The bubble and its hostility

The influence of social media use on affective polarization in the Netherlands

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Abstract

This thesis investigates the question on how social media use relates to affective polarization in the Netherlands. Worries in Dutch society exist regarding the influence of social media on turmoil in society. It is theorized that social media is positively related to this turmoil (affective polarization). By using a new measurement of affective polarization, more insight is gained on whether and how social media use fuels affective polarization. Moreover, this thesis researches whether or not this relation can be explained by both self-selected and pre-selected exposure. Additionally, it is researched to what extent using social media as a primary news source, political ideology and differences in platforms (Facebook, Instagram and YouTube) influence the relation between social media use and affective polarization. It is found that the use of social media is negatively related to affective polarization, contrary to the initial expectation. This effect can be partially explained by both self- and pre-selected exposure. However, no effects were found regarding using social media as a primary news source and political ideology. Additionally no differences between platforms were found. These findings give reason to further research the nature of the relation, especially when it comes to the frequency of social media use.

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1. INTRODUCTION

Over the years fake news and conspiracy thinking have gained a growing amount of attention in the Netherlands. In 2020, harassment against politicians during COVID-19 demonstrations led to unsafe situations, with people calling names, spreading out conspiracy theories, or even physically harassing politicians (NOS, 2020). Other incidents that led to a growing amount of attention towards fake news and conspiracy thinking, were the conspiracy podcasts of a famous Dutch rapper, fantasizing about killing the Dutch prime minister (NOS, 2020). Worries in the Dutch society concerning the connection between demonstrations and conspiracy theories are on the rise, as the use of social media is booming. Terms as the *'fabeltjesfuik'* (roughly translated as 'fable net') emerged (Algemeen Dagblad, 2020), which is a Dutch term for 'filter bubble'. It refers to a rigid state of mind which occurs within people on social media who become hardly exposed to other views than their own, arguably through the use of personalizing algorithms. These personalizing algorithms are computerized 'rules' for reasoning and processing of data that can cause this rigid state of mind by selecting information for the user to see. It is hypothesized that one of the consequences of concepts like filter bubbles is the development of phenomena such as polarization (Borgesius et al., 2016). Worries regarding social media use and its consequences in Dutch society reach all the way to the government. On the 21th of September, 2021, the Dutch government decided to pay more attention to the spread of fake news and its turmoil on social media (NOS, 2021).

Other worries concern the use of social media by commercial actors, such as social media platforms themselves. An experiment by Kramer et al. in 2014 showed how Facebook was able to manipulate consumers' emotions by manipulating content. An example of how use of social media by such commercial actors rightly sparked worries, is the Trump presidential campaign in 2016. During the campaign, Cambridge Analytica microtargeted voters in the United States. Ten thousand different advertisements were targeted at (older) social media users across the United States and were viewed billions of times. Algorithms were updated and changed on users' social media platforms according to the feedback they received about the targeted voters. Because of this targeting, it is said that Cambridge Analytica was able to influence the election in favor of Donald Trump (The Guardian, 2019). This shows the enormous outreach in which actors may influence the way of thinking among a specific population. If it were the actions of Cambridge Analytica that made the impact on Trump's election to become president, democracy would definitely be at stake.

Consequences of social media use would be less alarming, if it not were for an increasing amount of social media use. Research agency Sociaal Cultureel Planbureau (SCP) with other partners, conducted a study on time and frequency use of social media in the Netherlands. It showed that with the arrival of the smartphone, social media use was increasing each year. On average people spent 22 minutes on social media per day in 2018 compared to 19 minutes in 2015 and 20 minutes in 2013. In 2020, the average use of social media among adolescents (ranging from 15 to 19) was more than two hours a day (NOS, 2020). Among younger target audiences, almost 100% of media use is conducted via smartphone, compared to the average of 62% among older target audiences (Waterloo et al., 2019). Due to this discrepancy between younger and older audiences, it is expected that the use of social media will continue to rise over time.

