Algorithm awareness as a path to user dissatisfaction and surveillance concerns.

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ABSTRACT

Recently, personalization of content became integral to social media platforms, as it optimizes business operations, increases customer satisfaction, and maintains a competitive edge. For social media users, personalization is convenient as it presents content based on their interests. With the importance of social media in people's everyday life, questions are raised about the impact of algorithms on one's identity. Algorithm responsiveness describes the extent to which personalized content relates to one's identity, where algorithms either support one's identity or ignore it. While algorithms may prioritize biased content or suppress a part of one's identity, users can lack cognitive resources to determine authentic content. Since personalized content relates to one's identity, it shapes one's self-perception, whilst users mutually shape personalized content by engaging with it.

Nevertheless, people are generally not aware of algorithms or the impact of user behavior on personalized content and do not protect their privacy. Additionally, individuals' perceptions of algorithms are contradictory, as some personalized content is refused and some is accepted. Scholars argue that algorithm awareness can determine the perception of algorithms, as when users become aware of algorithms they either appreciate the benefits of personalization or feel threatened. With algorithm awareness, users become more concerned about surveillance and are more likely to avoid personalized content, yet some scholars report the contrary. Since there is no research analyzing the aforementioned and as there are existing contradictory findings, this study aims to uncover "to what extent does algorithm responsiveness explain the impact of algorithmic awareness on personalization concerns of Instagram users living in the Netherlands?". In this research, algorithm responsiveness is a mediator between algorithm awareness and the dependent variables surveillance concern and personalized content avoidance, while time spent on Instagram and age are control variables.

By conducting a survey experiment (N=107), the level of participants' algorithm awareness is manipulated, where explanations of algorithms are provided to two groups. However, the level of algorithm awareness did not have significant effects on algorithm responsiveness. Mediation analysis revealed that 8 out of 10 hypotheses are rejected, where algorithm responsiveness is not a significant mediator. Based on manipulated and non-manipulated algorithm awareness, perceived algorithm insensitivity increased the likelihood of personalized content avoidance. It was found that younger Instagram users perceive more responsiveness and less insensitivity and that they are more likely to avoid personalized content than older Instagram users. Based on the non-manipulated algorithm awareness, algorithm awareness increased perceived algorithm responsiveness. Thus, media entities should ensure that especially young users perceive algorithm responsiveness. Additionally, future research should utilize different stimuli and the scale for algorithm awareness and ensure a large and representative sample. The insignificant findings can be useful for scholars and policymakers, who place high importance on the level of algorithm awareness but should analyze other factors like age.

Keywords: *Algorithm awareness, algorithm responsiveness, personalization, concerns, Instagram.*

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1. Introduction

The recent advancement in machine learning development led to its increased utilization in various industries to optimize business operations, increase customer satisfaction, and remain at the forefront of competition (Allen, 2022; Ramos et al., 2020). The rise of the social media platform TikTok was grounded in the innovative use of personalization, which is a system of algorithms identifying people's interests and behavior to tailor content to their needs (Fan & Poole, 2006). The success of TikTok motivated other social media platforms, like Instagram, to shift their business models from a relationship-building approach to an algorithmic-driven approach, making personalization an integral part of the social media industry (Boeker & Urman, 2022). While the impact of social media in people's everyday life has long been the topic of scholarly discussion, with the rise of personalization, questions are raised about its effects on one's behavior and identity (Siles et al., 2020).

In the midst of an overwhelming amount of content on social media, personalization of content becomes a convenient and easy solution for people to satisfy their goals, as the information is presented according to their past and present interests (Aguirre et al., 2015). Thus, people are generally positive about personalization and justify embedded surveillance as an inseparable aspect of the benefits of social media (Siles et al., 2020). Nevertheless, algorithms may often oversimplify choices available to users, as they cannot grasp the complexity of human behavior (Ytre-Arne & Moe, 2020). As algorithms provide personalized content based on user behavior on that platform, personalization may lead to a one-sided perspective that limits users from expanding their worldviews beyond their current or past interests. Such notions are usually referred to as filter bubbles and echo chambers, which describe the threat of users being exposed to pre-existing limited views lacking countervailing viewpoints (Dutton et al., 2017). Thus, algorithms are also seen as a threat to democracy and autonomy as they may lead to the creation of biased beliefs, which may often be based on dominant discourses (Aguirre et al., 2015; Ytre-Arne & Moe, 2020).

In recent years, concerns about the negative impact of algorithms have been increasingly salient in the public debate and media, especially due to several personal data misuse cases. For example, Cambridge Analytica and Meta, which is the owner company of Instagram, personalized content according to user interests and identity to gain public support for Trump as a presidential candidate (Seadle, 2019). Despite increasing concerns about personalization, it has been found that most social media users are not aware of the presence and consequences of algorithms and do not adopt privacy-protective behavior (Ramos et al., 2020; Xie et al., 2022). With lack of algorithm awareness and high information overload on social media, users may lack cognitive recourses, like attention, to determine the authenticity of given information (Banker & Khetani, 2019). Hence, by believing that the content on social media is unbiased and objective, users may rely on such content and experience algorithm overdependence. Nevertheless, it is crucial for people to become aware of personalization and its consequences to view personalized information critically and to adopt privacy-protective behavior when needed. For instance, social media users are often unaware that algorithms present extreme edited content of female bodies, which can lead to mental health risks and eating disorders, while marketers are aware of such dramatic consequences and continue to target users with such content for their profit (Harriger et al., 2022). This example shows the importance of understanding if individual's level of algorithm awareness would change their perceptions of personalization, particularly by increasing one's personalization concerns.

As the content that users consume on social media relates to their self-representation, by presenting particular content, algorithms shape user identity, self-perception, and behavior. While it can be argued that algorithms control user identity, recent scholarship approaches the relationship between algorithms and user identity as a mutual production where both algorithms and people's actions shape each other (Karakayali et al., 2017). Taylor and Choi (2022) discuss the aforementioned referring to algorithm responsiveness and argue that if algorithms present content that is highly connected to people's identity, they would be more positive about engaging with algorithms and would be more negative if it is the contrary. Interestingly, other research found contradictory results where if personalized content is highly related or not related to people's identities, they would be more aware of the presence of algorithms and would be less positive about the use of their data and the quality of the provided content (Boerman et al., 2017; Karizat et al., 2021). Thus, it can be argued that when people become aware of algorithms that present highly relevant or highly irrelevant content, they would be more concerned about surveillance by external parties and would also be more likely to avoid such content to direct algorithms to show more interesting content.

User perception of personalized content may be considered contradictory, as some personalized content is refused and some are accepted (Beveridge, 2022; Jin & Villegas, 2007). While scholars argue that user algorithm awareness may be determinant of their perception of personalization, there is no existing research analyzing its effect, and the current research on user perception of personalized content is very limited (Boerman et al., 2017; Ytre-Arne & Moe, 2020). Nevertheless, it can be argued that it is crucial to analyze the aforementioned as personalization can offer great benefits for both users and external parties. For example, as personalization is an efficient approach for targeted advertising, it highly increases the revenue of advertisers which, consequently, increases the revenue of social media platforms (McFarlane, 2022; Nidhi, 2021). Thus, to ensure the greatest benefits of personalization for both users and external parties, this research aims to study the aspects that may be determining user perception of personalization. Hence, the following research question is proposed:

"To what extent does algorithm responsiveness explain the impact of algorithmic awareness on personalization concerns of Instagram users living in the Netherlands?".

1.1 Scientific and societal relevance

The ubiquity and importance of social media in people's everyday life urge scholars to understand its impacts on one's identity and behavior, especially with personalization being an integral part of people's social media experience (Siles et al., 2020). Nevertheless, there is limited research analyzing people's perceptions of personalization (Ytre-Arne & Moe, 2020) and some research presents contradictory findings, where some personalized content is refused and some is accepted (Beveridge, 2022; Jin & Villegas, 2007). Thus, it is important to understand the factors that influence one's perception of personalization. Scholars argue that one's algorithm awareness may be determinant of the perception of personalization, but there is no previous research analyzing such relationship (Boerman et al., 2017). Thus, this research aims to cover the gap by exploring the impact of the level of algorithm awareness on the perception of personalized content.

This research also aims to cover a gap of the limited choices of social media platforms that were examined in previous research. While Instagram is one of the most-used platforms worldwide, there was no research focusing on Instagram in the context of algorithm awareness and the perception of personalization (Statista, 2023). This research is particularly interested in analyzing people's perception of algorithms on Instagram, as by following TikTok's success with the recommender system, during past years, Instagram implemented a similar recommender system which drastically changed the platform (Hern, 2022). With a large prevalence of algorithms in the user interactions with the platforms, useres expressed their dissatisfaction with Instagram as it previously had a different business model, focused on connecting people with each other, but became highly similar to TikTok with the focus on personalized entertaining content. Previously, Instagram users could only see posts of followed people or pages, but now people mainly see random short videos, called Reels. Additionally, during the past years, with the implementation of algorithms, Instagram's owner company, called Meta, was highly criticized due to several data misuses, like in the case of Cambridge Analytica (Seadle, 2019). As such data misuse cases gained high public attention and concern, it can be assumed that it may impact one's algorithm awareness and the perception of personalization. Thus, in the context of this research, Instagram serves as an interesting case that may offer new insights.

Since personalization of content can be beneficial for both users and external parties, the findings of this research can be useful for most parties involved. Firstly, as this research believes that algorithm awareness may be crucial for people to rationally assess personalized content, it is assumed that they need to possess higher algorithm awareness. With higher algorithm awareness, individuals can be able to protect themselves from potentially harming content and fully enjoy the benefits of personalization by training algorithms to correctly determine their interests (Boerman et al., 2017; Karakayali et al., 2017). For instance, previous research found that people are not aware of the impact of their behavior on personalized content, which may be essential to rationally engage with personalized content (Zarouali et al., 2021). Thus, if this research finds that the level of algorithm awareness impacts one's perception of algorithms, it shows why it is important for policymakers to increase user algorithm awareness by proving simple and clear explanations of algorithms, their risks, and ways of protecting them from potential harm.

Furthermore, the findings of this research can be beneficial for external parties, like advertisers, to increase their revenue and customer satisfaction. By understanding the satisfactory level of personalization, which may depend on one's demographic characteristics, marketers may be able to better shape the content (Boerman et al., 2017; Swart, 2021). This may increase their revenue and customer satisfaction, which consequently, increases the revenue of social media platforms, as advertising is their main source of revenue (McFarlane, 2022; Nidhi, 2021). Lastly, the results of this research can be beneficial for social media companies to further improve and develop better recommender systems, which may lead to new technological innovations (Bandy, 2021).

1.2 Chapter outline

After introducing this research and its relevance, as well as providing the research question, the next chapter will discuss the theoretical framework of this research. There, the findings from existing research will be discussed and the hypotheses will be established. Afterward, the Methods chapter provides details on the research design, including the sample, operationalization, and research ethics. Later, the Results chapter provides an overview of the results by accepting or rejecting the proposed hypotheses. Lastly, the last two chapters discuss the findings by connecting them to the existing research, provide the answer to the research question, as well as discuss the implications, limitations, and suggestions for future research.

2. Theoretical framework

While algorithms highly impact people's lives and identities, research on people's perceptions of algorithms is very limited and urges to cover the gap (Taylor and Choi 2022; Xie et al., 2022). This chapter of the thesis provides an overview of the factors that impact people's responses to personalized content and the hypotheses of this research. Figure 1 presents the research model where it is proposed that algorithm awareness has an impact on algorithm responsiveness which has an impact on surveillance concerns and personalized content avoidance.

