered employing dummy variables in the regression models. However, to avoid redundancy and ensure model parsimony, they were ultimately not included in the main regressions but were contemplated in interaction effects related to privacy.

Willingness to Pay (WTP)

WTP can be calculated using the following equation:

$$\beta_k + \beta_1 * \beta = 0 \rightarrow \delta = -\frac{\beta_k}{\beta_1}$$

Where:

δ: Price an individual is willing to pay for a specific attribute (Privacy or Personalization)

β_k: Coefficient of the attribute

β_1 Coefficient of the Price attribute (always negative)

The equation is derived from the regression model, where the coefficient β_k represents the effects of the attributes (Privacy or Personalization), and β_1 represents the effect of price. By rearranging the equation, we solve for, which represents the price an individual is willing to pay for the specific attribute.

The price coefficient (β_1) is always negative; a more negative value indicates that individuals prefer lower prices. A positive k suggests a preference for the corresponding attribute (Privacy or Personalization). The larger the positive value, the stronger the individual's desire for increased Privacy or Personalization and their potential WTP.

3.4. Choice Experiment Design

Our study employs a Discrete Choice Experiment (DCE), particularly useful for investigating and understanding participants' preferences. The DCE presents the participants with hypothetical scenarios involving different options. Each option is defined by a set of attributes and their corresponding levels. Participants choose the option that best aligns with their preferences. (Wang et al., 2021).

Our experiment has three attributes: price, Privacy, and Personalization. The first has four different levels (0, 50, 100, and 150 NOK), and the two latter ones have three levels each (High, Low, or No). A full factorial design would yield 36 scenarios with these attributes and levels. However, presenting these many options could lead to participant fatigue and possibly biased choices.

To address this, we opted for a fractional factorial design instead. This approach involves strategically selecting a subset of scenarios from the full factorial design , allowing for a robust analysis of participant preferences (Gunst & Mason, 2009). We used a technique to generate design matrices for experiments with a limited number of factors (fractional factorial designs) in the statistical software R Studio, which generated all possible combinations of attribute levels and ensured equal representation of each attribute level within the design matrix (CRAN, n.d.). We recognized that certain combinations, like high Privacy and Personalization, are not feasible; we excluded these scenarios from the design.

To minimize potential order bias, we randomized the order of the choice sets presented to participants. This randomization ensures that the order in which options are presented does not influence participant selections. Through this process, we minimized the choice sets from 36 to 7. This tailored design matrix balances comprehensiveness with participant engagement, promoting reliable data collection for our DCE.

3.5. Attributes and Levels

In a DCE, it is important to define attributes relevant to the stated research questions and assign different levels for each. The attributes we have chosen are specific to show the trade-offs between Privacy, Personalization, and users' WTP. Respondents should easily understand the attributes, which should vary meaningfully and realistically (Hall et al., 2004). A table illustrating our attributes and levels can be found below.

Individuals have different preferences regarding what they are willing to share online. A high Privacy preference implies a high level of data protection, where no user data is shared. Low Privacy suggests a moderate level of data usage, such as improving service quality or user experience. In contrast, no Privacy indicates a scenario where user data might be fully accessible and used for various purposes, such as targeted advertising.

High Personalization means the service or product is highly tailored to the user's preferences and behavior. Low Personalization indicates a lesser degree of customization, while no Personalization means the service or product is generic and not customized to the individual user.

The price attribute is represented in Norwegian Krone (NOK) with four distinct levels: 0 NOK, 50 NOK, 100 NOK, and 150 NOK. These levels were chosen to reflect the range of what users might realistically be willing to pay for the service or product being evaluated. The increment of 50 NOK between each level ensures a clear distinction between options while maintaining a manageable number of choices for respondents. This structure is based on analyzing existing premium offers on similar platforms, ensuring the price points are relevant to the decision context.

Table 2: Attributes and Levels

Attributes	Levels
Privacy	High Low No
Personalization	High Low No
Price	0 NOK 50 NOK 100 NOK 150 NOK

3.6. Example of choice sets

Alternative 1			Alternative 2			Alternative 3		
Low Privacy	High Personalization	0 NOK	High Privacy	No Personalization	150 NOK	High Privacy	Low Personalization	50 NOK

3.7. Data Collection

The survey was created using Qualtrics software (Appendix 6) to minimize respondent burden and maximize completion rates. To achieve this, the introduction was deliberately kept concise.

It offered essential background information about the study's purpose and presented clear yet brief definitions of the evaluated attributes. This approach aimed to engage respondents quickly without overwhelming them with excessive details at the outset.

The survey itself was divided into two distinct sections. The first section focused on gathering demographic data from participants. This data is crucial for understanding the sample's representativeness and identifying potential subgroups within the respondent pool. In addition to demographics, the first section assessed participants' attitudes toward the various attributes under investigation. This information provides valuable context for interpreting the choices made later in the survey and helps researchers understand the underlying factors influencing those decisions.

The second section of the survey presented respondents with seven separate choice sets. Each choice set required participants to select a single option from a set of alternatives that varied based on the predefined attribute levels. To ensure participants made informed decisions within each choice set, a concise recap of the attribute definitions was provided before they proceeded. This approach helped to refresh respondents' memory and minimized the risk of inaccurate responses due to forgetting the specific details of each attribute.

To target social media users, we distributed the survey through Facebook and encouraged further sharing by reaching out to family and friends. This approach maximized our exposure to the intended demographic. We received 180 initial responses. To ensure data quality, we cleaned our data by removing incomplete submissions and checking for any response inconsistencies. This resulted in our final sample consisting of 147 usable responses.