As stated before, the use of social media can be linked to turmoil in society, which regards hostility towards the Dutch prime minister and other politicians. Such hostilities that can be defined as affective polarization (having negative feelings such as dislike and distrust toward the other group (Iyengar et al., 2019)), as they pertain to negative feelings toward another group. Where a certain amount of ideological polarization can be beneficial for society by stimulating criticism and discussion, affective polarization emphasizes differences and feeds hostilities (Harteveld, 2021). Should rising trends in social media use stimulate affective polarization, it would be alarming for society.

As has become clear, worries exist on the effect of social media use on the turmoil within society. This research will focus on these worries. It will focus on how social media use in the Netherlands relates to this agitation. Specifically, it will focus on how social media use relates to affective polarization: having negative feelings such as dislike and distrust toward the other group (Iyengar et al., 2019). That illuminates the main research question, which is defined as follows:

How does the use of social media relate to affective polarization in the Netherlands?

To answer this broadly defined question, various sub-questions have to be asked and answered. In order to demonstrate a main effect between social media use and polarization the following question must be answered:

Q1: To what extent relates using social media more frequently on a daily basis, when compared to using social media less frequently on a daily basis, to more affective polarization?

Firstly, more frequent use of social media compared to using none at all, may lead to more affective polarization. Consumers who use social media more frequent could have more polarized opinions, possibly through mechanisms of selective exposure.

Once the relation between social media use and affective polarization can be established, it is necessary to explain this relation: how does social media use relate to affective polarization? According to Sears and Freedman (1967), people tend to select the information that is in line with their pre-existing opinions. The reason for this is when people find issues that are not psychologically consistent with each other, also known as cognitive dissonance, they tend to make these inconsistent issues more consistent (Festinger, 1962). This means that when a person has to choose between large amounts of information, it is likely for them to select that information that is in agreement with their own opinions. In 2017, Trilling et al. found evidence that this selection of information occurred among the Dutch population. Within this research, this form of selective exposure is called 'self-selected exposure' as defined by Borgesius et al. (2016). This definition does not include the influence of algorithms.

Bishop (2009) found that in several cases in his research, homogenous groups become more extreme in their thinking. Members of these homogenous groups often tend to adopt extreme positions, as group members constantly compare their actions and beliefs to that of the group. It becomes socially advantageous to adopt these extreme positions, as taking risks is in all likelihood valued more in society compared to taking less risks. As a result, in group settings, individuals want to appear to take more risks by adopting slightly more extreme positions compared to the group average (Forsyth, 2018). Furthermore, behavioral patterns show that members of homogenous groups often ignore facts that prove their arguments being wrong (Spohr, 2017). The consequence is that group members become entangled within an echo chamber in which other points of view are ignored and slightly more extreme ideas and actions are continuously adopted. Due to self-selected exposure, social media consumers may become entangled within these echo chambers. Based on the previously stated mechanisms, the following question is asked.

Q2: To what extent explains self-selected exposure the relationship between social media use and affective polarization?

Another issue related to the use of social media, is that social media platforms select the information for its consumers. When a person who views lots of videos about the stock market opens the front page of YouTube, that page has a totally different look compared to a person who mostly searches videos of cute animals. Nowadays most social media platforms work with so-called algorithms. These algorithms are computer-based processes that are self-learning through calculations. They 'feed' consumers their messages or videos on the social platform, based on previous consuming behavior. In the words of Pariser (2011, p. 9), these algorithms are

> "prediction engines, constantly creating and refining a theory of who you are and what you'll do and want next. Together, these engines create a unique universe of information for each of us [...] which fundamentally alters the way we encounter ideas and information."