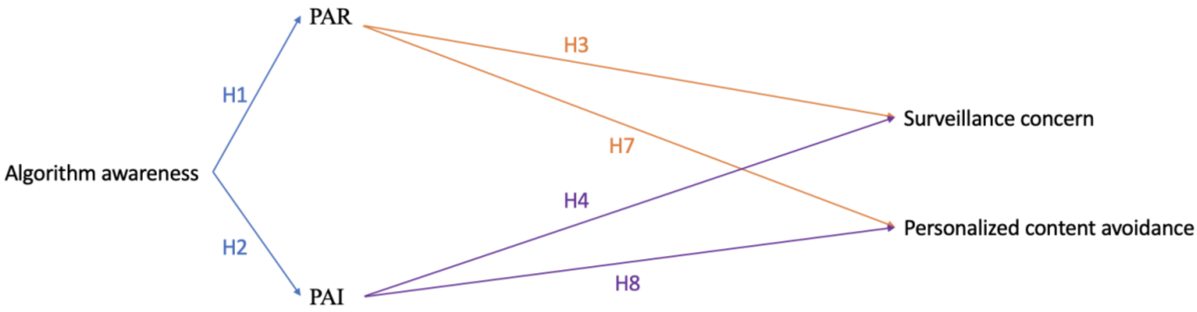


Figure 1: Research model

2.1 Relationship between user identity and algorithms

With the emergence of algorithms on social media, social media platforms are no longer neutral spaces where individuals have all the agency to determine their preferred self-representation, which is the collection of objects that represent one's self (Bhandari & Bimo, 2022). Nowadays, people's self-representation is a part of larger economic infrastructures, where companies utilize personal data to create personalized content to increase their profit. Such personalized content controls people's identity as algorithms categorize users based on their online behavior and determine which content is presented on their social media feeds (Bhandari & Bimo, 2022). Thus, individuals construct their identity via algorithmic categorization and refer to it as algorithmic identity (Karizat et al., 2021).

Since personalized content presents a particular perspective, algorithms define how people view themselves and others, which shapes their identity and sense of self (Taylor and Choi 2022). Through personalized content, users learn about the explicit social labels that the platform attributed to them, as it reflects that they exhibited such traits when interacting with the platform (Summers et al., 2016). By encountering such social labels, individuals become encouraged to explore them in relation to their self-perception, and if the label fits their identity, people would like to behave consistently with it, making it a part of their identity. While some consequences of social labels may be positive, for instance, when a person was interested in light-saving bulbs that signals to the algorithm to employ a sustainability label, it was also found that algorithms may prioritize some characteristics of a person while undermining other. For instance, it was found that marginalized social identities, like Queer identity, are suppressed by the algorithm which impacts one's experience and behavior (Karizat et al., 2021). As algorithms do not possess sentience, which includes understanding and meaning-making, they are seen as reductive, as human identity is too complicated for algorithms to understand which leads to algorithmic biases (Bishop, 2021; Ytre-Arne & Moe, 2020). Additionally, it was also found that in general, useres like to receive personalized content that is based on diverse traits of their self.

Nevertheless, it can be argued that the abovementioned perspectives of the relationship between algorithms and users undermine user agency, therefore, algorithms should not be perceived as isolated entities (Zarouali et al., 2021). Recent research argues that the relationship between algorithms and the user is dynamic and is based on co-production where both the algorithm and user change reciprocally (Karakayali et al., 2017). Siles et al. (2020) argue that as users perceive that they are interacting with the platform, they believe that they and the algorithm hold particular roles in their relationship and are required to conduct specific tasks. It has been proposed that users and algorithms are interconnected through a feedback loop, where users believe that that algorithm has to continuously improve the relevancy of personalized content, while users have to train the algorithm by providing feedback on the given personalized content, by either liking that content or purposefully rewatching it (Siles et al., 2020). Thus, while people shape the algorithms with their choices online, algorithms also shape people, by requiring them to self-reflect and by mediating people's relation to society and themselves.

Because people believe that algorithms know them well, scholars examine the relationship between the algorithm and the user through the scope of interpersonal relationships. Karakayali et al. (2017) argue that algorithms can be referred to as intimate experts who users both have constant dialogue with and also see algorithms as experts, like doctors. Siles et al. (2020) argue that users engage in mutual personalization, where they shape the algorithm with their personality traits while perceiving the algorithm as a human-like entity. People base their behavior with the algorithm on their existing understanding of friendship, which is usually based on their personal background, which also determines the positive or negative perception of algorithms. Additionally, people believe that algorithm has a necessary surveillance role which is justified by receiving accurately personalized content (Siles et al., 2020).

2.1.1 Algorithm responsiveness

Similar to the above-mentioned interpersonal relationship approaches to the relationship between the algorithm and the user, Taylor and Choi (2022) expand the notion of responsiveness. Responsiveness was initially discussed in the context of intimate partners, and it refers to the process where people perceive that their partner is supportive of the core aspects of their identity, by reacting to their personal information with care, which increases the intimacy in their relationships. As the concept of responsiveness was utilized in diverse fields, including the communication between humans and robots, responsiveness has been recognized as the general concept of interpersonal interaction. Taylor and Choi (2022) expand the idea of responsiveness to algorithm responsiveness since people tend to treat their relationship with machines through the usual scope of interpersonal interactions. Algorithm responsiveness is used to explain the relationship between algorithms and users, where if algorithmically curated content accurately relates to user goals and identity, users can better understand their identities and increase engagement with such content. To understand people's perceptions of algorithms, current research is mainly focused on folk theories, which are people's 'theories' on the way algorithms work which guide their behavior when engaging with algorithms (Karizat et al., 2021). One of the main folk theories uncovered that users aim to perceive algorithms with respect to their own identity and people rely on the theories to negotiate their self-perception with the representation provided by algorithms. Taylor and Choi (2022) argue that it is perceived instead of real responsiveness that impacts one's identity and behavior.

Algorithm responsiveness consists of two dimensions, perceived algorithm responsiveness (PAR) and and perceived algorithm insensitivity (PAI). PAR describes user belief that algorithms understand and support them by providing relevant content, whereas, PAI represents the opposite, where user belief that algorithms misunderstand their self by providing irrelevant content. By analyzing PAR and PAI, one can determine people's perception of the connection between their algorithmic and actual identities. Similarly to the responsiveness process between intimate partners, algorithm responsiveness begins with people's self-disclose through their digital traces, like views, based on which, algorithms then provide personalized content. Afterward, users recognize personalized content and assess the level of responsiveness of the algorithm. Lastly, users produce the outcome, by behaving according to the personalized content. Similar, to the abovementioned perspectives of the relationship between algorithms and users, Taylor and Choi (2022) argue that the responsiveness process is cyclical, where by interacting with the personalized content, both algorithms, and users change reciprocally.

2.2 Importance of algorithm awareness

Taylor and Choi (2022) argue that algorithm awareness is a prerequisite for people to establish their perception of algorithms, however, there is a gap in the research on user perception of algorithms (Zarouali et al., 2021). Additionally, there is a gap in the research analyzing how personalized content can impact people's algorithm awareness and how individual's algorithm awareness impacts their relationship with algorithms (Boerman et al., 2017). Current research on human-algorithm interaction mainly focuses on folk theories that represent people's awareness of the existence of algorithms that guides user's behavior and can shape both algorithm and the user (Taylor and Choi 2022). Lomborg and Kapsch (2019) argue that, instead of folk theories, scholars should rather use the concept of decoding as it addresses the fact that people fill the gaps in their understanding of algorithms with their existing knowledge and background. One can argue that both folk theories and the concept of decoding indicate that people have limited knowledge about algorithms and rely on their own perceptions.

While most research found that people generally have limited knowledge about the algorithm, some findings indicate contradicting results, where people argue that they are generally aware of algorithms (Segijn et al., 2022). Algorithm awareness, in this context, is the accuracy of people's perceptions of the way algorithms function (Zarouali et al., 2021). Since in recent years, there is an increase in negative media coverage about algorithms and personalized content, like the Cambridge Analytica scandal, people are becoming increasingly aware of algorithms, especially on social media (Segijn et al., 2022). Besides media coverage, people may also gain knowledge about algorithms from interactions with others or formal learning (Oeldorf-Hirsch, 2021). Additionally, as folk theories suggest, people become aware of algorithms by interacting with the platform and noticing a change in personalized content, where algorithms may present more relevant or irrelevant content (Cotter, 2020).

Nevertheless, scholars agree that there is an information asymmetry between platforms and users, because while platforms have an extensive amount of information about users, the users have limited knowledge of how their data is utilized (Boerman et al., 2017). Additionally, it is nearly impossible for users to understand how algorithms work, due to the large opaqueness and covertness that surrounds tracking and personalization on social media (Eslami et al., 2016). The lack of transparency about personalized content is usually justified by the platform's need to protect intellectual property, as well as, by platform's goal to create a seamless design, where users believe that they receive relevant content without making any effort (Eslami et al., 2016). Hence, individuals generally do not know the extent of data collection and are usually not aware that personalized content is based on their behavior, and not only on the developer's choices (Zarouali et al., 2021). They also do not know that personalized consent is based on dominant commercial, political, social, and cultural logics, and may rely on the content on their social media platforms by believing that it is objectively trustworthy (Cotter, 2020). While by engaging with algorithms, people may establish folk theories, Boerman et al. (2017) argue that such mental models can be misconceptions. People undervalue the negative consequences of algorithms and are not aware how and why they should protect their privacy (Xie et al., 2022). Additionally, people often believe that the collection of personal data is an acceptable cost of free services on social media (Boerman et al., 2017) which naturalizes and justifies issues of surveillance (Siles et al., 2020).

While scholars found differences in perceptions of algorithms based on algorithm awareness, Taylor and Choi (2022) argue that initially, algorithm awareness leads to lower satisfaction with a platform while then, it leads to higher satisfaction, as people establish competence when using it. It should also be stated that Taylor and Choi (2022) found that algorithms responsiveness and algorithm awareness are theoretically different concepts since being aware of algorithms does not mean that people perceive algorithms as responsive to their identity. As Taylor and Choi (2022) only argue that algorithm responsiveness depends on algorithm awareness and found that people who are aware of algorithms view PAR slightly positively and PAI slightly negatively, this research aims to understand how perceived algorithm responsiveness and perceived algorithm insensitivity changes based on the level of algorithm awareness. Additionally, following the method and the aforementioned findings of Taylor and Choi (2022), PAR and PAI are studied separately to uncover if there are differences in people's perceptions of highly personalized or irrelevant content based on their algorithm awareness. This is further essential as there are contradictions in people's perception of the level of personalized content, where some personalized content is accepted and some is rejected (Boerman et al., 2017; Kozyreva et al., 2021).

Furthermore, this study examines the relationships between algorithm awareness and PAR and PAI separately, as the results of existing research may be considered contradictory. Particularly, other research found that people with low algorithm awareness have a more neutral perception of algorithms while people with high algorithm awareness have a more negative perception of algorithms (Kozyreva et al., 2021). Additionally, other research found that people receiving highly relevant content feel a lack of autonomy and control because they are aware of being constantly watched by external parties, which relates to algorithm awareness (Boerman et al., 2017; Segijn et al., 2022). Nevertheless, it can be argued that these findings are contradictory to the finding of Taylor and Choi (2022), where people who are aware of algorithms view PAR slightly positively and PAI slightly negatively. Additionally, existing research reported that in general, people are positive about relevant personalized content as it reduces the cognitive load when searching for content (Aguirre et al., 2015). One can argue that the positive perception of the relevant personalized content can be related to the perception of the relationship between algorithms and users from the scope of interpersonal relationships. People appreciate the increase in relevance of personalization, as they consider it as an effort from the entities that they previously engaged with (Eg et al., 2023). If people consider algorithms being responsive, they showcase increased engagement with such content as it allows them to better understand their identities (Taylor & Choi, 2022). On the other hand, if algorithms are not responsive to people's identities, especially if algorithms suppressed a part of their identity, people perceive such personalization more negatively (Karizat et al., 2021). Due to the aforementioned findings and as this research follows the research of Taylor and Choi (2022), it is proposed that *Higher algorithm awareness increases PAR (H1)* while *Higher algorithm awareness decreases PAI (H2).*

2.3 Perceptions of algorithms

Aguirre et al. (2015) argued that algorithm awareness shapes the way people perceive the situation and behave in the future. Cotter (2020) found that the level of personalization affects people's algorithm awareness, as people notice changes in content which leads to a particular perception of personalized content. When people feel in control of their online activities, they are less aware of algorithmic curation (Dogruel et al., 2020). Nevertheless, when people notice a change in personalization, where it can become highly relevant or highly irrelevant, they become aware of the presence of algorithms. In such cases they feel a loss of autonomy and freedom of choice leading to a negative perception of algorithms. Additionally, when people learn that personalized content is based on user data, they feel vulnerable, threatened, and manipulated and are guided by their fear as they perceive such personalization as a violation of privacy and social norms (Moore et al., 2015). Such personalization is viewed as intrusive and leads to digital irritation, which can be noticed in feelings of anger, frustration, or annoyance (Ytre-Arne & Moe, 2020).