Validity, reliability, and ethical considerations are essential aspects of research methodology. Validity encompasses accuracy and appropriateness for the intended purpose (Hughes, 2018). Despite some respondents' reluctance to answer certain questions, the overall data quality remains acceptable for further analysis. On the other hand, reliability focuses on the consistency and trustworthiness of data. While the survey's distribution via Facebook challenges 100% reliability, efforts such as filtering out responses from unintended demographics were undertaken to enhance data accuracy. Moreover, model fit tests were conducted to ensure the reliability and validity of our analysis, affirming the robustness of our findings despite the inherent challenges with data collection.

Ethical considerations, including anonymity in survey distribution, were meticulously upheld to safeguard participant privacy. While challenges such as respondent reluctance and sample biases exist, the study's adherence to ethical guidelines and efforts to ensure data validity and reliability contribute to the robustness of its findings.

4. Results

Table 3: Demographics

Demographics and Percentages

Category	Demographic	Percentage
Age	16-30	58%
	31-60	35%
	60 <	6%
Degree	Bachelor	38%
	High School	12%
	Master	35%
	Ph.d.	0%
	Vocational education	12%
Gender	Female	65%
	I prefer not to answer	0%
	Male	33%
Income	High income	35%
	Low income	37%
	Medium income	27%
Knowledge	Low level	55%
	Medium level	43%
	High level	1%

The demographics of the respondents are presented in Table 3. There is a clear variation in age among the participants, with the largest category being 16-30 years old (58%). This is followed by the 31-60 age group (35%), and those above 60 years old account for only 6% of the respondents.

Regarding gender, the survey leans toward females, with 65% of respondents identifying as female. 33% identified as male, and 0% preferred not to answer.

The income distribution reveals that 37% of respondents fall into the low-income category (less than 300,000 NOK), 35% reporting medium income (between 300,000 NOK and 600,000 NOK), and the remaining 27% classified as high income (above 600,000 NOK). It's worth noting that the average salary in Norway is around 600,000 NOK (Fløtre & Tuv, 2022), so this sample skews slightly towards lower-income earners.

As for educational background, a significant portion of respondents hold either a Bachelor's or Master's degree (73%), with 12% having a vocational education background. High school graduates make up 12%, and none of the respondents reported having a Ph.D.

The respondents' data usage knowledge level is divided, with 55% indicating a low knowledge level, 43% reporting a medium level of knowledge, and only 1% classified as having a high level of knowledge when it comes to user data collection.

Due to the skewed demographics, particularly towards younger age groups and lower income levels, the results may not be generalizable to the entire population. This is because younger generations and those with lower incomes tend to have different valuations of preferences when it comes to Privacy, Personalization, and WTP compared to the general population.

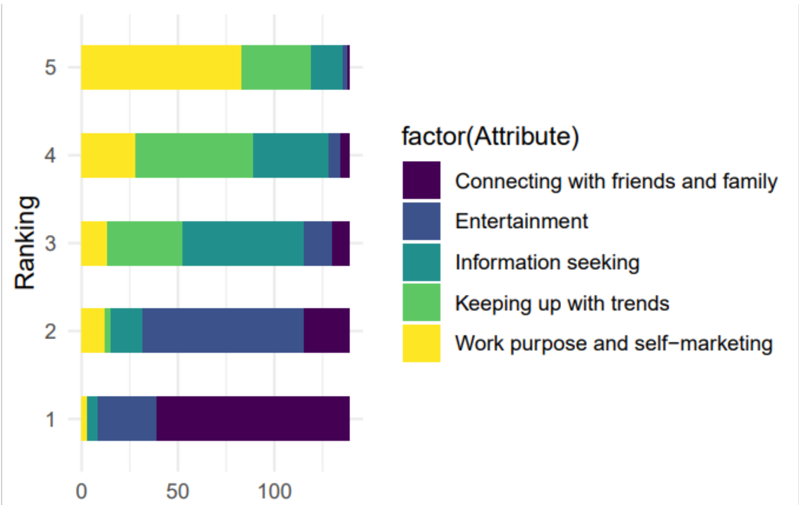


Figure 2: Consumer ranking of attributes

The respondents were also asked what was most important to them when it came to why they used their preferred social media platform. Figure X shows a stacked bar chart showcasing the different consumer rankings for each attribute, 1 for most important and 5 for least. The chart shows that 72% of the respondents found that connecting with friends and family is the most important, 29% of these showed a preference for Privacy, and 9% showed preference for Personalization. 60% ranked work purposes and self-marketing as the least important when using social media.

Furthermore, the second most important feature was entertainment; 60% of our respondents ranked it second, and 23% ranked it as the most important. Considering the respondents that ranked entertainment as the most important 50% of them preferred Privacy and 25% preferred Personalization. Information seeking and keeping up with trends is kept as a middle ground for most respondents. Figure 2: Consumer ranking of attributes gives us an overall idea of what is most valued and important to our respondents regarding their social media usage, which may further pinpoint what is important regarding privacy and personalization

Model 1: Multinomial Logistic Regression results w/ main variable for each preference

	Dependent variable:
	Choice_Privacy
Price	0.029^{***}
	(0.004)
Constant	-1.992^{***}
	(0.351)
Akaike Inf. Crit.	126.819
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

	Dependent variable:
	Choice_Personalization
Price	0.007^{*}
	(0.004)
Constant	-2.577^{***}
	(0.454)
Akaike Inf. Crit.	100.682
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In both models in Model 1, Price has a positive statistically significant coefficient, indicating that the preference for choice also increases for one unit increase in Price. Although the coefficients are both positive, the coefficient for Privacy (0.029) is stronger than it is for Personalization (0.007). Indicating a stronger influence of price on preference for Privacy than Personalization.