This means that people could, in addition to the self-selecting exposure as stated by Sears and Freedman (1967), receive their information on social media through an underlying algorithm. Apart from the limitation of exposure to other opinions through self-selected exposure, personalization – not just on sites like YouTube but also on news websites – could also lead to limitation of the diversity of content people are exposed to. Where people used to be exposed to the same news on television and in newspapers when watching the identical news outlet, nowadays people may not receive the same information (or suggested information) when using the same social media or website compared to other people. The worries lie with a possible ramification of personalization called the 'filter bubble' (Pariser, 2011). Once being trapped in a filter bubble, people will be partially or completely deprived from views that contest their own. The term pre-selected exposure will be used when referring to this second form of selective exposure, as stated by Borgesius et al. (2016). Based on the previous mechanisms, the following question is asked:

Q3: To what extent explains pre-selected exposure the relationship between social media use and affective polarization?

As trends show, personalized content is becoming more of a substantial source each year in the context of the multi-party system in the Netherlands (SCP, 2018). This trend regards personalized content such as social media. However, it does not describe what the nature of the social media use is. Do people use it as entertainment or as news source? Using social media as a news source in combination with its personalizing nature may affect people differently as compared to using it for other purposes. Therefore, it is of essence to describe the nature of social media use. Social media use may lead to polarization, but this effect different when the nature of the use is different?

Q4: To what extent differs the relationship between social media use and affective polarization for people who use social media as a primary news source and people who do not use social media as a primary news source?

To establish whether or not people with different opinions become entangled in either echo chambers or filter bubbles (due to self- and/or pre- selected exposure), the possible relationship between social media use and affective polarization should be tested for different points of view. People in homogenous groups can become entangled in an echo chamber, which may lead to more affective polarization. Moreover, being strongly partisan might influence the way in which one uses social media. Jiang et al. (2021) found that echo chambers on Twitter were more prevalent among Republicans than among Democrats in the United States of America. This could mean that there is a difference among ideological groups between social media use and affective polarization. To study if this is true for social media in the Netherlands, a distinction has to be made in homogenous groups. In this research the distinction is made between the ideological right and the ideological left based on the previous distinction of republicans and democrats. Hence, the following question.

Q5: To what extent differs the relationship between social media use and affective polarization for people who strongly identify themselves with the ideological left wing and those who identify themselves with the ideological right wing?

Finally, due to differences between platforms, distinctions must be made between different social media platforms. For example, YouTube may prioritize more extreme content compared to other social media platforms (Whittaker et al., 2021). Social media platforms most often used in the Netherlands in 2020 were Facebook, YouTube and Instagram (van der Veen et al., 2020). Based on the assumption that the three most used platforms in the Netherlands differ in the relationship between social media use and affective polarization, the final sub-question is defined:

Q6: To what extent differs the relationship between social media use and affective polarization for people who use Facebook, Instagram and YouTube?

Background

During the most substantial part of the 20th century the Netherlands was ideologically pillarized (Dutch: verzuiling). This meant that people identified themselves with one of four ideological standpoints called 'pillars' (Dutch: zuilen): the Catholics, Protestants, liberals and socialists. These pillars would hardly ever mix and each pillar had its own media outlets. Socialists read newspapers such as *Het Parool* and listened to the radio station *VARA*. Liberals had their own broadcast of AVRO and read the *Algemeen Handelsblad*. Protestants read papers such as *De Standaard* and had their broadcast of NCRV whilst the Catholics read *De Volkskrant* and listened to the *KRO*. In the de-pillarization period during the 1960s individualism became more accepted within Dutch society. During this decade, people started identifying themselves as individuals instead of exclusively belonging to a collective pillar. It means that people were no longer bound to the media outlets of their pillar and new media outlets started up to originate with no bonds to pillars, such as *TROS*.