While in most cases scholars found that higher relevance of personalized content leads to a negative perception of algorithms (Boerman et al., 2017), some scholars found that people expressed positive feelings with higher personalization (Eg et al., 2023). Aguirre et al. (2015) found that people want higher personalization, as it reduced cognitive overload in finding relevant content to satisfy their needs. It was found that even with higher algorithm awareness, people express higher satisfaction and appreciation of higher content relevance (Eg et al., 2023). Moreover, users appreciate higher relevance of personalization from the parties that they previously engaged with, as it showcases that these parties made additional efforts to satisfy their customers (Eg et al., 2023). Due to such contradictions in people's perception of algorithms and acceptance of personalized content, where in some cases highly personalized content is perceived as threatening and some is perceived as satisfying, it is crucial to further explore why some personalized content is accepted and some is rejected. This research is particularly interested in exploring surveillance concerns and personalized content avoidance, which were not the focus of previous research but seem to be vital in people's acceptance of personalized content.

As surveillance became the business model of social media channels, every personalized content is a reminder that one is being under a constant external gaze that will then exploit such knowledge (Harborth & Pape, 2020; Siles et al., 2020). It was found that users believe that platforms utilize creepy tactics where they stalk, track, gather, and utilize one's data (Boerman et al., 2017). While people believe that platforms know too much personal information and highly personalized content leads to a feeling of losing control and freedom from being constantly surveilled, it is not clear when people perceive such data collection as being too extensive. Segijn et al. (2022) found that higher algorithm awareness may be essential to increase people's surveillance concerns, as individuals may perceive it as a violation of their rights and increase their concerns about their autonomy and privacy, which would lead to a negative perception of algorithms. In this research, surveillance concern is the perception that one is being watched by someone who gains personal information (Segijn et al., 2022).

Prince et al. (2021) found that by acquiring higher privacy literacy, people feel higher privacy concerns. Additionally, when people become aware that the platform shares the data with external parties, they become more skeptical about personalization. Since in recent years, the majority of people became more aware of negative issues surrounding data collection on social media, most people also increasingly expressed their privacy concerns and argued for the need for the protection of their data (Boerman et al., 2017). As there is no previous research analyzing surveillance concerns in the context of algorithm awareness and level of personalization, this research aims to cover that gap and proposes that *PAR increases surveillance concerns (H3)* and *PAI increases surveillance concerns (H4)* and that *PAR mediates the relationship between algorithm awareness and surveillance concerns (H5)* and *PAI mediates the relationship between algorithm awareness and surveillance concerns (H6)*.

Personalized content avoidance is considered as an act of user agency of regaining freedom of choice and control over personalized content. Personalized content avoidance describes user actions to reduce exposure to the content, such as skipping content or not interacting with it (Baek & Morimoto, 2012). As people believe that they can work with an algorithm and direct it to show more relevant content, they may change their online behavior to instruct algorithms to present content that aligns better with their interests (Karizat et al., 2021). The aforementioned can also be enacted if an individual becomes aware of their algorithmic identity that does not align with their preferred self-perception which may also undermine their marginalized social identity (Karizat et al., 2021). Either, people can change their behavior to avoid highly personalized content because people express their dissatisfaction when algorithms show repetitive content (Bhandari & Bimo, 2022).

Previous research found that algorithm awareness may be fundamental to the relationship between personalized content avoidance and the relevancy of content. When people get to know about data collection practices, they experience a chilling effect with the need to change their behavior (Boerman et al., 2017). In such cases, they feel highly vulnerable and perceive a high risk of privacy violation and intrusion which leads to a lower positive perception of personalization and its avoidance. Nevertheless, it was found that when people are already aware of algorithms, their positive intentions toward personalized content remain unchanged (Boerman et al., 2017). Interestingly, it was found that in some cases, an increase in personalization increased people's positive responses, while in some cases, it lead to personalized content avoidance (Boerman et al., 2017). Since previous findings suggest highly contradicting findings regarding personalized content avoidance, this study aims to cover the gap and proposes that *PAR increases personalized content avoidance (H7)* and *PAI increases personalized content avoidance (H8)* while *PAR mediates the relationship between algorithm awareness and personalized content avoidance*

(H9) and *PAI mediates the relationship between algorithm awareness and personalized content avoidance (H10).*

Lastly, previous research also found contradicting results regarding the impact of time spent on the platform and age on the relationship between algorithm awareness, perception of personalized content. In general, it is argued that social media are experience technologies and it was found that most frequent users, which is usually the younger generation, would have more competence and experience with the platform, leading to higher algorithm awareness (Cotter, 2020). Still, some findings indicated that such folk theories would be most likely misconceptions. Yet, in some cases, such experience would lead to fewer privacy concerns, as such users would be more used to conducting their activities online and would have higher awareness of privacy-protective techniques (Boerman et al., 2017). In other cases, more experienced users would have higher criticism about personalized content and higher surveillance concerns, as well as, it was found that younger adults are more likely to adopt privacy-protective behavior (Cotter, 2020; Kezer et al., 2016). Due to the aforementioned contradicting findings and limited excising research, this research will also control if time spent on social media and age would impact the relationships between algorithm awareness, algorithm responsiveness, surveillance concerns, and personalized content avoidance.

Since most research on user perception of algorithms on social media is usually focused on the United States as a target population, its results may not be generalizable to other countries and urge to cover the gap (Hargittai et al., 2020). As previous research found that people in the Netherlands value diverse content, it is interesting to analyze their perception of algorithms on Instagram, as it is the third-most-used platform in the Netherlands (Bodó et al., 2018; Statista, 2022). This research is particularly interested in analyzing the awareness and perception of both Dutch and international people living in the Netherlands, as one’s awareness and perception is shaped by the society that the individuals live in (Riley, 1996). As people in the Netherlands value diverse content and the government aims at protecting personal data, it is assumed that such values may be shared throughout the population, regardless of one’s nationality, as there is a high proportion of international people living in the Netherlands (Leiden University, 2017). In the next chapter, the method of this research will be discussed, after which, the results and discussion will be provided.

3. Methodological framework

This chapter discusses the method of this research and provides details into research design, sampling, operationalization, and further data analysis.

3.1 Justification of the method

This research takes a quantitative method to analyze “to what extent does algorithm responsiveness explain the impact of algorithmic awareness on personalization concerns of Instagram users living in the Netherlands?”. Particularly, a survey was conducted as it is useful to investigate the complex relationships between several variables (Babbie, 2016), which are algorithm awareness, algorithm responsiveness, surveillance concerns, and personalized content avoidance. Additionally, as this research explores the impact of algorithm awareness on the perception of algorithms, it is interesting to understand changes in people’s perception of algorithms based on the level of their algorithm awareness. Thus, this research conducted a survey experiment, where by manipulating the level of algorithm awareness, the causal relationship between algorithm awareness and user perception of algorithms can be determined (Gaines et al., 2007). By randomly assigning participants into three groups, where the level of algorithm awareness is manipulated, the researcher can uncover the change in people’s perception of algorithms based on their algorithm awareness. Furthermore, conducting a survey is beneficial as it allows the researcher to control for other variables, like time spent on Instagram and age, which may also be important factors in the relationship between algorithm awareness, algorithm responsiveness, and the perception of algorithms.

Another reason for conducting a survey experiment and its main benefit is the ability to gain a comprehensive view that can be generalized to a particular population (Babbie, 2016). Since it can be challenging to find participants that are representative of the study population, a survey allows the researcher to reach the target population and parts of its underrepresented population. Additionally, the accessibility of an online survey experiment may motivate people to participate in the study, as it demands fewer resources, like time, than a traditional experiment in a fully controlled environment. Thus, by conducting a survey experiment, it is feasible for the researcher to gain a representative population which benefits the generalizability of the findings (Babbie, 2016). Lastly, as this research aims at expanding the research by Taylor and Choi (2022), it follows their quantitative methodology, as it proved a significant relationship between algorithm responsiveness and algorithm awareness from the conducted survey.

3.2 Sample

As described in the previous chapters, this research is interested in analyzing the relationships between algorithm awareness, algorithm responsiveness, and perception of personalization based on user experiences using Instagram. Therefore, utilizing Instagram is the first sampling criteria of this research. As described in the theoretical framework of this research, it is interesting to uncover the perceptions of people living in the Netherlands, thus the second sampling criteria is living in the Netherlands. As this includes both Dutch and international people living in the Netherlands, the survey was created in English and no question about nationality was asked.

Age is the last sampling criteria, as people with higher usage of the platform have higher algorithm awareness, which is of interest in this research (Boerman et al., 2017). Thus, people from 18 to 64 were recruited, as they considerably use Instagram in the Netherlands (Statista, 2023). Therefore, the unit of analysis in this research is people living in the Netherlands who are from 18 to 64 years old and use Instagram. To gain a representative sample, the survey invitation did not mention age requirements but stated that people living in the Netherlands who use Instagram are recruited. This research utilized non-probability sampling, a snowball sampling, where when sharing the invitation to participate in the study, participants were asked to share the survey with their social network (Etikan et al., 2016). The reason to use such a sampling technique and its main advantage is the ability to gain enough participants that are part of a study population. Nevertheless, this may also lead to a disadvantage of using snowball sampling, as participants may share the survey with people alike, like their friends or family, who have similar knowledge or perception (Etikan et al., 2016). This may create a non-representative population, as such participants may not be representative of all people living in the Netherlands, which can lead to a lack of generalizability of the findings.

To find the participants, the survey was shared on several websites, like SurveySwap and SurveyCircle, where the researcher had to first gain credits by answering surveys of other researchers and then give credits to people who answer their survey. The survey was also shared on Instagram and Facebook, as they are both owned by Meta and may have similar users. On such platforms, the survey was also shared on the researcher’s personal network. Additionally, it was shared on Instagram’s and Facebook’s public groups, like ‘Privacy: Public’ and ‘Security and Privacy’ where topics related to one’s data are discussed, as well as, in groups like ‘Survey Exchange’ where researchers share their survey to find participants. Such public groups were also found on Reddit and the survey was also shared with Reddit users.

In total, there were 216 participants in the study, out of which, 125 participants satisfied the sampling criteria of this research. Furthermore, 16 participants were excluded due to an unsatisfactory attention check and 2 participants were excluded due to spending less than 40% of the median response time on the survey. Therefore, there were 107 participants eligible for the analyses of this research. As it was a survey experiment, participants were randomly divided into three experimental groups. The group that received the long explanation of algorithms was the smallest (N = 33), while the group that received the short explanation was the largest (N = 38). It should be stated that 19.6% of respondents were 22 years old (M = 27.38, SD = 7.36) and 67.3% of respondents were female.

3.3 Procedure

The survey was created on Qualtrics, the access to which was granted by Erasmus University Rotterdam. At the beginning of April 2023, firstly, a pre-test was conducted, where 9 people from the target population were asked to participate in the study and provide their feedback regarding the questions or the flow of the survey. The feedback from the pre-test group was useful to determine the time spent on the survey and while reading the explanations of algorithms. Furthermore, based on the feedback from the pre-test group, the two explanations of algorithms were slightly shortened to ensure that participants read the explanations carefully. Moreover, the pre-tests served as a confirmation of a successful random assignment of participants to the experimental conditions. When the survey was finalized considering the feedback from the pre-test respondents, the survey was shared on all the aforementioned platforms with an invitation to participate. The survey was available for 26 days and it took approximately 5 minutes to complete. The survey can be found in Appendix A.

At the beginning of the survey, informed consent was asked which describes the overall topic, the average time to complete it, and emphasizes that answers are anonymous and confidential. If consent was granted, participants were asked to specify their age, gender, and if they reside in the Netherlands. Afterward, they were asked if they use Instagram and two questions were asked to measure how often they use it. Three aforementioned questions, which are consent, their residency, and the use of Instagram served as sampling criteria for this research, consequently, if participants did not fit them, they were transferred to the end of the survey. If sampling criteria were satisfied, people are randomly assigned to three groups where algorithm awareness was manipulated. One of such groups did not receive an additional question, while two other groups received an additional question where the function of algorithms was explained. Additionally, one of the two groups received a more elaborate explanation of the negative consequences of algorithms. Afterward, three groups were given the same questions. First, questions for algorithm responsiveness were asked, after which, questions for surveillance concerns, personalized content avoidance, and algorithm awareness were provided. At the end of the survey, participants were thanked for participation, offered a summary of this research, and provided the researcher's email. The end note also included the codes to gain credits in SurveySwap and SurveyCircle.

It should be stated that to ensure validity, one question was an attention check asking participants to select 'Strongly agree' to exclude participants who were not focusing on the survey. Additionally, the additional questions about the explanation of algorithms included timers with an average time to read provided explanations, which were 7 and 25 seconds for simple and elaborative explanations, respectively. Furthermore, to ensure that participants did not miss essential questions, the questions related to the sampling criteria included a function of a mandatory response, while other questions had a reminder in case participants missed a question.