Model 2: Multinomial Logistic Regression with control variables and interaction effects

	Dependent variable:
	Choice_Privacy
Price	0.030^{***}
	(0.005)
Transparency	-12.948^{***}
	(0.0002)
GenderMale	0.281
	(0.544)
Knowledge	-0.306
	(0.523)
Origin1	14.702^{***}
	(0.632)
Age31-60	1.036
	(0.664)
Age60 <	0.968
	(1.172)
IncomeLow income	1.062
	(0.800)
IncomeMedium income	0.708
	(0.735)
Choice_Privacy:Transparency	35.836^{***}
	(0.0002)
Constant	-17.354^{***}
	(0.632)
Akaike Inf. Crit.	126.756
Note:	*p<0.1; **p<0.05; ***p<0.01

	Dependent variable:
	Choice_Personalization
Price	0.007
	(0.005)
Transparency	-9.951^{***}
	(0.0002)
GenderMale	-0.231
	(0.729)
Knowledge	0.001
	(0.607)
Origin1	-1.172
	(1.309)
Age31-60	-0.017
	(0.717)
Age60 <	-8.377^{***}
	(0.0005)
IncomeLow income	0.249
	(0.888)
IncomeMedium income	0.306
	(0.765)
Choice_Personalization:Transparency	23.525^{***}
	(0.00001)
Constant	-1.523
	(1.953)
Akaike Inf. Crit.	104.350
Note:	*p<0.1; **p<0.05; ***p<0.01

In both models in Model 2, the main effect of Transparency is statistically significant and negative. This indicates that all else being equal, an increase in Transparency is associated with a decrease in the likelihood of choosing personalization or privacy features. This suggests that higher levels of Transparency are generally related to lower preferences for both Personalization and Privacy.

However, the positive coefficients for the interaction terms Choice_Personalization x Transparency (23.525) and Choice_Privacy x Transparency (35.836) indicate that the effect of Transparency on the likelihood of choosing Personalization or Privacy features differs depending on the level of choice. Specifically, these positive interaction coefficients suggest that the negative impact of Transparency on the likelihood of choosing personalization or privacy is reversed when users express a stronger preference for Personalization or Privacy. In other words, the negative effect of Transparency regarding Personalization and Privacy preferences is diminished or even reversed for users who strongly favor Personalization or Privacy.

Therefore, while the main effect of Transparency suggests a general trend of lower preferences for Personalization and Privacy as Transparency increases, the positive interaction effects highlight the importance of user preferences in moderating the impact of Transparency on their choices.

Model 3: Linear regression, factors influencing WTP

	Dependent variable:
	Price
Choice_Privacy	87.258^{***}
	(7.786)
Choice_Personalization	61.677^{***}
	(11.970)
Transparency	-2.387
	(20.256)
GenderMale	-13.997^{*}
	(7.661)
Knowledge	2.022
	(7.041)
Origin1	6.583
	(17.322)
Age31-60	-3.217
	(9.033)
Age60 <	14.229
	(15.419)
IncomeLow income	-21.595^{**}
	(9.994)
IncomeMedium income	-4.562
	(9.407)
Choice_Privacy:Transparency	32.427
	(26.899)
Choice_Personalization:Transparency	50.221
	(36.876)
Constant	18.951
	(24.357)
Observations	139
R^2	0.617
Adjusted R^2	0.580
Residual Std. Error	40.124 (df = 126)
F Statistic	16.893^{***} (df = 12; 126)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The regression analysis in Model 3 aims to understand the factors influencing the WTP for Privacy and Personalization. The dependent variable, "Price," represents the highest amount a respondent is WTP in Norwegian Krone (NOK).

The results indicate that the Privacy preference (Choice_Privacy) significantly impacts WTP. Specifically, for each additional unit increase in the Privacy preference, WTP increases by 87.258 NOK, holding other variables constant. Similarly, the preference for Personalization (Choice_Personalization) also has a significant positive effect on WTP. Each additional unit increase in the preference for Personalization results in a 61.677 NOK increase in WTP.

However, the coefficient for Transparency is -2.387 NOK and not statistically significant. This suggests that changes in Transparency alone do not significantly affect WTP.

Regarding demographic factors, gender appears to play a role, albeit marginally. The coefficient for Gender (Male) is -13.997 NOK, with a p-value of 0.0701. This indicates that males are WTP 13.997 NOK less than females.

Income level also significantly affects WTP. Respondents with low income are WTP 21.595 NOK less than those with high income, holding other variables constant ($p = 0.0326$).

Furthermore, the interaction terms between choice and Transparency are not significant. Indicating that the combined effect of choice and Transparency on WTP is insignificant.

In summary, preferences for Privacy and Personalization significantly increase WTP in NOK, while Transparency does not have a significant impact. Additionally, gender and income level also influence WTP, with males and low-income respondents showing a lower WTP.

4.1. Evaluating hypothesis with model insights

H1: User preference for Privacy will be negatively related to WTP.

Not supported: All models show that preference for Privacy is positively related to WTP. Specifically, Model 3 shows that the preference for Privacy (Choice_Privacy) significantly impacts WTP, with each additional unit increase in Privacy preference resulting in an 87.258 NOK increase in WTP.

H2: User preference for Personalization will be positively correlated to WTP.

Supported: Similarly to H1 all models show that a preference for Personalization is positively related to WTP. Model 3 also indicates that the preference for Personalization (Choice_Personalization) significantly affects WTP, with each additional unit increase in Personalization preference resulting in a 61.677 NOK increase in WTP.

H3: Users that have a preference for privacy are WTP more than users that prefer personalization.

Supported: Model 3 showcases higher WTP increase for Privacy preference (87.258 NOK) compared to Personalization preference (61.677 NOK). Looking at the other models as well, the coefficients are higher for Privacy when it comes to Price than they are for Personalization.

H4: The effect of user preference (privacy vs. personalization) on willingness to pay (WTP) is dependent on platform transparency.