Where during the pillarization people were bound to only few media outlets, after the pillarization period an increasing number of news outlets became available. For example commercial tv media outlets became more available and nowadays -social- media outlets are countless. When scrolling through Facebook, one can choose between a large variety of news outlets to consume news from. When searching on YouTube, one can choose between hundreds of videos that tell you what happened today in the world. When scrolling on Instagram thousands of accounts can show you the latest fashion trends. These modern ways of media consumption spark questions on how these media are different from traditional media, as they may have a different influence on society compared to traditional media. A large difference between the two kinds of media is that through modern (social) media outlets consumers can access vast amounts of information. Obviously, a single person cannot consume all available information and one must select the information one wants to consume. Next to that, one must now filter out the large amounts of misinformation which are prevalent in the vast amount of available information, in order to be rightly informed. The impossibility of individuals to filter information effectively may blur the boundary between factual and incorrect information.

Societal relevance

In 2016 Borgesius et al. argued that empirical evidence showed that at that time there was no warrant for worrying about filter bubbles. They concluded that personalization was still at an infant stage and personalized content was not a substantial information source for most citizens (in the United States). On the other hand, they concluded that there are potential negative effects of filter bubbles, such as polarization. They also pointed at the risk that commercial actors could gain power because they can control the algorithm behind their platform. They specifically referred to the previously mentioned experiment that showed how Facebook was able to manipulate consumers' emotions by manipulating content (Kramer et al. 2014, p. 1). As personalized content becomes increasingly mainstream (SCP, 2018), these findings spark concerns about this trend.

For this reason, and due to the ever-changing world of social media, it is of major importance to study this manipulation process. In short, due to self-selected and pre-selected exposure on social media, people may become merely exposed to their own views. If such relation between social media use and affective polarization exists, the consequence for society may be that it becomes progressively and affectively polarized. If this were the case, mechanisms, effects and groups behind social media use and (affective) polarization should be identified and turmoil regarding the subsequent topic can be tackled. For instance, an explanation may be found on how groups of people come to physically harass politicians and even fantasize about killing them. Additionally, an explanation may be found on how certain groups, such as extreme left- or right-wing groups, come to view other groups as negative or hostile. By knowing how people become polarized in such rigid mindset, solutions can be undertaken to tackle the problem. Moreover, should it be concluded that society becomes affectively polarized by the use of social media, we may explore effective solutions how to adequately manage these problems for the current and future generations.

Along with the rise of social media, discussions emerged whether social media is appropriate for children and young adolescents (O'keefe et al., 2011). Research regarding the use of social media and affective polarization will give insight on whether social media use will affect society for future generations. Moreover, should the findings be alarming, proper legislation regarding the use of social media and social media companies could prevent alarming consequences.

Scientific relevance

The issues of selective exposure by media and affective polarization comprise of a variety of topics. For one, a difference can be made between self-selected and pre-selected exposure. Concerning the former, one can also choose to focus on selective avoidance. Furthermore, it is important to distinguish whether or not to conduct research in a two-party system (such as the United States), as selective exposure may have a different impact on polarization in a two-party system as compared to a multi-party system. For example, selective exposure is more likely to lead to partisanship in a two-party system (Coe et al., 2008). Lastly, literature distinguishes between selective exposure in traditional media and selective exposure regarding social media. Studies researching the former concept often use the theory of self-selected exposure. Studies focusing on the latter often do so with theories on pre-selected exposure. Although self-selected exposure is still relevant today, pre-selected exposure must be considered with the arrival of social media.

As particular attention is paid to selective exposure (partisanship) and media with focus on the two-party system in the United States (e.g. Coe et al., 2008; Dilliplane, 2011; Stroud, 2010; Iyengar and Hahn, 2009), research also concentrates on selective exposure and polarization within the multiparty system of the Netherlands. Contrary to the previously mentioned articles, Bos et al. (2016) and Trilling et al. (2017) researched self-selected exposure and media use in the Netherlands. These studies, however, all focus on self-selected exposure regarding traditional media outlets. More recent studies do research social media and selective exposure (e.g. Bozdag et al., 2014; Bruns, 2019; Groshek et al., 2017; Kleinnijenhuis et al., 2019; Min and Wohn, 2020; Nordbrandt, 2021; Seargeant and Tagg, 2019;

Sphor, 2017; Wittaker et al. 2021). In other words, where previous studies either focus on self-selected exposure on traditional media outlets or pre-selected exposure on social media within a two-party system, this research distinguishes itself by centering both self-selected and pre-selected exposure on social media. Moreover, this research is relevant for the multi-party system of the Netherlands, on which less research regarding the subject has been conducted (Bos et al., 2016; Bozdag et al., 2014; Kleinnijenhuis et al., 2019; Nordbrandt, 2021; Trilling et al., 2017).