3.4 Stimuli

It should also be stated that this research utilized ChatGPT to create stimuli by specifying to "explain what are algorithms on social media" and "what are risks of algorithms on social media". The researcher further improved the output from ChatGPT to ensure that the explanations did not cover irrelevant details and were short enough for participants to read it carefully. Additionally, the researcher simplified the wording of the explanations by avoiding terminology like 'computational processes' when explaining algorithms or 'filter bubbles' when referring to its effects. The simple explanation of what are algorithms, which includes the fact that algorithms utilize user behavior to create personalized content, was given to two manipulated groups. One such group had an additional paragraph explaining the dangers of algorithms, like biased content or dangers of privacy. The overview of the stimuli can be found in Appendix A, where the whole survey is included. By providing the same simple explanation and adding the dangers of algorithms, one can analyze the change in people's perception by comparing the results of both conditions. Thus, by looking at three conditions, where there was no explanation given, where there was a simple explanation provided, or where the dangers of algorithms were also included, one can understand the impact of the manipulated level of algorithm awareness.

3.5 Operationalization

Most questions were measured with 7-point Likert scales by asking participants to what extent they agree to the following statements (Strongly agree, Agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Disagree, Strongly disagree), as such scale allows seeing smaller differences in people's answers (Preibusch, 2013). For some questions, like demographics, a multiple-choice question was asked and for two other questions, age and precise time spent on Instagram, an empty field where respondents type their answer was given. After excluding participants who did not satisfy the sampling criteria of this research and before conducting mediation analyses, factor and reliability analyses were conducted, based on which, some questions from the initial scales were excluded.

3.5.1 Algorithm responsiveness

Based on Taylor and Choi (2022), 15 questions were asked to measure algorithm responsiveness. As this research suggests different user perceptions and results for PAR and PAI and because Taylor and Choi (2022) analyzed them separately, this research also analyses them separately. To measure PAR, a belief that algorithms provide relevant content, 8 questions are asked. PAI, which is a belief that algorithms provide irrelevant content, is measured by 7 questions. The questions for PAR and PAI are almost identical, as the questions measure the opposite. For instance, '… understands me' and '… is attentive to my needs' compared to 'Instagram does NOT really understand my wants and needs'. The 15 items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on the two-factor solution originating from Taylor and Choi (2022), KMO = .86, $\chi2$ (N = 107, 105) = 938.08, p <.001. The resultant model explained 57.8% of the variance in algorithm responsiveness. The results for factor and reliability analyses can be found in Table 1. During factor analysis, questions 'is attentive to my needs' and 'is responsive to my needs' loaded for both PAR and PAI. Nevertheless, as the sign of loading values for the aforementioned questions matched the signs of other questions in PAR and did not match the sign of questions for PAI, the aforementioned questions were assigned to PAR, as proposed by Taylor and Choi (2022). In this research, Cronbach's alpha for PAR is .96 while for PAI is .90.

Table 1. Factor loadings and reliability analyses for algorithm responsiveness (N=107)

Item	*PAR*	*PAI*
The Instagram algorithm...		
... really listens to me	.88	
... responds to what I am thinking and feeling	.95	
... understands me	..62	
... tries to see where I'm coming from	.60	
... is attentive to my needs	.42	(-.43)
... is responsive to my needs	.46	(-.47)
... takes my interests seriously	.51	
... really gets who I am	.48	
... does NOT understand my feelings and concerns		.65
... ignores who I am		.97
... dismisses my interests		.75
... seems to ignore the things that are most important to me		.87
... does NOT really understand my wants and needs		.72
... does NOT really take my personal interests seriously		.82
... often does NOT listen to my needs		.75
Eigenvalue	1.58	7.20
Cronbach's α	.96	.90

3.5.2 Algorithm awareness

Based on Taylor and Choi (2022), algorithm awareness, which is the accuracy of people's perceptions of the way algorithms function, was measured through *content filtering* and *human-algorithm interplay* (Zarouali et al., 2021). Thus, this research also analyzed algorithm awareness based on the above-mentioned variables. Content filtering measures people's awareness that content is personalized based on their data, where 4 questions, like

‘Algorithms are used to recommend posts to me on Instagram’ were asked. For human-algorithm interplay, 3 questions were asked measuring people’s awareness that their behavior influences the personalized content, like ‘The posts that algorithms recommend to me on Instagram depend on my online behavior on that platform’. The 7 items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .73, $\chi 2$ (N = 107, 21) = 233.43, p <.001. The resultant model explained 60.7% of the variance in algorithm awareness. The results for factor and reliability analyses can be found in Table 2. While factor analysis revealed two components with Eigenvalues > 1.00, which indicates human-algorithm interplay and content filtering, the question ‘Algorithm are used to show someone else different posts than I get to see on Instagram’ loaded on human-algorithm interplay. Thus, the aforementioned question was assigned to human-algorithm interplay, with Cronbach’s alpha of .71, while based on Zarouali et al. (2021) it is a part of the content filtering scale. During reliability analysis for content filtering, the question ‘Algorithms are used to tailor certain posts to me on Instagram’ was deleted as it increased Cronbach’s alpha by .05. Thus, the variable content filtering was created with 2 items and Cronbach’s alpha of .88. Questions for algorithm awareness were manipulation checks, as at the beginning of the survey, two experimental groups were provided with explanations of algorithms, and one of them was also provided with negative consequences of algorithms. By comparing the algorithm awareness of three experimental groups, after the manipulation, the research aims to uncover if gaining higher algorithm awareness would increase dissatisfaction with algorithms and surveillance concerns.

Table 2. Factor loadings and reliability analyses for algorithm awareness (N=107)

Item	*Human-algorithm interplay*	*Content filtering*
The posts that algorithms recommend to me on Instagram depend on my online behavior on Instagram	.55	
The posts that algorithms recommend to me on Instagram depend on my online behavioral data	.96	
The posts that algorithms recommend to me on Instagram depend on the data that I make available online	.93	
Algorithms are used to recommend post to me on Instagram		.94
Algorithms are used to prioritize posts on Instagram above others		.85
Algorithms are used to tailor certain posts to me on Instagram		.51
Algorithms are used to show someone else different posts than I get to see on Instagram	.57	
Eigenvalue	3.13	1.12
Cronbach's α	.71	.88

3.5.3 Surveillance concerns

Based on Segijn et al. (2022) 3 questions, such as 'I believe that my Instagram viewing habits are monitored at least part of the time', were asked to measure surveillance concerns. In this research, surveillance concerns is the perception that one is being watched by someone who gains their personal information. The 3 items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .57, $\chi 2$ (N = 107, 3) = 169.84, p <.001. The resultant model explained 70.4% of the variance in surveillance concerns and, as expected, only one component was extracted with Eigenvalues > 1.00. During reliability analysis, the question 'I believe that my Instagram viewing habits are monitored at least part of the time' was removed as Cronbach's alpha for surveillance concerns increased from .89 to .94. The results for factor and reliability analyses can be found in Table 3, which also includes the results for personalized content avoidance while the variables were not analyzed together.

3.5.4 Personalized content avoidance

Nyheim et al. (2015) asked 5 questions, like ‘I intentionally ignore any personalized content on Instagram’, in the scale ad avoidance. This research utilized this scale to measure personalized content avoidance, describing user actions to reduce exposure to the content (Baek & Morimoto, 2012). Nevertheless, this research did not include the question 'I have asked marketers to take me off their email (email and telephone) lists' from the scale ad avoidance as it does not fit the aim of this research. The 4 items were entered into factor analysis using Principal Components extraction with Direct Oblimin rotation based on Eigenvalues (> 1.00), KMO = .73, $\chi 2$ (N = 107, 6) = 176.20, p <.001. The resultant model explained 66.1% of the variance in personalized content avoidance. As expected, only one component was extracted with Eigenvalues > 1.00, and the variable personalized content avoidance was created with Cronbach’s alpha .83. The results for factor and reliability analyses can be found in Table 3.

Table 3. Factor loadings and reliability analyses for surveillance concerns and personalized content avoidance (N=107)

Item	*Surveillance concerns*	*Personalized content avoidance*
I believe that my Instagram viewing habits are monitored at least part of the time	.61	
I am concerned that companies are collecting too much information about my Instagram viewing habits	.94	
I am concerned that companies may monitor my Instagram viewing habits	.93	
I intentionally ignore any personalized content on Instagram		.91
I hate any personalized content on Instagram		.91
It would be better if there were no personalized content on Instagram		.79
I discard personalized content on Instagram immediately without opening (reading, watching, or listening to) it		.80
Eigenvalue	2.11	2.75
Cronbach’s α	.94	.83

3.6 Research ethics

The main ethical consideration of this research is grounded in the nature and the drawback of experiments. As the invitation to participate in the research and the informed consent did not state that people will be participating in a survey experiment but only presented it as a survey, people may feel deceived, as they were not aware of the true manipulative nature of this research (Gaines et al., 2007). Nevertheless, the topic of this research is not sensitive and an overall description of the study is provided in the consent. Furthermore, at the end of the survey participants were debriefed on the deceptive nature of experimental research which stated that they participated in a survey experiment. Additionally, people under 18 years old were not recruited and because it is an online survey experiment, it ensures that people feel comfortable participating in the familiar sittings instead of a fully controlled environment like in traditional experiments. Moreover, informed consent highlighted that the survey was anonymous and that data was treated confidentially, which also eliminates social desirability bias (Pallant, 2016)

The research ethics connected to validity and reliability of this research should also be discussed. By having a large sample of this research (N=107), as well as, conducting a pre-test prior to starting the data collection, validity of this research is ensured. Reliability is also ensured by presenting questions identically to each participant and phrasing them simply. By utilizing existing valid scales and following similar existing research, reliability is ensured (Pallant, 2016). Validity is further strengthened by making an attention check, placing the timer for the additional explanations of algorithms, and having a function of either a mandatory response or a reminder in case participants missed a question. Lastly, by checking the time spent on the survey and excluding people who took the survey too fast, during the data analysis, validity is further granted.

3.7 Data analysis

When data was collected, it was transferred to SPSS. The data was first cleaned, where the cases that did not satisfy the sampling criteria of this research were removed, and the missing cases were specified to not eliminate participants who missed several questions. It should be stated that while the survey included two questions to measure participants' time spent on Instagram, only the question 'How many times do you check Instagram per day?' was utilized for the analysis. This was due to the fact that it included more accurate values of their time spent on Instagram, where in some cases, the researcher calculated the average of the input. Then, the data was analyzed for descriptive statistics, reliability analysis, and factor analyses, and the final variables were created (Pallant, 2016). Afterward, the PROCESS macro was utilized to conduct Mediation Regression analysis and uncover differences between three experimental groups. In this research algorithm awareness is an independent variable, PAR and PAI are mediators, while surveillance concern and personalized content avoidance are dependent variables. Time spent on Instagram is a control variable. The following chapter discusses the result of this research in relation to the proposed hypotheses. Afterward, the discussion and conclusion are provided.

4. Results

Prior to examining the proposed hypotheses of this research, descriptive, reliability, and factor analyses, as well as, the manipulation check were conducted. Additionally, a test for normality, though measures of Skewness and Kurtosis, demonstrated that the scales for algorithm awareness, algorithm responsiveness, surveillance concerns, and personalized content avoidance are normally distributed, as their values are between -3 and +3. After the aforementioned assumption checks, the hypotheses can be tested. For that, this research conducts mediation regression analyses to uncover the relationships between algorithm awareness, algorithm responsiveness, and perception of algorithms, in the presence of control variables, age and time spent on Instagram, which are added in all the analyses. This research utilizes PROCESS macro model 4 to conduct mediation regression analyses for all the relationships between the variables. This chapter reports on the results of this research, by accepting or rejecting the hypotheses. As the experimental design did not have a significant effect on the self-reported awareness manipulation check, it could be argued that the manipulation of the level of algorithm awareness was potentially not as effective as expected. Hence, this research also conducted analyses based on the scales of algorithm awareness, which are discussed after the results of the experimental design. The next chapter discusses the results of this research in the context of the theoretical framework, after which, the conclusion with implications, limitations, and suggestions for future research are provided.