$H4_a$: Increased user perception of platform transparency leads to a decreased WTP for Privacy

Not supported: While Transparency has a negative direct effect in model 2, models 2 and 3 show it doesn't significantly impact users' WTP when they already have a clear preference. This means that for users who already strongly prefer Privacy, platform Transparency has no effect on their WTP.

$H4_b$: Increased user perception of platform transparency leads to a decreased WTP for Personalization

Not supported: Similarly to $H4_a$, Transparency has a negative direct effect, but again, Models 2 and 3 show that there is no significant impact on WTP when considering its interaction with user choice of Personalization.

5. Discussion

The purpose of this study was to investigate the relationship between user preferences for Privacy and Personalization and their willingness to pay (WTP), as well as how platform Transparency influences these preferences and WTP. The hypotheses were tested using multinomial and logistic regression models, which provided insights into the significance of various factors influencing user choices and WTP.

5.1. Academic contribution

The objective of this study was to quantify the trade-off between Privacy and Personalization in social media users' preferences and evaluate the impact of platform Transparency on users' WTP for Privacy and Personalization features.

Previous research has explored the importance of Privacy and Personalization individually, but there is limited understanding of how users balance these preferences, particularly in the context of social media platforms. Additionally, the role of platform transparency in influencing these preferences and WTP remains under-explored.

This study is one of the first to empirically quantify the trade-off between Privacy and Personalization in social media, incorporating the moderating role of Transparency. It provides a nuanced understanding of user preferences and their WTP, which has practical implications for social media platform design and policy.

Research suggests that users value personalized content and experiences, but they are increasingly wary of the trade-offs involved. On the one hand, personalized feeds and targeted advertising contribute to a richer user experience and enable platforms to generate revenue (Chandra et al., 2022; Busch-Casler & Radić, 2022). On the other hand, users are becoming more cautious about sharing personal information, driven by concerns over data privacy and security (Swant, 2019; FRA, 2020; Hsu et al., 2022).

Despite regulatory efforts, the tension between Personalization and Privacy persists, potentially shaping users' (WTP) for enhanced features and services on social media platforms.

Recent studies have delved into the relationship between user preferences, particularly Privacy and Personalization, and their WTP for social media services. Furthermore, our findings reveal intriguing insights into the dynamics at play.

Firstly, there is a clear positive relationship between Privacy preferences and WTP. Users who prioritize Privacy are willing to pay more for social media services, indicating their importance on maintaining control over their data. This aligns with the growing trend of users demanding greater transparency and accountability from social media platforms regarding their data practices. However, previous studies suggest the contrary, users are generally unwilling to pay to protect their Privacy (Athey et al., 2017).

Similarly, preferences for Personalization also positively influence WTP. Users value personalized experiences that cater to their interests and preferences, recognizing the added value it brings to their social media usage (Belkacem et al., 2022). However, the impact of Personalization preferences on WTP appears to be slightly lower than Privacy preferences.

Interestingly, users exhibit varying preferences for Privacy and Personalization based on age and income. Older users, for example, tend to prioritize Privacy more than younger users, who may emphasize Personalized content more. This highlights the complex interplay between user characteristics, preferences, and WTP for social media services (Hsu et al., 2022).

Furthermore, although Transparency was proven to not be significant in all our models, we still found clear evidence that Transparency influenced the likelihood of choosing Personalization or Privacy features. As previous studies suggested, platforms with high transparency and high user control are more likely to be trusted by users than platforms with low transparency or control. (Martin et al., 2017; FRA, 2020)

In our study, similar to Martin et al's (2017) and FRA's (2020) findings, we observed that higher Transparency, generally made users less likely to prefer Privacy, indicating that when users trust the platform, the need for high Privacy is less remarkable as the user will trust the platform to act in their best interest.

Moreover, contrary to our hypothesis suggesting a positive relationship between Transparency and Personalization, we found that a high level of Transparency was associated with a lower preference for Personalization. However, we also found that the effects of Transparency on the likelihood of choosing Personalization or Privacy features varied depending on the level of choice. For users with a strong preference for Personalization or Privacy, the negative impact of Transparency was mitigated or even reversed.

In addition, an important finding of our study was that despite transparency affecting preference for Privacy and Personalization features, it did not significantly impact the WTP. One might expect that low transparency would lead to a higher WTP for privacy features, due to reduced trust, prompting users to pay more for greater control over their data. This highlights the complex trade-off and interaction between features, Transparency and Price in determining WTP for platform users.

Also, same-side network effects highlight new users' value to existing users within the same group (Schilling, 2002). For social media platforms, increasing users enhances connectivity, making the platform more attractive as connecting with friends, family, and like-minded individuals becomes easier. This is evident in our study, in which 72% of respondents indicated that connecting with friends and family is the most important reason for using their preferred social media platform.

Lastly, this study contributes to the theory of network effects. It illustrates how privacy concerns can moderate the value users derive from increasing network size and personalization. Furthermore, the findings highlight the dual role of Privacy and Personalization in value creation for users and value appropriation for platform owners, underlining the possible need for a balanced approach. By quantifying WTP, this research adds to the behavioral economics literature on Privacy, providing concrete data on user trade-offs and preferences.

5.2. Managerial Implications

The purpose of our study was to explore the trade-off between Personalization and Privacy among platform users and to determine whether they are willing to pay (WTP) for these features, ultimately considering the possibility of making Privacy and Personalization subscription-based features.

A significant finding from our study is that users with a strong preference for either Privacy or Personalization are indeed WTP for these features. However, when it comes to Privacy features specifically, managers need to weigh the loss of revenue from not being able to use user data in their AI and machine learning models—since encrypted data cannot be used in these models—against the subscription fees. AI and machine learning provide valuable insights into customer behavior and preferences for both existing and potential customers, and a company could face losses if all users increase their privacy settings, as they would lose access to this valuable information.