Kleinnijenhuis et al. (2019) examined the question whether perceptions and preferences of voters in the Netherlands are affected by self-selected news content on both traditional media and social media. In some regards this research can be compared to that of Kleinnijenhuis et al. (2019). For example, this research will focus on self-selected news content on social media in the Netherlands through a survey. However, this research will also take into account pre-selected exposure on social media and it does not focus on traditional media. Moreover, it considers the possible consequence of social media use of affective polarization, where Kleinnijenhuis et al. (2019) centered their research around on political perceptions and preferences.

Nordbrandt (2021) researched the influence of social media use on affective polarization in the Netherlands. This research attempts to innovate the former research by using a different measurement of affective polarization. Moreover, this research innovates by researching the distinction between self-selected and pre-selected exposure, differences in social media platforms, and partisanship regarding left and right. By adding the new measurement of affective polarization, the possibly more 'troubling expressions' of polarization as stated by Nordbrandt (2021) may be clarified, as opposed to her way of operationalizing affective polarization regarding sympathizing with political parties. Due to this unique measurement, different results may be found for the Netherlands. Furthermore, the studies described above often ignore the possible self-selected exposure aspects on social media. This research innovates, by researching both distinct concepts of self-selected and pre-selected exposure on social media. It is also innovating regarding the distinction between three social media platforms. A study on such distinction has never been performed previously in the Netherlands. This may result in finding different outcomes for different platforms. Additionally, this study differentiates itself from other studies on the Netherlands by exploring social media as a primary news source. Lastly, it adds to the difference in partisanship between left and right wing voters, another distinction that has not yet been made earlier in the Netherlands regarding this subject.

2. THEORY

Definition of polarization

In order to answer the main question of this research (*How does the use of social media relate to affective polarization in the Netherlands?*) theory must be provided. Moreover, to provide this theory, a clear definition of affective polarization must be given. In order to do so, one must firstly understand what polarization in itself means. An example of a plain definition of polarization is that of Dimaggio et al. (1996). They defined the state of polarization as "the extent to which opinions on an issue are opposed in relation to some theoretical maximum." The process of polarization is explained as an increase of opposed opinions over time. They argue that polarization militates against social and political stability, due to the reduction of the likelihood of group formation at the center of the distributions of opinions. Moreover, they state that polarization increases the probability of formations of different groups that have irreconcilable preferences.

It can be stated that polarization at its core can be defined as the discrepancy between ideological preferences. For a clear understanding of polarization, a thorough exposure of ideological preferences is mandatory. Therefore, it is important to research the individual's ideological preferences, which can be used as an indicator for polarization within a group. Furthermore, it is also important to examine whether individuals experience polarization and how they experience this.

According to Wilson et al. (2020), polarization can be divided into three types. Firstly, it can occur as ideological polarization, in which partisans are increasingly divided by their preferred policy positions. Secondly, it can occur as perceived or false polarization, a state in which partisans perceive the amount of ideological distance between their group and the other group to be larger than it is in reality. Thirdly, polarization can occur as affective polarization, in which partisans experience negative feelings such as dislike and distrust toward the other group and tend to avoid them.