4.1 Relationships based on the experimental design

This research conducted a survey experiment where the level of respondents' algorithm awareness was manipulated by either giving an additional question with a short or long explanation of algorithms or not providing an explanation at all. By utilizing PROCESS macro and Mediation Regression analysis, the differences between people who read the short explanation of algorithms compared to people who did not receive any explanation, as well as, the differences between people who read the long explanation of algorithms compared to people who did not receive any explanation can be uncovered by looking at the standardized coefficients. This section first reports on the first step of Mediation analysis, which includes testing of H1 and H2, which are identical in both models of this research. After which, the second step with both dependent variables is discussed separately. The results of this Mediation analysis are illustrated in Figure 2.

4.1.1 Algorithm awareness and algorithm responsiveness

As a first step of Mediation Regression analysis, H1 and H2 are analyzed. For H1, 'higher algorithm awareness increases PAR', the model is not found to be significant, $F(4, 89) = 2.49$, $p = .167$, $R^2 = .10$, thus, there is no relationship found between algorithm awareness and PAR. As the *p*-value is higher than .05, there are no significant relationships found between algorithm awareness (short explanation vs. no explanation, and long explanation vs. no explanation) and PAR, thus, H1 is rejected. The effects of receiving a short explanation compared to not receiving any explanation did not have a significant impact on PAR, where $b^* = -.12$, $p = .646$. Similarly, the effects of receiving a long explanation compared to not receiving an explanation did not have a significant impact on PAR ($b^* = .20$, $p = .434$). The control variable time spent on Instagram is also not a significant predictor ($b^* = -.05$, $p = .620$). Nevertheless, the control variable age is a significant predictor ($b^* = .39$, $p = .016$) for PAR. As in this research, the b^* value for the relationship between age and PAR is positive, it can be argued that younger Instagram users perceive more algorithm responsiveness than older ones.

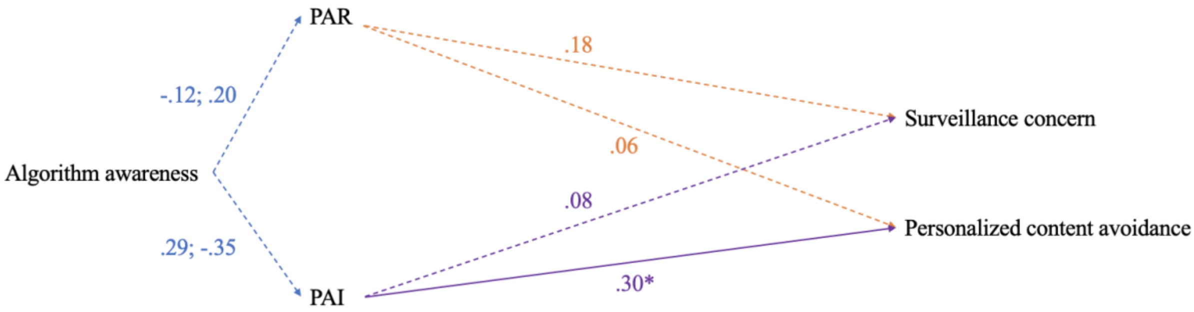
For H2, 'higher algorithm awareness decreases PAI', the model is also not significant, where $F(4, 89) = 2.28$, $p = .177$, $R^2 = .09$. Thus, there is no relationship found between algorithm awareness and PAI, consequently, H2 is rejected. The effects of receiving a short explanation compared to not receiving any explanation did not have a significant impact on PAI, where $b^* = .29$, $p = .566$. Likewise, the effects of receiving a long explanation compared to not receiving an explanation did not have a significant impact on PAI ($b^* = -.35$, $p = .336$). The control variable time spent on Instagram is also not a significant predictor ($b^* = -.01$, $p = .067$). However, age is again a significant predictor ($b^* = -.37$, $p = .011$) for PAI. As the b^* value for the relationship between age and PAI is negative, it can be argued that younger Instagram users perceive more algorithm insensitivity than older ones.

4.1.2 Mediation analysis for algorithm awareness, algorithm responsiveness, and surveillance concerns

After conducting the first step of the analysis, the second step of mediation analysis can be examined. This section analyses the relationship between algorithm responsiveness and surveillance concern, by testing H3, H4, H5, and H6 of this research. The second step of mediation regression analysis revealed that the relationship between algorithm responsiveness, controlling for algorithm awareness, is not significant, $F(6, 87) = .90$, $p = .502$, $R^2 = .16$. PAR in this relationship is not a significant predictor ($b^* = .18$, $p = .628$), as well as, PAI with *b** = .08, p = .592. Based on the aforementioned results, it can be concluded that there is no relationship found between algorithm responsiveness and surveillance concern, as the relationships are not significant. Thus, H3 and H4 of this research can be rejected. Nevertheless, one can argue that due to the positive value of *b** in the relationships between PAR and PAI with surveillance concern, it can be assumed that with higher PAR and PAI, the respondents of this research would be more concerned about surveillance on Instagram. Such positive relationships are proposed by H3 and H4 but were not found to be significant in this research. As both parts of mediation analysis were not significant, it can be concluded that there is no mediation found between algorithm responsiveness, algorithm awareness, and surveillance concern. This means that algorithm responsiveness is not a significant mediator in the relationship between algorithm awareness and surveillance concerns, consequently, rejecting H5 and H6 of this research. The control variable time spent on Instagram is also not a significant predictor, with *b** = -.08, p = .442. Lastly, the control variable age is also not a significant predictor of surveillance concern, with *b** = -.02, p = .891.

4.1.3 Mediation analysis for algorithm awareness, algorithm responsiveness, and personalized content avoidance

To answer H7, H8, H9, and H10, which analyze the relationship between algorithm responsiveness and personalised content avoidance, controlling for algorithm awareness, the second step of mediation analysis is conducted, while accounting for the insignificant aforementioned results of step one. The second step revealed that the relationship between algorithm responsiveness and personalized content avoidance is significant, $F(6, 87) = 3.73$, $p = .002$, $R^2 = .21$, which is different from the results of the relationship between algorithm responsiveness and surveillance concerns. PAR in this relationship is not a significant predictor (*b** = .06, p = .759), while PAI is a significant predictor with *b** = .30, p = .032. Based on the aforementioned results, it can be concluded that there is no relationship found between PAR and personalized content avoidance, thus, H7 of this research is rejected. Nevertheless, H8 is accepted as there is a significant relationship between PAI and personalized content avoidance. Based on the positive value of *b** in the relationship between PAI and personalized content avoidance, the hypotized relationship is confirmed, where with the increase in perceived algorithm insensitivity, there is an increase in personalized content avoidance. Since in the relationship between PAR and personalized content avoidance, *b** also has a positive value, it can be assumed that in the sample of this research, people would also avoid personalized content with the increase in PAR like was hypotized in this research but was not found to be significant. While there is a significant relationship between PAI and personalized content avoidance, it can be concluded that there is no mediation found between algorithm responsiveness, algorithm awareness, and personalized content avoidance, as the first step of Mediation analysis was not significant. This means that algorithm responsiveness is not a significant mediator in the relationship between algorithm awareness and personalized content avoidance, consequently, rejecting H9 and H10 of this research. The control variable time spent on Instagram is also not a significant predictor, with $b^* = -.01$, $p = .904$. Lastly, the control variable age is a significant predictor, with $b^* = -.36$, $p = .013$. While there is no relationship found between time spent on Instagram and personalized content avoidance, there is a significant relationship between age with personalized content avoidance. Based on the negative b^* value, it can be argued that older Instagram users are less likely to avoid personalized content.



Notes: Significance levels: * $p < .05$

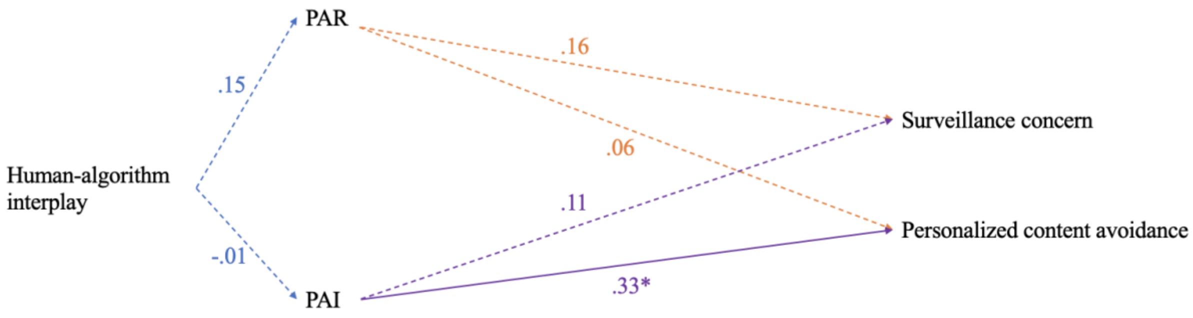
Figure 2: Mediation model for experimental design

4.2 Relationships based on survey design

Based on all the aforementioned results, 9 out of 10 proposed hypotheses are rejected, where only H8 is accepted. Consequently, it can be concluded that algorithm responsiveness is not a significant predictor in the relationship between algorithm awareness and the perception of algorithms. Additionally, by manipulating the level of respondents' algorithm awareness, this research did not find any significant differences between the three experimental groups. Thus, it can be argued that by increasing one's level of algorithm awareness, respondents did not significantly change their perception of algorithm responsiveness and its impact on the perception of algorithms. Nevertheless, by looking at positive or negative b^* values of the abovementioned results, it can be argued that some of the proposed hypotheses predicted the direction of the relationships between the variables. While this research did not find significant results, it is still important to further analyze the proposed relationships considering that the manipulation may have not been strong enough to cause effects.

Therefore, further analyses are conducted by not accounting for experimental conditions and not comparing the change in the level of algorithm awareness, but by analyzing algorithm awareness through self-reported human-algorithm interplay and content filtering, which are two scales measuring algorithm awareness in this research. The analysis is conducted according to the relationship in the proposed hypotheses of this research, by accounting for algorithm awareness through human-algorithm interplay and content filtering, with the presence of control variables. Such analysis is identical to the abovementioned analysis, as it also includes two steps of mediation regression analysis.

Based on the results from the survey design PAI has a positive significant relationship with personalized content avoidance, both in the presence of human-algorithm interplay ($b^* = .33$, $p = .021$) and content filtering ($b^* = .33$, $p = .020$). Thus, H8 is still accepted and it can be argued that people who perceive algorithms as insensitive are more likely to avoid personalized content. Moreover, based on the survey design, there is a significant negative relationship found between content filtering and PAR ($b^* = -.25$, $p = .011$). As the aforementioned finding is in line with H1, which proposed that higher algorithm awareness increases PAR, H1 is accepted. Thus, through the scale of content filtering, algorithm awareness is a significant predictor for PAR, where the increase in algorithm awareness increases perceived algorithm responsiveness. Furthermore, identically to the findings from the experimental design, age has a positive significant effect on PAR, as well as, negative significant effects on PAI and personalized content avoidance. Since both in experimental and survey designs, age had a significant impact on the variables, the researcher separately conducted correlation analyses for age and human-algorithm interplay and content filtering. However, there was a small correlation found between age and human-algorithm interplay ($r = .21$, $p = .036$) and no correlation between age and content filtering ($r = .01$, $p = .893$). The results of the mediation analyses for human-algorithm interplay and content filtering as independent variables can be seen in Table 1 and Table 2 and are visualized in Figure 3 and Figure 4, respectively.