On the other hand, another key finding was that the WTP for these features was relatively low among users who did not have a strong preference for either Privacy or Personalization. Therefore, the revenue loss from implementing Privacy features would likely be limited to a smaller segment of customers who are willing to pay for this feature.

Additionally, we found that platform users generally preferred to use these platforms to connect and engage with friends and family. Thus, it is likely that users would be more willing to pay for platforms that facilitate this type of interaction, as opposed to platforms with other purposes. This suggests that platforms creating value through interaction and engagement have a higher likelihood of successfully introducing a fee for Privacy and Personalization features.

Lastly, another important finding of our study was that while Transparency had a negative relationship with preferences for Privacy and Personalization, this relationship was mitigated or even reversed for users with a strong preference for either feature. Although this was not further explored in our study, it may indicate that users who are more informed about how platforms use their data have a greater desire to protect their data through enhanced privacy features. Therefore, the level of Transparency that platforms choose to maintain impacts user preferences for Privacy and Personalization and should be a consideration for managers in their strategic planning.

Overall, Social media companies can use these insights to design features and pricing strategies that better align with user preferences, particularly emphasizing privacy features. Furthermore, the findings suggest that while Transparency is crucial, its impact on WTP is complex and contingent on user preferences, guiding platforms in effectively communicating data usage practices. Lastly, the results can inform policymakers about the importance of Privacy in user decisions, supporting the development of regulations that protect user data while allowing for personalized experiences.

6. Limitations

Sample Representativeness:

Demographic Skew: The sample primarily consists of younger individuals and those with lower income levels. Specifically, 58% of respondents were aged 16-30, and a significant portion of the sample reported incomes below the national average. This demographic skew may limit the generalizability of the findings to the broader population, as older age groups and higher income brackets might have different preferences and WTP.

Gender Imbalance: With 65% of respondents identifying as female, the results may not fully capture the perspectives of male users, potentially introducing gender bias into the findings.

Hypothetical Scenarios in DCE:

The DCE methodology relies on hypothetical scenarios to elicit preferences. While this method is useful for understanding trade-offs, respondents' stated preferences may not always align with their actual behavior in real-world settings. For example, there may be a gap between respondents' willingness to pay and their actual payment behavior. Furthermore, as we had to drop a lot of choice scenarios in order to avoid incomplete responses on our survey due to fatigue, we therefore do not know if incorporating other scenarios would have affected the result and outcome of our study.

Complexity of Privacy and Personalization Preferences:

Privacy and Personalization are multi-faceted constructs, and the study's operationalization might not capture all dimensions. The levels of Privacy and Personalization used in the scenarios might not fully reflect the nuances of user preferences, such as specific types of data privacy concerns or particular personalization features.

Transparency Measurement:

Transparency in data usage is a complex and context-dependent concept. The study's measure of Transparency might not encompass all relevant aspects, such as communication clarity and user comprehension. Additionally, the interaction effects observed may not fully capture the broader implications of transparency practices.

Cultural and Regional Variations:

The study was conducted within a specific cultural and regulatory context (Norway). Cultural norms and legal frameworks regarding data privacy vary significantly across regions. Therefore, the findings may not directly apply to other countries with different privacy regulations and cultural attitudes toward data sharing and personalization.

Incomplete Responses and Sample Size:

Due to incomplete responses, a portion of the collected data had to be discarded, potentially reducing the statistical power of the analysis. With a larger sample size, more robust conclusions could have been drawn from the data, potentially uncovering additional insights or strengthening the observed relationships between variables.

Time Limitations and Lack of Focus Groups:

Time limitations constrained the study and prevented the implementation of focus groups as a supplementary data collection method. Focus groups could have offered richer qualitative insights into participants' attitudes, perceptions, and decision-making processes regarding Privacy, Personalization, and Transparency on social media platforms. This could have provided insights that complemented the analysis and additional context when interpreting the results.

7. Future research

Further research on the trade-off between Personalization and Privacy among platform users and its relationship with willingness to pay (WTP) can provide valuable insights for platforms when analyzing and modifying their business models. As the use of technological tools such as AI and machine learning continues to grow in the digital world, and as awareness of data usage increases alongside the introduction of laws and regulations like the GDPR, businesses must continually assess the market and user segments to remain relevant and profitable while complying with legal requirements. Personalization and Privacy features may become a point of differentiation in order for platforms to retain their users.

Therefore, further research should investigate other factors that might affect WTP for Privacy and/or Personalization. For example, examining how network effects and the intended use of a platform influence WTP could provide important insights for platforms when evaluating their features. Additionally, it would be beneficial to explore how transparency directly impacts WTP for privacy features, by treating transparency as a dependent variable rather than a moderator, as our study did not find significant results using it as a moderator. This approach could offer useful insights for platforms in deciding their level of transparency with users.

Furthermore, it would be interesting to study the willingness to accept (WTA) if all Privacy or Personalization features were removed, as users often exhibit a higher willingness to pay to retain existing features/products than to pay for new ones.

Finally, while finishing our thesis, it was announced that Meta intends to train models on each user's personal content and images, as a part of their new approach to the use of AI in their business model. This spurred a discussion amongst both users and researchers within the field of AI, leading to protests and statements clarifying that platform users do not agree to this new business approach. (Kaldestad, 2024; Gundersen, 2024; Faktisk, 2024). What the outcome of this discussion will be is still not clear, but it highlights the importance of future research regarding the use of AI in business models and how it affects platform users and their right to privacy.

8. Conclusion

As platforms evolve in the digital era, the need to utilize data and technological tools for effective value creation and user value propositions has sparked debate over data collection and user privacy rights. Privacy often comes at the expense of product quality and personalization, so we sought to investigate the relationship between Privacy, Personalization, and Price in platform features. We therefore decided to use willingness to pay (WTP) to measure the importance of Privacy and Personalization to platform users. We designed a discrete choice experiment, focusing on Privacy, Personalization, and Price as attributes to obtain the best insights into our research questions.