Where polarization describes the discrepancy between groups, affective polarization describes this discrepancy whilst having negative feelings toward the other group. Iyengar et al. (2019) described this form of polarization as having feelings of dislike and distrust toward the other group, much like the definition of Wilson et al. (2020). Tappin and Mackay (2019) on the other hand, defined it as having negative feelings towards opposing partisans and positive feelings towards co-partisans. This research will focus on the aspect of the feelings towards the opposing partisans, the ones with other ideological preferences, which is defined as the outgroup. More specifically, the definition of affective polarization is specified to experiencing negative feelings toward the outgroup.

Social media and polarization

To answer the question whether social media use can lead to affective polarization in the Netherlands, it is important to determine the literature that is available about this possible relation. Lee (2016) found that social media use can in fact lead polarization. However, this conclusion was found in the context of the Umbrella movement in Hongkong in 2016. Lee (2016) states that these finding cannot be generalized to every context, as the polarizing nature of social media may only be true for the highly polarizing context in which Hongkong was situated at the time.

In addition to this expectation, in their research, Campbell et al. (2019) found that through the homophily principle, as explained in the introduction section, and greater connectivity, extreme news content and polarization become more prevalent.

Based on these findings one may expect that social media use will lead to polarization in the Netherlands. This relation has been researched by Nordbrandt (2021). She found that affective polarization affects the use of social media. Possibly because affectively polarized individuals are confident enough in their political views to resist cognitive dissonance (discrepancy between issues and own opinions) that would refute their own views. Those individuals who are not so confident in their views, may be more prone to cognitive dissonance, which in turn may discourage the use of social media. Due to this finding, one may expect affective polarization to lead to more social media use.

Due to different measurements of both social media and affective polarization, results in this research may differ from those of Nordbrant (2021). In her research affective polarization was measured by unsympathetic feelings toward specific political parties and elites. Political parties' supporters were left out of the measurement. When focus lies more on people with other political differences (supporters of certain political parties) instead of the elites and politicians associated with that party, research shows that social media use leads to affective polarization (Lee et al. 2021). Moreover, this relation is found for both the dual party-system of the United States as for the multi-party system of Japan. As in this research focus lies on affective polarization regarding out-groups rather than politicians and elites, it is expected that social media use in the Netherlands will lead to more affective polarization. Therefore the first hypothesis will be:

H1: The use of social media leads to more affective polarization.

Self-selected exposure

In 1967 Sears and Freedman stated that people tend to select the information they want to incorporate that is in accordance with their pre-existing opinions. It may be that most people seem to be disproportionately exposed to communications that agrees with their pre-existing opinions. Yet under some conditions, such as being heavily involved in a certain topic, people may also prefer information that contradicts these opinions. In both cases, it is clear that people tend to select information. At first, when people find issues that are not psychologically consistent with their own opinions, cognitive dissonance occurs and people tend to make them more consistent (Festinger, 1962). This statement supports the notion that people tend to select information that is in accordance with their pre-existing opinions to avoid cognitive dissonance. It may however also support the notion that people do not select information in accordance with their pre-existing opinions, but that they evaluate this information differently from the information that is not in accordance with their pre-existing opinions. Borgesius et al. (2016) defined this form of selective exposure as self-selected exposure, compared to pre-selected exposure that will be explained in the section "pre-selected exposure". The former describes how the individual itself selects information to incorporate.

Trilling et al. (2017) researched the proposition that (self-)selective exposure would lead to polarization in the Netherlands. Based on their research, one can state that there is evidence that self-selected exposure does occur in the Netherlands, supporting the notion that people tend to select information that is in accordance with their pre-existing opinions. The question on whether selective exposure can lead to polarization could not be answered by Trilling et al. (2017), as respondents in their research tended to have moderate opinions which are less likely to lead to polarization. Moderates often may not even perceive themselves to choose a side, which makes them less likely to 'radicalize'. For this reason, the notion that self-selected exposure can lead to polarization may not be applicable for moderates. Additionally, the notion may only be true for people with expressionist opinions. As Trilling et al. (2017, p. 206) stated:

"For selective exposure to fuel a process of polarization, thus, it might be necessary that there is a certain amount of polarization to start with."