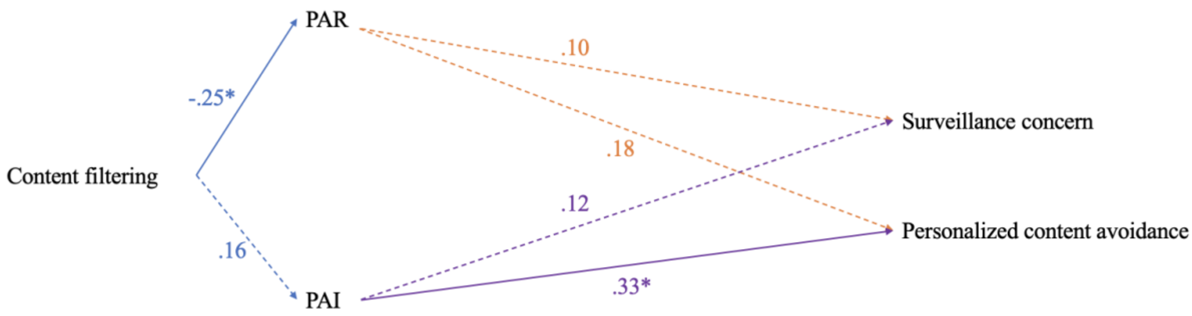
Notes: Significance levels: * $p < .05$

Figure 3: Mediation model for human-algorithm interplay

Table 4: Mediation model for human-algorithm interplay, algorithm responsiveness, and personalization concerns (N=94)

	PAR *b**	PAI *b**	Surveillance concerns *b**	Personalized content avoidance *b**
Human-algorithm interplay	.15	-.01	-	-
PAR	-	-	.16	.06
PAI	-	-	.11	.33*
Time spent on Instagram	-.04	-.02	-.10	-.01
Age	.37*	-.24*	-.03	-.24*
R^2	.08	.06	.07	.17
F	2.79	1.94	1.33	3.78**

Notes: Significance levels: * $p < .05$ ** $p < .01$



*Notes: Significance levels: * p < .05*

Figure 4: Mediation model for content filtering

Table 5: Mediation model for content filtering, algorithm responsiveness, and personalization concerns (N=94)

	PAR *b**	PAI *b**	Surveillance concerns *b**	Personalized content avoidance *b**
Content filtering	-.25*	.16	-	-
PAR	-	-	.10	.18
PAI	-	-	.12	.33*
Time spent on Instagram	-.17	-.01	-.09	-.00
Age	.37**	-.24*	.01	-.35*
R^2	.14	.19	.03	.18
F	5.03**	2.84*	.515	3.76**

Notes: Significance levels: * $p < .05$ ** $p < .01$

5. Discussion

To understand "to what extent does algorithm responsiveness explain the impact of algorithmic awareness on personalization concerns of Instagram users living in the Netherlands?" 10 hypotheses were proposed and were analyzed through mediation regression analysis. Firstly, the results from the experimental design were analyzed and due to a potentially weak manipulation, the results from the survey design, where algorithm awareness is analyzed through human-algorithm interplay and content filtering, were examined. This chapter discusses the main findings of this research while connecting them to the theoretical framework of this research, after which, the conclusion is provided by answering the aforementioned research question. Later, the implications for society, limitations of this research, and suggestions for future research are also provided.

5.1 Algorithm awareness and algorithm responsiveness

Based on both the findings from the experimental design and survey design, 8 out of 10 hypotheses were rejected. While based on the experimental design, there was no significant relationship found between algorithm awareness and algorithm responsiveness, the survey design uncovered a significant negative relationship between content filtering and perceived algorithm responsiveness. As this relationship is in line with H1, which proposed that higher algorithm awareness increases PAR, H1 is accepted. Thus, through the scale of content filtering, algorithm awareness is a significant predictor of PAR, where by gaining more algorithm awareness, people are more likely to perceive algorithm responsiveness. It can be argued that this finding is in line with the findings of Taylor and Choi (2022), as they found that individuals who are aware of algorithms view PAR slightly positively. In general, people are more positive about relevant personalized content as it reduces the cognitive load when searching for content (Aguirre et al., 2015). The positive attitude can be further explained by the fact that people perceive interaction with algorithms from the scope of interpersonal relationships. Users appreciate the algorithm's efforts of responsiveness, as it allows them to better understand their identities which increases their engagement with such content (Eg et al., 2023; Taylor & Choi, 2022).

Yet, this research did not find a significant relationship between algorithm awareness and perceived algorithm insensitivity. Interestingly, although neither experimental design nor human-algorithm interplay reached significance with algorithm responsiveness, the value of *b** in their relationships was not according to the proposed hypotheses, while content filtering had the proposed effect on both PAR and PAI. Even though this research found significant proposed relationship between content filtering and PAR, several possible limitations of this research should be acknowledged. Firstly, it can be argued that the scale for algorithm awareness may not have been completely suitable for this research. This is due to the fact that during factor analysis, the items were assigned differently compared to the original scale and one question was further removed during reliability analysis. Additionally, while not expecting, the values of b^* differed between human-algorithm interplay and content filtering. Furthermore, it can be argued that the provided explanations of algorithms were not as effective in changing one's perception of algorithms, or it can be assumed that the respondents did not read the explanations carefully, even though there was a timer included to prevent this. Lastly, one can suggest that this research may have required a larger sample to ensure statistical power to detect smaller effects. Thus, this research still acknowledges that the proposed hypotheses for the relationship between the level of algorithm awareness and algorithm responsiveness may be true and should be further examined.

Nevertheless, if future research reveals that the abovementioned limitations are not the cause for insignificant findings of this research, it can be assumed that the level of one's algorithm awareness is not a significant predictor for user perception of algorithms. Additionally, it can be argued that other factors, like one's age, may be more influential in the perception of algorithms and personalization and should be the focus of future research. The aforementioned can serve as relevant scientific findings as existing research places high emphasis on the possible impact of the level of algorithm awareness on the perception of personalized content. For instance, the current Privacy Paradox scholarship suggests that algorithm awareness is an essential condition for users to engage in a rational trade-off between the benefits of personalized content and the costs of information disclosure (Kokolakis, 2017). Such belief establishes higher need for policymakers to ensure that users are aware of algorithms which creates stricter regulations for companies like social media platforms. For example, with the recent adoption of Digital Services Act within the EU, social media companies have to increase transparency about data collection and personalization (European Commission, 2023). However, it can be argued that if there is no relationship between the level of algorithm awareness and user perception of algorithms, such approach may not be as effective in changing user perception of algorithms.

5.2 Effects on personalized content avoidance and surveillance concerns

While most hypotheses of this research are rejected, H8, which argued that PAI increases personalized content avoidance on Instagram, is accepted. This means that people are more likely to avoid personalized content if they perceive it as being insensitive toward their perceived self. It can be argued that this is in line with previous research analyzing folk theories. Siles et al. (2020) found that people believe that they can work with algorithms to direct them to show more relevant content. Karizat et al. (2021) discovered that this is mainly because algorithms may prioritize specific aspects of one's self while undermining other, which may relate to characteristics of marginalized identities, like Queer identity. People may perceive such content as being insensitive towards their identity and based on the findings from previous research, by avoiding it, users demonstrate their agency to shape algorithmically curated content to align with their identities (Ytre-Arne & Moe, 2020).

While the hypothesis for PAI is accepted, the hypothesis for PAR and personalized content avoidance, H7, is not accepted. Even though some existing research provides convincing arguments for H7, where perceived algorithm responsiveness would increase personalized content avoidance, this research provides new and interesting insights which may suggest that there is no relationship between PAR and personalized content avoidance. The insignificant relationship between PAR and personalized content avoidance may be further connected to the significant relationship of content filtering and PAR. Particularly, some previous research found that people who are already aware of algorithms will not change their positive intentions towards personalized content (Boerman et al., 2017). One can suggest that due to the benefits of PAR, people would not be likely to avoid such content. Specifically, perceived algorithm responsiveness is reported when people believe algorithms understand and support their multifaced identities, interests, and motivations (Taylor & Choi, 2022). Taylor and Choi (2022) argue that PAR increases positive attitude towards personalized content and increases user engagement with such content, since through such content, individuals believe that they can better understand their own identities. While previous research argued that users would be motivated to avoid highly personalized content due to feeling loss of control (Boerman et al., 2017) or encountering similar content (Bhandari & Bimo, 2022), this research suggests that people may not avoid personalized content if they perceive algorithm responsiveness. Therefore, it may be suggested that social media companies and advertisers should not be concerned about providing highly relevant content to users and should focus on other aspects, like age, that may be more determining user personalized content avoidance. Nevertheless, it should be stated that the value of b^* in the relationship between PAR and personalized content avoidance is positive, suggesting that the increase in perceived algorithm responses increases personalized content avoidance. Therefore, this research believes that future research should further examine the relationship between PAR and personalized content avoidance to confirm the aforementioned arguments.

The hypotheses for the relationships between algorithm responsiveness and surveillance concerns were also not accepted, as there were no significant relationships found in both experimental or survey designs. Nevertheless, it should be stated that the value of *b** in all analyses between algorithm responsiveness and surveillance concerns were negative, which is proposed in H3 and H4. Since existing research provides convincing arguments for the positive significant relationship between algorithm responsiveness and surveillance concerns and due to the research gap (Boerman et al., 2017), it can be suggested for future research to analyze these relationships with a larger sample. Nevertheless, it can also be argued that there may not be any relationships between these variables. This can be explained by the fact that people perceive surveillance as a necessary condition for the benefits of social media, and particularly personalization, which naturalizes issues of surveillance (Siles et al., 2020). Such perceptions are especially relevant in the context of algorithm responsiveness, as people view social media platforms from the view of interpersonal relationships. Siles et al. (2020) explain this by referring to 'mutual personalization' where users shape the platform according to their personality, which can be partially confirmed by accepting H8 of this research, while believing that the platform has human-like characteristics. Hence, people treat the platform from their conceptions of friendship and public behavior, and believe that surveillance becomes necessary for a social media platform to offer a higher good for them, like the benefits of personalization (Siles et al., 2020).

Despite accepting H1 and H8 and discussing the *b** values that predicted the direction of the proposed hypotheses, it can be concluded that in this research, algorithm responsiveness is not a mediator in the relationships between algorithm awareness, surveillance concerns, and personalized content avoidance. Therefore, H5, H6, H9, and H10 of this research are rejected.

5.3 Effects of control variables

Lastly, the effects of the control variables, time spent on Instagram and age, should be discussed. The results for age as a control variable provided interesting insights, where age is a significant predictor for algorithm responsiveness and personalized content avoidance. Specifically, age has a positive significant relationship with PAR and a negative significant relationship with PAI. Based on these relationships, it can be argued that younger Instagram users perceive more responsiveness and less insensitivity than older Instagram users. Additionally, age has a negative significant relationship with personalized content avoidance, where it can be argued that older Instagram users are less likely to avoid personalized content than younger Instagram users.

Based on previous research, younger users are more likely to adopt privacy-protective behavior than older users (Kezer et al., 2016). One can argue that the aforementioned is confirmed by the negative significant relationship between age and personalized content avoidance in this research. Such behavior can be explained by the fact that younger users are more engaged with identity management (Van Den Broeck et al., 2015) and seek higher control over personalized content (Vallejos et al., 2021). Furthermore, this research found that younger Instagram users perceive more responsiveness and less insensitivity when engaging with personalized content than older users. This means that younger Instagram users perceive Instagram algorithms to be more supportive of their identity and motivations than older users. This finding can be connected to the relationship between age and personalized content avoidance. Based on Taylor and Choi (2022), PAR relates to algorithm's appropriate responsiveness to new information, like new interests. Since individuals have multifaced dimensions of identity (Taylor & Choi, 2022) and because younger users place higher importance to self-representation though personalized content, they may be more likely to avoid personalized content (Van Den Broeck et al., 2015). By training algorithms to identify their current interests and goals, younger Instagram users align their algorithmic self to their actual self, which can lead to a higher perception of responsiveness and lower perception of insensitivity (Taylor & Choi, 2022).

Nevertheless, some scholars argue that younger adults would be less skeptical of personalized content, as they have lower surveillance concerns due to higher awareness of privacy-protective behavior (Boerman et al., 2017; Van Den Broeck et al., 2015). While scholars explain the adoption of privacy-protective behavior with the fact that younger adults are more aware of the privacy risks and ways of protecting their privacy, this research did not find a significant correlation between age and the scales for algorithm awareness, thus, cannot confirm such a relationship. Furthermore, this research did not find any significant relationship between age and surveillance concerns and cannot support any existing findings. Additionally, it should be stated that the sample of this research may have not been fully representative of the study population, as 19.6% of respondents were 22 years old. Thus, it is important to further analyze the effects of age on algorithm responsiveness and personalized content avoidance while ensuring a more heterogeneous sample. Lastly, it should be stated that time spent on Instagram is not a significant predictor in any analyses and it has a negative b^* for all the variables of this research.

6. Conclusion

Based on the results of this research, it can be concluded that algorithm responsiveness, through PAR and PAI, is not a significant mediator in the relationships between algorithm awareness with surveillance concerns and personalized content avoidance. Nevertheless, the analysis based on non-manipulated algorithm awareness revealed that higher algorithm awareness, through the scale of content filtering, increased perceived algorithm responsiveness. Additionally, during both experimental and survey designs, this research uncovered that perceived algorithm insensitivity increases the likelihood of personalized content avoidance. Lastly, this research found that younger Instagram users perceive more responsiveness and less insensitivity and that they are more likely to avoid personalized content than older Instagram users. Nevertheless, due to several possible limitations of this research, the researcher acknowledges that both significant and non-significant results should further be analyzed, while utilizing a more effective stimuli, improving the scales for algorithm awareness, and ensuring a large and representative sample.