Our study found that users are WTP for Privacy or Personalization features when they have a strong preference for these features. This aligns with our hypothesis that user preference for Privacy and Personalization would be positively related to WTP. Furthermore, users with a preference for Privacy demonstrated a stronger WTP than those with a preference for Personalization, suggesting that Privacy can be a valuable feature of a platform business model and value proposition.

We also found that a preference for Privacy was negatively related to platform Transparency, which was expected. However, contrary to our hypothesis, we discovered that a preference for Personalization was also negatively related to platform Transparency, not positively as we had predicted. Although surprising, our overall results showed no evidence that Transparency affects WTP for privacy features. This indicates a need for further research in this area, as different measures of platform Transparency might significantly impact WTP for privacy features.

Overall, our findings suggest that the trade-off between Privacy and Personalization could become an important factor for platforms when shaping their business and revenue model, especially given the growing user awareness of data usage. These features could therefore become key differentiation factors for platforms in the future. However, further research is necessary, as price is a complex and critical factor in understanding user behavior and preferences.

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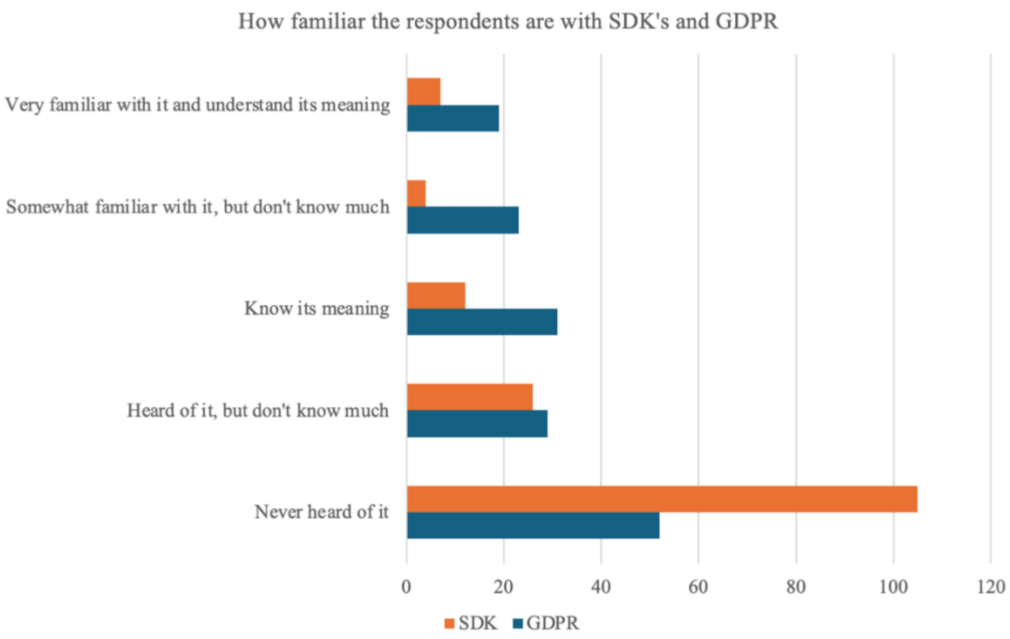
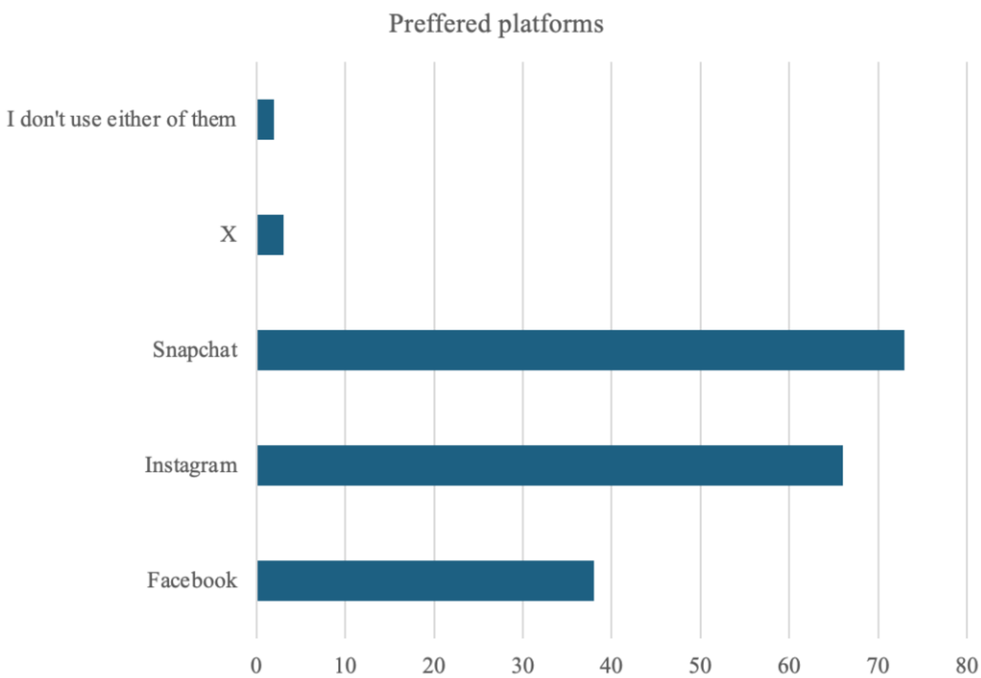
https://doi.org/10.1016/j.indmarman.2021.06.001