In the context of the United States however, strong evidence suggests that selective exposure can explain rising levels of polarization (Stroud, 2010). To review the statement of Trilling et al. (2017), a dual-party system may have more initial polarization compared to a multi-party system, increasing the chance of self-selected exposure fueling polarization. Indeed, Trilling et al. (2017) did not find any evidence that self-selected exposure fuels polarization in the multi-party system in the Netherlands.

On the contrary, Tsfati and Chotiner (2016) found evidence of the influence of self-selected exposure on polarization in the multi-party context of Israel. For this strong indication of influence in a multi-party context, one can assume that self-selected exposure may also lead to polarization in the Netherlands. The question remains however, if this is also true for social media use and if it can explain a possible relation between social media use and polarization. This question is answered by Bakshy et al. (2015), as they researched how online platforms such as Facebook influence exposure to perspectives that cut across ideological lines. They examined 10.1 million (U.S.) Facebook users and found that individuals' choices played stronger roles in limiting exposure to cross-cutting content compared to algorithmic ranking of news feeds (pre-selected exposure).

Again the quote of Trilling et al. (2017) is of importance here. The notion that self-selected exposure fuels polarization might be true for a polarized context such as in Israel (Tsfati and Chotiner, 2016), that does not mean it is automatically true for the less polarized context of the Netherlands. However, less studies have involved *affective* polarization in research regarding self-selected exposure. Zhu et al. (2021) found that seeking out information in accordance with pre-existing political views is associated with affective polarization during elections in the United States. This finding indicates that there may be a positive relation between self-selected exposure and affective polarization for other contexts. The question remains unanswered whether this is the case for the context of the Netherlands.

Based on the above mentioned research the expectation can be derived that social media use can lead to limitation of cross-cutting content due to self-selected exposure (Baksy et al., 2015; Trilling et al., 2017), which in turn can lead to polarization when there is a certain amount of initial polarization (Stroud, 2010; Trilling et al., 2017; Tsfati and Chotiner, 2016). When viewing this relation in the context of affective polarization, research in the United States suggests the same notion as to 'regular' polarization. Because of this expectation, the following hypothesis is stated:

H2: The relation between social media use on affective polarization can be explained by self-selected exposure.

Pre-selected exposure

When researching social media and affective polarization, the term pre-selected exposure is of essence. There is much debate going on among scholars regarding the dangers of this form of selective exposure. Contrary to self-selected exposure, as the name suggests, pre-selected exposure is selective exposure that is predetermined for the consumer. This form of selective exposure can only occur digitally. Pre-selected exposure is characterized by an underlying algorithm that determines a consumers view of a social media 'feed' or news website. This view is determined by the persons previous consuming behavior and his or her network.

Algorithms

It is important to understand how this pre-selected exposure works in order to explore its relation with social media use and affective polarization. As stated above, pre-selected exposure is characterized by an underlying algorithm that determines how a social media feed or news website is displayed to a consumer. The Cambridge dictionary defines an algorithm as:

> "a set of mathematical instructions or rules that, especially if given to a computer, will help to calculate an answer to a problem" – Cambridge dictionary (2021).

Algorithms can be used for different purposes such as calculations, automated reasoning or processing of data. In this research it is essential to comprehend how algorithms work regarding personalization on social media. A clear example of how an algorithm can work is given by Bucher (2012). Bucher provides an explanation of Facebook's EdgeRank algorithm in 2012.[*] According to Bucher Facebook deploys an automated and predetermined selection mechanism to establish relevancy to the user. Relevant posts, or 'objects' will pop up on a user's 'feed': a constantly updating column in which posts of a user's friend, pages the user follows and 'relevant' posts are displayed. Interactions with an object, such as 'liking' or 'commenting' create a so called 'Edge'. The algorithm (EdgeRank) displays different objects on the feed according to different factors based on the Edges. The rank of an Edge is determined by three components:

- Affinity. This pertains to the nature of the relationship between the user and the objects creator.
- Weight. This pertains to the weight Facebook assigns to an Edge. For example, a comment has more weight than a like.
- Time decay. This pertains to the 'freshness' of an edge. Older ones are less important than new ones.