6.1 Implications for society

With the majority of the hypotheses being rejected, the findings of this research may be relevant for scholars, policymakers, individuals, as well as, social media platforms and agencies. Firstly, even though this research acknowledges that the proposed hypotheses may still be valid in future research, it can be argued that the non-significant findings of this research provide valuable insights for scholars, policymakers, and social media platforms. It can be argued that if there are no significant relationships found in future research, it is important to recognize that the increase in one's algorithm awareness does not impact the perception of personalization and algorithms. Since existing research suggest a strong relationship between the aforementioned, it can be argued that if the impact of the level of algorithm awareness would be considerably strong, this research would still find its effects. Additionally, due to the significant impact of age on the majority of variables, it can be argued that there may be other factors that are more essential in one's perception of personalization, like age. The insignificant effect of the level of algorithm awareness can be a crucial finding, as existing research believes that algorithm awareness may be the key to users' rational online behavior. For instance, in the context of Privacy Paradox, it is believed that with an increase in algorithm awareness, people would be able to engage in a rational trade-off between the benefits of personalized content and the costs of information disclosure (Kokolakis, 2017). Such beliefs increased the demands for transparency about data collection and personalization from social media platforms which have to comply with new rules, like, the recently adopted Digital Services Act within the EU (European Commission, 2023).

Furthermore, the significant relationships of this research provide new insights into the research gap of factors affecting the perception of personalized content. Particularly, this research found that the non-manipulated algorithm awareness, through the scale of content filtering, increases perceived algorithm responsiveness. Thus, it can be argued that users perceive the relevancy of personalization positively, as it provides them with content that is in line with their identities, interests and motivations (Taylor & Choi, 2022). Apart from covering the existing research gap, these findings provide insights for media entities, like advertisers or social media platforms, who seek to understand why some personalized content is refused and some are accepted (Jin & Villegas, 2007). It can be suggested that advertisers and social media companies should tailor the content that aligns with user identity and motivations. Furthermore, this research proved that perceived algorithm insensitivity increases personalized content avoidance and found that younger Instagram users perceive more responsiveness and less insensitivity and that they are more likely to avoid personalized content than older Instagram users. With these findings, it is suggested that media entities should aim to ensure that users do not perceive algorithm insensitivity and can tailor the degree of personalized content depending on user's age. Particularly, they should ensure that younger Instagram users perceive responsiveness while older Instagram users have a moderate perception of responsiveness when using the platform.

Lastly, as this research acknowledges the possible significance of the proposed hypotheses, it still assumes that it is crucial for Instagram users to have higher algorithm awareness. Particularly, it is important for users to be aware that their online activities shape personalized content, as this impacts their identity and may lead to negative consequences if the algorithm suppresses a part of their identity (Karizat et al., 2021). It is assumed that in case users are not satisfied with the responsiveness of algorithms, by gaining algorithm awareness, they may be able to avoid such content and protect themselves from potential harm. One can argue that such a premise can be related to the significant results for age. Specifically, since this research found that younger users perceive more responsiveness and less insensitivity and are more likely to avoid personalized content, it is assumed that young adults place higher importance to the appropriate responsiveness of algorithms as it relates to their self-representation (Van Den Broeck et al., 2015). Particularly, younger Instagram users aim to consume the content that relates more to their identities, which may motivate them to train algorithms by avoiding personalized content. Consequently, it can be argued that young adults should be aware of the impact of their behavior on personalized content to be able to gain a stronger feeling of control over personalized content, for instance, by avoiding such content (Boerman et al., 2017). Thus, it is still believed that government and social media companies should raise user awareness about personalization, to ensure that people who want to have more control over their personalized content are able to achieve it.

6.2 Limitations and suggestions for future research

The insignificance of the majority of hypotheses and slight contradictions of the results suggests that there might be several limitations that may have impacted the significance of the results. Firstly, it is assumed that this research required a larger sample, especially to ensure statistical power to detect smaller effects. Additionally, while the findings of this research uncovered significant results related to age, it should be stated that 19.6% of respondents were 22 years old. Thus, it can be argued that the sample of this research was not completely representative of the study population and, consequently, the findings of this research cannot be fully generalized to any other sample of this population. One reason that may have led to a non-representative population relates to the method of recruitment of participants, where a lot of participants were recruited through social media communities or websites like SurveySwap. One can argue that such participants may not have taken the survey carefully, which could also impact the validity and reliability of the findings. For instance, it can be argued that participants may not have carefully read the explanation of the algorithms which may have impacted the significance of the findings from the experimental design. Furthermore, as factor analysis uncovered unexpected loadings of items in the scale of algorithm awareness and one question was further removed based on reliability analysis, it can be argued that the scale was not fully reliable based on Zarouali et al. (2021) which might have impacted the reliability and validity of the findings. Moreover, based on the difference in findings related to human-algorithm interplay and content filtering, it can be also assumed that the scales for algorithm awareness may not have been suitable for this research. Lastly, it can be also argued that the stimuli of the experimental design may not have been as effective to change people's perceptions, or the explanations could be too long for some of the respondents, further limiting the reliability and validity of this research.

Due to all aforementioned, this research believes that it is essential to further analyze the proposed relationships. Therefore, this research acknowledges the possibility that the proposed hypotheses can be confirmed in future research. Nevertheless, this research also admits that there may be a possibility of findings no relationships between the insignificant variables of this research. Since previous research suggested the level of algorithm awareness is the key to user rational behavior online, it can be assumed that if its effects would be considerably strong, they would be found in this research, especially since there were some significant relationships found even with the limitations of this research (Kokolakis, 2017). Thus, this research believes that scholars should also research other factors, like age, that may be more determinant of user perception and behavior online. Additionally, this research suggests that even the significant relationships should be confirmed in future research, as some limitations, like the sample, could also have impacted their significance. Hence, future research should replicate this research by focusing on ensuring a representative larger sample of the population and improving both the stimuli and the scales for algorithm awareness. Moreover, future research should analyze other social media platforms, like TikTok, as it could be assumed that people's perceptions of algorithms differ per each platform. It can be argued that the method of this research is useful as it is essential to reveal if there is a change in one's perception of algorithms based on one's level of algorithm awareness. Additionally, it is crucial to study the proposed relationships as there is a gap in the current research. By analyzing such relationships, one can understand the factors that may influence the relationships between users and personalized content, as personalized content holds significant power over one's identity and behavior and should be studied from the perceptions of the users (Karizat et al., 2021).

7. References

Aguirre, E., Mahr, D., Grewal, D., de Ruyter, K., & Wetzels, M. (2015). Unraveling the Personalization Paradox: The Effect of Information Collection and Trust-Building Strategies on Online Advertisement Effectiveness. *Journal of Retailing*, *91*(1), 34–49. https://doi.org/10.1016/j.jretai.2014.09.005

Allen, V. (2022, February 7). *How Instagram Uses AI to Enhance The User Experience*. Daffodil Software. Retrieved March 18, 2023, from https://insights.daffodilsw.com/blog/how-instagram-uses-ai-to-enhance-the-user-experience

Babbie, E. R. (2016). The Basics of Social Research (7th ed.). Cengage Learning.

Baek, T. H., & Morimoto, M. (2012). Stay Away From Me. *Journal of Advertising*, *41*(1), 59–76. https://doi.org/10.2753/joa0091-3367410105

Bandy, J. (2021, February 3). *Problematic Machine Behavior: A Systematic Literature Review of Algorithm Audits*. arXiv.org. https://arxiv.org/abs/2102.04256

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. *Journal of Public Policy & Marketing*, *38*(4), 500–515. https://doi.org/10.1177/0743915619858057

Beveridge, C. (2022, March 30). 150+ Social Media Statistics that Matter to Marketers in 2022. Social Media Marketing & Management Dashboard. Retrieved January 6, 2023, from https://blog.hootsuite.com/social-media-statistics-for-social-media-managers/#Social_media_advertising_statistics

Bhandari, A., & Bimo, S. (2022). Why's Everyone on TikTok Now? The Algorithmized Self and the Future of Self-Making on Social Media. *Social Media + Society*, *8*(1), 205630512210862. https://doi.org/10.1177/20563051221086241

Bishop, J. M. (2021). Artificial Intelligence Is Stupid and Causal Reasoning Will Not Fix It. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.513474

Bodó, B., Helberger, N., Eskens, S., & Möller, J. (2018). Interested in Diversity. *Digital Journalism*, *7*(2), 206–229. https://doi.org/10.1080/21670811.2018.1521292

Boeker, M., & Urman, A. (2022). An Empirical Investigation of Personalization Factors on TikTok. *Proceedings of the ACM Web Conference 2022*. https://doi.org/10.1145/3485447.3512102

Boerman, S. C., Kruikemeier, S., & Zuiderveen Borgesius, F. J. (2017). Online Behavioral Advertising: A Literature Review and Research Agenda. *Journal of Advertising*, *46*(3), 363–376. https://doi.org/10.1080/00913367.2017.1339368

Cotter, K. (2020, January 28). Algorithmic Knowledge Gaps: A New Horizon of (Digital) Inequality. *International Journal of Communication*. https://ijoc.org/index.php/ijoc/article/view/12450

Dogruel, L., Facciorusso, D., & Stark, B. (2020). 'I'm still the master of the machine.' Internet users' awareness of algorithmic decision-making and their perception of its effect on their autonomy. *Information, Communication & Society*, *25*(9), 1311–1332. https://doi.org/10.1080/1369118x.2020.1863999

Dutton, W. H., Reisdorf, B. C., Dubois, E., & Blank, G. (2017). Social Shaping of the Politics of Internet Search and Networking: Moving Beyond Filter Bubbles, Echo Chambers, and Fake News. *Social Science Research Network*. https://doi.org/10.2139/ssrn.2944191

Eg, R., Tønnesen, Ö. D., & Tennfjord, M. K. (2023). A scoping review of personalized user experiences on social media: The interplay between algorithms and human factors. *Computers in Human Behavior Reports*, *9*, 100253. https://doi.org/10.1016/j.chbr.2022.100253

Eslami, M., Karahalios, K., Sandvig, C., Vaccaro, K., Rickman, A., Hamilton, K., & Kirlik, A. (2016). First I "like" it, then I hide it. *Human Factors in Computing Systems*. https://doi.org/10.1145/2858036.2858494

Etikan, I., Alkassim, R., & Abubakar, S. (2016). Comparision of Snowball Sampling and Sequential Sampling Technique. *Biometrics & Biostatistics International Journal, 3*(1). https://doi.org/10.15406/bbij.2016.03.00055

European Commission. (2023, March 23). *European Commission*. The Digital Services Act Package. Retrieved March 20, 2023, from https://digital-strategy.ec.europa.eu/en/policies/digital-services-act-package

Fan, H. & Poole, M. S. (2006). What is personalisation? Perspectives on the design and implementation of personalization in information systems. *Journal of Organizational Computing and Electronic Commerce*, *16*(3&4), 179-202. https://doiorg.eur.idm.oclc.org/10.1080/10919392.2006.9681199

Gaines, B. J., Kuklinski, J. H., & Quirk, P. J. (2007). The Logic of the Survey Experiment Reexamined. *Political Analysis*, *15*(1), 1–20. https://doi.org/10.1093/pan/mpl008

Harborth, D., & Pape, S. (2020). How Privacy Concerns, Trust and Risk Beliefs, and Privacy Literacy Influence Users' Intentions to Use Privacy-Enhancing Technologies. *Data Base*, *51*(1), 51–69. https://doi.org/10.1145/3380799.3380805

Hargittai, E., Gruber, J., Djukaric, T., Fuchs, J., & Brombach, L. (2020). Black box measures? How to study people's algorithm skills. *Information, Communication & Society*, *23*(5), 764–775. https://doi.org/10.1080/1369118x.2020.1713846

Hern, A. (2022, July 26). 'Stop trying to be TikTok': user backlash over Instagram changes. *The Guardian*. https://www.theguardian.com/technology/2022/jul/26/instagram-changes-user-backlash-trying-to-be-tiktok

Jin, C. H., & Villegas, J. (2007). Consumer Responses to Advertising on the Internet: The Effect of Individual Difference on Ambivalence and Avoidance. *CyberPsychology &Amp; Behavior*, *10*(2), 258–266. https://doi.org/10.1089/cpb.2006.9960

Karakayali, N., Kostem, B., & Galip, I. (2017). Recommendation Systems as Technologies of the Self: Algorithmic Control and the Formation of Music Taste. *Theory, Culture*

Karizat, N., Delmonaco, D., Eslami, M., & Andalibi, N. (2021). Algorithmic Folk Theories and Identity: How TikTok Users Co-Produce Knowledge of Identity and Engage in Algorithmic Resistance. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–44. https://doi.org/10.1145/3476046

Kezer, M., Sevi, B., Cemalcilar, Z., & Baruh, L. (2016). Age differences in privacy attitudes, literacy and privacy management on Facebook. *Cyberpsychology*, *10*(1). https://doi.org/10.5817/cp2016-1-2

Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. Computers & Security, 64, 122–134. https://doi.org/10.1016/j.cose.2015.07.002

Leiden University. (2017, October 4). *The Netherlands one of the leaders in privacy protection*. https://www.universiteitleiden.nl/en/news/2017/09/the-netherlands-one-of-the-leaders-in-privacy-protection

Lomborg, S., & Kapsch, P. H. (2019). Decoding algorithms. *Media, Culture & Society*, *42*(5), 745–761. https://doi.org/10.1177/0163443719855301

McFarlane, G. (2022). How Facebook (Meta), X Corp (Twitter), Social Media Make Money From You. *Investopedia*. https://www.investopedia.com/stock-analysis/032114/how-facebook-twitter-social-media-make-money-you-twtr-lnkd-fb-goog.aspx#:~:text=Social%20media%20companies%20primarily%20make,their%20accounts%20to%20be%20free.