Appendix

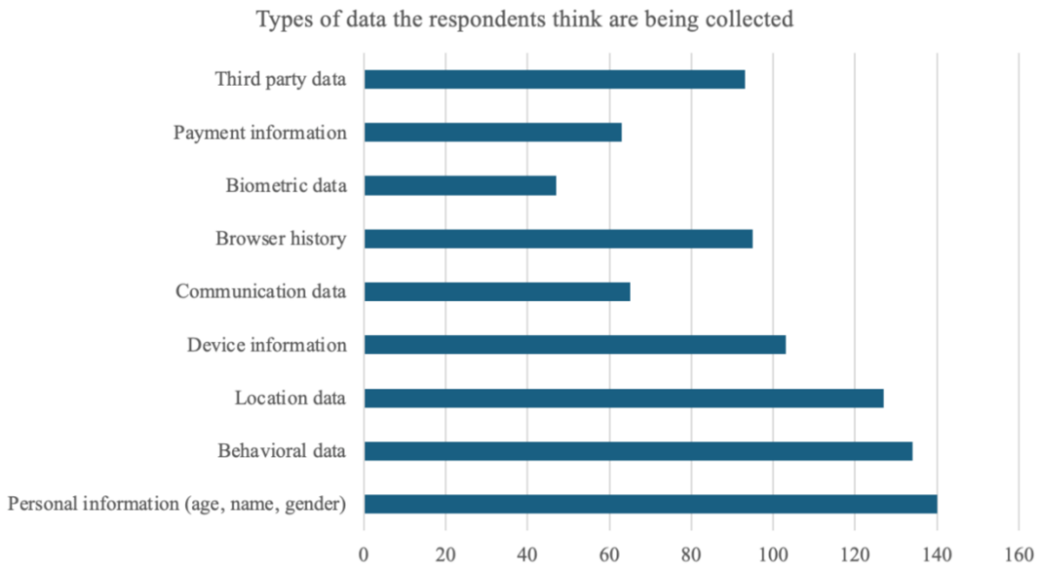
Appendix 1



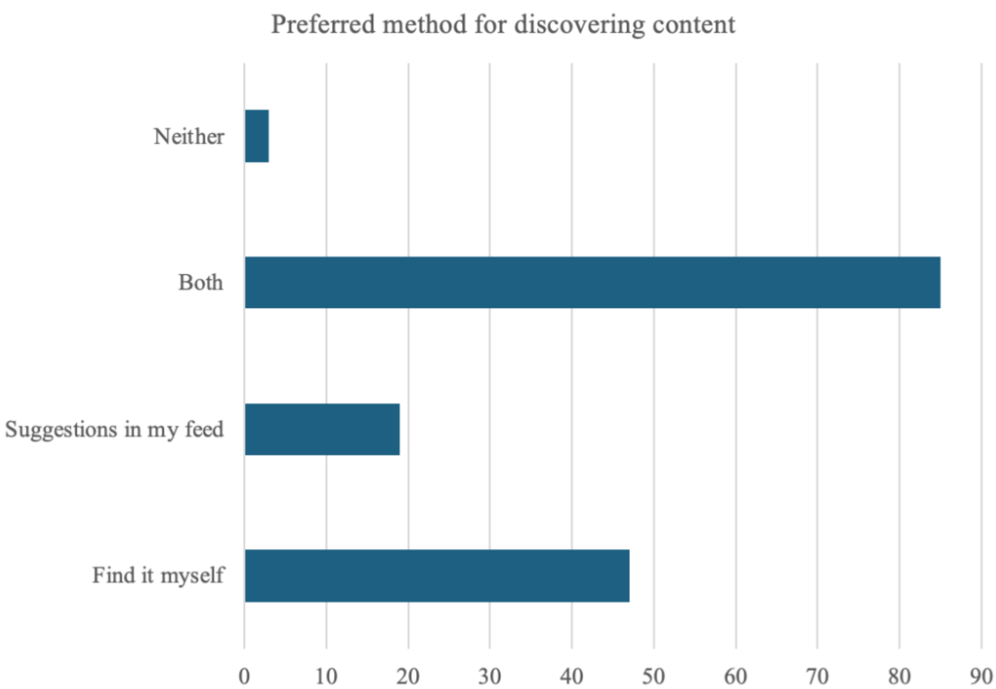
Appendix 2



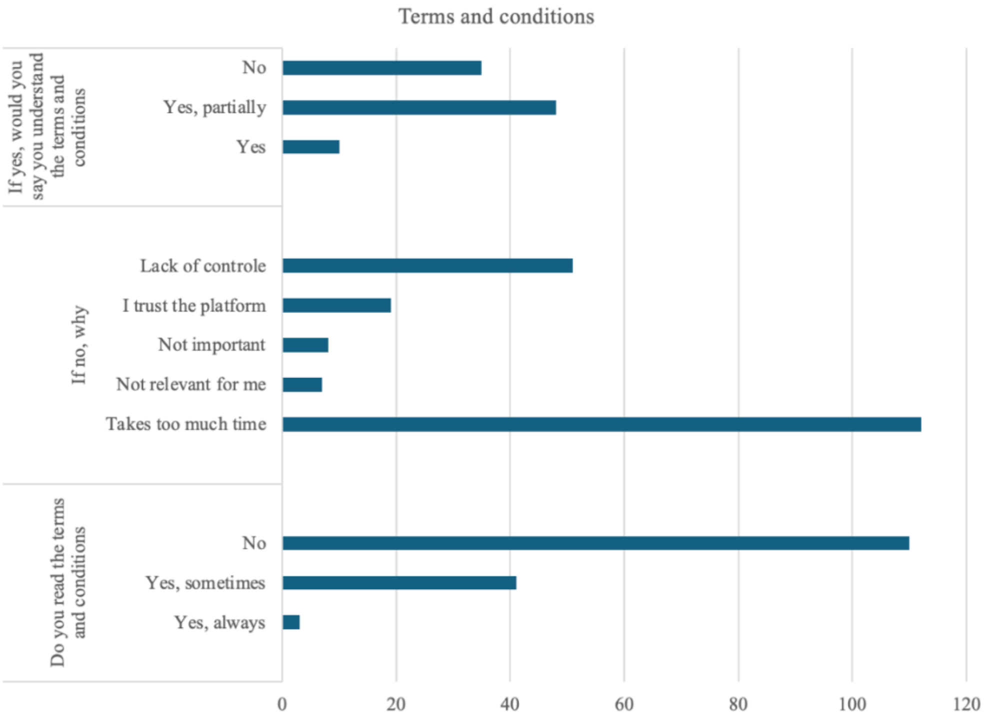
Appendix 3



Appendix 4



Appendix 5



Appendix 6: Survey

"The aim of this research study is to look into the trade-off between privacy, personalization, and WTP in concern to consumer preferences when it comes to social media platforms. You will not be personally identified in the analysis; we are conducting the survey through Qualtrics. And data will be stored in a secure academic database on university-licensed cloud storage to ensure confidentiality. Only the primary researchers will have access to your survey responses for the purpose of analysis. Consent: We will proceed with the survey only after you consent at the start of the survey. If you are willing to volunteer for this research, please indicate your consent: Would you like to participate in this survey?"

Do you use social media, if so, which platform do you prefer?
respondents were given a range of different social media platforms to choose from, in addition with "I don't use social media", If any respondents answered that they were sent to the end of the survey, thanking them for their participation.

Demographics:
Age: 16-30, 31-60 - 60<, prefer not to answer
Gender: Male, Female, prefer not to answer
Origin: Norway, Other:
Education: High School, Vocational Education, Bachelor, Master, PhD.
Income (NOK): 0-100 000, 100 001-300 000, 300 001 - 600 000, 600 001- 1 000 000, 1 000 001<, Prefer not to answer

On average, how often do you think you use social media?
Less than 1 hour a day, 1-2 hours a day, 2-4 hours a day, 4-6 hours a day, more than 6 hours a day

Rank these features from most important (1) to least important (5)

Connecting with friends and family; Work opportunities and self-marketing; Keeping up with trends; Information discovery.

How concerned are you, if at all, that some of the information you share on social media might be accessed by any third-party entities that you have not consented to?
Likert scale

You may have been asked to approve or consent to your data being processed when using online services, websites or apps. Do you read these terms and conditions?
yes, always; yes, sometimes; No

- If No, why do you not read the terms and conditions?
  Takes too long; not relevant for me; not important; I trust the platform; lack of control - I can't change the terms and conditions, so reading them is futile.
- If Yes, would you say you understand the terms and conditions when you approve or consent to your data being used?
  Yes; Yes, partially, no

Do you feel as though platforms are transparent about what types of data they collect and what they are used for?
Likert scale

What types of data do you think social media platforms collect:
Personal information (Age, name, gender); behavioral data (likes, shares, comments, following, groups); Location ; Device information (devices you use, operating systems, browsers, IP - address); communication data (content of you messages, emails, conversations taken place on the platform); browser history; biometric data (face recognition, voice recordings) Payment information; Third - party data (data obtained from third party sources, such as data intermediaries or advertisers)

How familiar are you with SDK's (Software Development Kit) and GDPR (General Data Protection Regulation?
two separate questions
Never heard of; have heard about it; but don't know much of what it is; I know some of what it is; familiar; very familiar, i understand what it is and how it is used.

What is your preferred method for discovering content on your feed?
Find it myself; have content suggested for me; both; neither

"Imagine that your favorite social media platform offers you a deal. You can pay a monthly fee to have more control over your privacy and how much of your data the platform can see. This data pertains to your activity on the platform, such as what posts you like or who you follow.

No Privacy (High Personalization):This is like allowing the social media platform to know everything about your online behavior. They know what kind of posts you like, what you comment on, and what you share. In return, the platform can show you highly specific content that matches your interests. Your feed will be very personalized.

Low Privacy (Low Personalization): This is like giving the platform some information about your online behavior. You can share some of your likes and comments, but not all. The platform can still show you content, but it might not be as specific or closely related to your interests. Your feed will have some personalized content but also some general content.

High Privacy (No Personalization): This is like not giving the platform any information about your online behavior. The platform doesn't know what to show you, so it only shows posts from people you follow, without further recommendations based on your interests.”

Appendix 7: Choise sets

Choice set 1

Alternative 1			Alternative 2			Alternative 3		
High Privacy	No Personalization	50 NOK	Low Privacy	High Personalization	100 NOK	Low Privacy	No Personalization	0 NOK

Choice set 2

Alternative 1			Alternative 2			Alternative 3		
High Privacy	No Personalization	0 NOK	Low Privacy	No Personalization	100 NOK	Low Privacy	High Personalization	50 NOK

Choice set 3

Alternative 1			Alternative 2			Alternative 3		
Low Privacy	High Personalization	0 NOK	Low Privacy	No Personalization	50 NOK	High Privacy	No Personalization	100 NOK

Choice set 4

Alternative 1			Alternative 2			Alternative 3		
Low Privacy	High Personalization	0 NOK	High Privacy	No Personalization	150 NOK	Low Privacy	No Personalization	100 NOK

Choice set 5

Alternative 1			Alternative 2			Alternative 3		
Low Privacy	No Personalization	0 NOK	High Privacy	Low Personalization	100 NOK	Low Privacy	High Personalization	150 NOK

Choice set 6

Alternative 1			Alternative 2			Alternative 3		
Low Privacy	High Personalization	0 NOK	High Privacy	Low Personalization	50 NOK	High Privacy	No Personalization	150 NOK

Choice set 7

Alternative 1			Alternative 2			Alternative 3		
High Privacy	No Personalization	0 NOK	High Privacy	Low Personalization	100 NOK	Low Privacy	High Personalization	50 NOK