Moore, R. S., Moore, M. L., Shanahan, K., & Mack, B. (2015, January 1). *Creepy Marketing: Three Dimensions of Perceived Excessive Online Privacy Violation*. ResearchGate. https://www.researchgate.net/publication/282329651_Creepy_Marketing_Three_Dimensions_of_Perceived_Excessive_Online_Privacy_Violation

Nidhi, A. (2021, November 12). *The value of getting personalization right—or wrong—is multiplying*. McKinsey & Company. Retrieved April 10, 2023, from https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right-or-wrong-is-multiplying

Nyheim, P., Xu, S., Zhang, L., & Mattila, A. S. (2015). Predictors of avoidance towards personalization of restaurant smartphone advertising. *Journal of Hospitality and Tourism Technology*, *6*(2), 145–159. https://doi.org/10.1108/jhtt-07-2014-0026

Oeldorf-Hirsch, A. (2021). *What Do We Know about Algorithmic Literacy? The Status Quo and a Research Agenda for a Growing Field*. https://www.semanticscholar.org/paper/What-Do-We-Know-about-Algorithmic-Literacy-The-Quo-Oeldorf-Hirsch-Neubaum/5b861df3790e2f9ee8718d43ddeb26fc51ce8b92

Preibusch, S. (2013). Guide to measuring privacy concern: Review of survey and observational instruments. International Journal of Human-Computer Studies, 71(12), 1133–1143. https://doi.org/10.1016/j.ijhcs.2013.09.002

Prince, C., Omrani, N., Maalaoui, A., Dabić, M., & Kraus, S. (2021). Are We Living in Surveillance Societies and Is Privacy an Illusion? An Empirical Study on Privacy Literacy and Privacy Concerns. *IEEE Transactions on Engineering Management*, 1–18. https://doi.org/10.1109/tem.2021.3092702

Ramos, G. P., Boratto, L., & Caleiro, C. (2020). On the negative impact of social influence in recommender systems: A study of bribery in collaborative hybrid algorithms. *Information Processing and Management*, *57*(2), 102058. https://doi.org/10.1016/j.ipm.2019.102058

Riley, R. W. (1996). Revealing Socially Constructed Knowledge Through Quasi-Structured Interviews and Grounded Theory Analysis. Journal of Travel & Tourism Marketing, 5(1–2), 21–40. https://doi.org/10.1300/j073v05n01_03

Seadle, M. (2019). The Great Hack (documentary film). Produced and directed by Karim Amer and Jehane Noujaim. Netflix, 2019. 1 hour 54 minutes. *Journal of the*

Association for Information Science and Technology, 71(12), 1507–1511. https://doi.org/10.1002/asi.24333

Segijn, C. M., Opree, S. J., & Van Ooijen, I. (2022). The validation of the Perceived Surveillance Scale. *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, *16*(3). https://doi.org/10.5817/cp2022-3-9

Siles, I., Segura-Castillo, A., Solís, R. P., & Sancho, M. (2020). Folk theories of algorithmic recommendations on Spotify: Enacting data assemblages in the global South. *Big Data & Society, 7*(1), 205395172092337. https://doi.org/10.1177/2053951720923377

Statista. (2022, March 30). *Leading social networks in the Netherlands 2021, by reach*. https://www.statista.com/statistics/1224092/leading-social-networks-netherlands/

Statista. (2023, February 14). *Biggest social media platforms 2023*. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/

Summers, C. J., Smith, R., & Reczek, R. W. (2016). An Audience of One: Behaviorally Targeted Ads as Implied Social Labels. *Journal of Consumer Research*, *43*(1), 156–178. https://doi.org/10.1093/jcr/ucw012

Swart, J. (2021). Experiencing Algorithms: How Young People Understand, Feel About, and Engage With Algorithmic News Selection on Social Media. *Social Media + Society, 7*(2), 205630512110088. https://doi.org/10.1177/20563051211008828

Taylor, S. H., & Choi, M. (2022). An Initial Conceptualization of Algorithm Responsiveness: Comparing Perceptions of Algorithms Across Social Media Platforms. *Social Media + Society, 8*(4), 205630512211443. https://doi.org/10.1177/20563051221144322

Vallejos, E. P., Dowthwaite, L., Creswich, H., Portillo, V., Koene, A., Jirotka, M., McCarthy, A., & McAuley, D. (2021). The impact of algorithmic decision-making processes on young people's well-being. *Health Informatics Journal, 27*(1), 146045822097275. https://doi.org/10.1177/1460458220972750

Van Den Broeck, E., Poels, K., & Walrave, M. (2015). Older and Wiser? Facebook Use, Privacy Concern, and Privacy Protection in the Life Stages of Emerging, Young, and Middle Adulthood. *Social Media and Society, 1*(2), 205630511561614. https://doi.org/10.1177/2056305115616149

Xie, X., Du, Y., & Bai, Q. (2022). Why do people resist algorithms? From the perspective of short video usage motivations. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.941640

Ytre-Arne, B., & Moe, H. (2020). Folk theories of algorithms: Understanding digital irritation. *Media, Culture &Amp; Society*, *43*(5), 807–824. https://doi.org/10.1177/0163443720972314

Zarouali, B., Boerman, S. C., & De Vreese, C. H. (2021). Is this recommended by an algorithm? The development and validation of the algorithmic media content awareness scale (AMCA-scale). *Telematics and Informatics*, *62*, 101607. https://doi.org/10.1016/j.tele.2021.101607

8. Appendix A

- Consent:

Dear participant, welcome to this survey!

My name is Daria, and this is the survey for my Digitalisation, Surveillance, and Societies Master's thesis at Erasmus University Rotterdam.

This survey is about algorithms on Instagram, and it takes approximately 5 minutes to complete. It is fully anonymous and the data will be only used for the purposes of this study.

If you have any questions or remarks or would like to receive a summary of this research, feel free to contact me via daria.survey.eur@gmail.com

Please, click 'I consent' to participate in the survey.

Thank you so much for your participation, it is really appreciated!

- o I consent
- o I do not consent

Q1: How old are you?

Q2: How do you describe yourself?

- o Male
- o Female
- o Non-binary / third gender
- o Prefer to self-describe
- o Prefer not to say

Q3: Do you live in the Netherlands?

- o Yes
- o No

Q4: How many times do you check Instagram per day?

Q5: If you have a 'screen time' option on your phone, could you write how much time you spend on Instagram per week?

Condition 1 – short explanation:

To ensure accurate and meaningful responses, it is important to have a shared understanding of algorithms on social media. Please, read the following text carefully.

Algorithms on social media are computer programs that analyse user behaviour and preferences to determine what content to show to each user. These algorithms take into account various factors such as past engagement, likes, comments, and shares to personalise the content shown to the user.

Condition 2 – long explanation:

To ensure accurate and meaningful responses, it is important to have a shared understanding of algorithms on social media. Please, read the following text carefully.

Algorithms on social media are computer programs that analyse user behaviour and preferences to determine what content to show to each user. These algorithms take into account various factors such as past engagement, likes, comments, and shares to personalise the content shown to the user.

Algorithms on social media can be problematic as they tend to present users with content that aligns with their existing beliefs and interests, resulting in a narrow and biased perspective. This can lead to exposure to false information and harmful content, and contribute to the spread of misinformation. Algorithms make social media more addictive and also can also create unrealistic expectations and social pressures that can lead to a decline in self-esteem and well-being. Furthermore, algorithms collect and use personal information, which can compromise user privacy.

Condition 3 – no explanation.

I am interested in what you think about the Instagram algorithm. Think about the posts, videos, and stories the algorithm curated for you this week, and then answer the following questions.

Appendix A1:

To what extent do you agree to the following statements? The Instagram algorithm...	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Q6: … really listens to me	○	○	○	○	○	○	○
Q7: … responds to what I am thinking and feeling	○	○	○	○	○	○	○
Q8: … understands me	○	○	○	○	○	○	○
Q9: … tries to see where I'm coming from	○	○	○	○	○	○	○
Q10: … is attentive to my needs	○	○	○	○	○	○	○
Q11: … is responsive to my needs	○	○	○	○	○	○	○
Q12: … takes my interests seriously	○	○	○	○	○	○	○
Q13: … really gets who I am	○	○	○	○	○	○	○
Q14: ... does NOT understand my feelings and concerns	○	○	○	○	○	○	○
Q15: ... ignores who I am	○	○	○	○	○	○	○

Appendix A2:

To what extent do you agree to the following statements? The Instagram algorithm...	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Q16: ... dismisses my interests	○	○	○	○	○	○	○
Q17: ... seems to ignore the things that are most important to me	○	○	○	○	○	○	○
Q18: ... does NOT really understand my wants and needs	○	○	○	○	○	○	○
Q19: ... does NOT really take my personal interests seriously	○	○	○	○	○	○	○
Q20: ... often does NOT listen to my needs	○	○	○	○	○	○	○

Appendix A3:

To what extent do you agree to the following statements?	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Q21: I believe that my Instagram viewing habits are monitored at least part of the time	○	○	○	○	○	○	○
Q22: I am concerned that companies are collecting too much information about my Instagram viewing habits	○	○	○	○	○	○	○
Q23: I am concerned that companies may monitor my Instagram viewing habits	○	○	○	○	○	○	○
Q24: I intentionally ignore any personalised content on Instagram	○	○	○	○	○	○	○
Q25: I hate any personalised content on Instagram	○	○	○	○	○	○	○
Q26: It would be better if there were no personalised content on Instagram	○	○	○	○	○	○	○
Q27: Please select 'strongly agree' to show that you are paying attention to this question.	○	○	○	○	○	○	○
Q28: I discard personalised content on Instagram immediately without opening (reading, watching, or listening to) it	○	○	○	○	○	○	○

Appendix A4:

To what extent do you agree to the following statements?	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Q29: Algorithms are used to recommend post to me on Instagram	○	○	○	○	○	○	○
Q30: Algorithms are used to prioritise posts on Instagram above others	○	○	○	○	○	○	○
Q31: Algorithms are used to tailor certain posts to me on Instagram	○	○	○	○	○	○	○
Q32: Algorithms are used to show someone else different posts than I get to see on Instagram	○	○	○	○	○	○	○
Q33: The posts that algorithms recommend to me on Instagram depend on my online behaviour on Instagram	○	○	○	○	○	○	○
Q34: The posts that algorithms recommend to me on Instagram depend on my online behavioural data	○	○	○	○	○	○	○
Q35: The posts that algorithms recommend to me on Instagram depend on the data that I make available online	○	○	○	○	○	○	○

- Final note:

Dear participant,

This was the final question of this survey. Thank you so much for your participation!

If you have any questions or remarks or would like to receive a summary of this research, feel free to contact me via daria.privacy1survey@gmail.com.

If you are using SurveySwap, the Survey Code is: *T0Q2-RZBG-AUVW* or via *https://surveyswap.io/sr/T0Q2-RZBG-AUVW*.

For SurveyCircle users: the Survey Code is: SVLJ-DMKP-BRE4-459F.

Have a great day!