The multiplication of these three factors determines the rank of an Edge. Other assumptions might also influence the rank. These are: the type of content, interaction with friends on Facebook, who posted the content and the distinction between friends (some 'count more' than others). The higher the rank, the more visible the object.

[*] Note that this description dates to 2012 and is merely an example of how an algorithm can work.

As Bucher states, these algorithms are rarely subjected to critical analyses. She states that due to the ‘black boxed’ nature of these algorithms they are hard to analyze, as some components are known and other remain obscure. Algorithms are a property, hence this secretive nature (van Dijck and Poell, 2013).

When looking at algorithms in the context of social media, it is not only the nature of the algorithm that provides an insight in the possible consequences of the implementation of these algorithms. It is also the aspect programmability of algorithms on social media platforms or websites that is of importance. It is the programmability that describes the influence humans have on these algorithms. Programmability can be defined as:

> “…the ability of a social media platform to trigger and steer users' creative or communicative contributions, while users, through their interaction with these coded environments, may in turn influence the flow of communication and information activated by such a platform.”- van Dijck and Poell (2013, p.5).

According to van Dijkck and Poell (2013) the power of algorithms lies in their programmability as programmers can steer user’s experiences, content and relations. This becomes especially clear when looking at the experiment of Kramer et al. (2014), showing how Facebook was able to manipulate consumers’ emotions by manipulating content. However it is not only the programmer that holds this power. It is also the users that are able to steer content and shape algorithmic mechanisms. One method to do so is massively ‘liking’ certain content (van Dijck and Poell, 2013).

Based on the nature of the algorithm and its programmability (through both influence of programmers and users) the influence of pre-selected exposure on polarization can be theorized.

Homophily

The principle of homophily in the context of social networks is defined as people engaging in new ties with other individuals that are similar to them. This is true for relationships with various natures such as friendship, work, marriage and so on. This results in people having homogenous networks regarding (for example) sociodemographic and behavioral characteristics. People have influence on the network they create. However, these homogenous networks also influence an individual’s attitudes and behaviors. People who are similar to one another, are more likely to have interpersonal communication which leads them to have more influence over one another (McPherson et al., 2001).

This influence expresses itself for example in the information they receive, the attitudes they form, and the interactions they experience (McPherson et al., 2001).

The principle of homophily can also be translated to the context of social media. People befriend other individuals which they already know in real life, with the consequence of creating a homogenous network on social media. Moreover, people with similar interests are more likely to become friends (Aiello et al., 2012). Algorithms such as the previously described EdgeRank additionally prioritize that specific content which the users friends have interacted with (Bucher, 2012). The friends with the most interactions with the user (for example through chatting) 'count the most' which means content which they interact with is weighed heavier. As a consequence, interest of more close friends (according to EdgeRank) are shown more often to the user. Due to the assumption of users creating their own homogenous networks because of user programmability (McPherson et al., 2001) and algorithms prioritizing interests similar to that of the user, one can assume that it is likely for users of social media to have homogenous networks (on platforms in which users can befriend other users with an algorithm which is comparable to EdgeRank).

Echo chambers

Since people tend to engage with people that appear to have similar interests, it may seem logical that when joining certain groups, these groups show similar characteristics to that of the individual at hand. The possible danger that comes along with such groups is that they may become more extreme in their thinking (Bishop, 2009). As stated in the introduction section, members of certain homogenous groups tend to adopt a slightly more extreme position on cases compared to the group average. By comparing one's own actions and beliefs to that of the group, individuals find it to be socially advantageous to adopt more extreme positions. This, along with the fact that individuals in these groups often ignore statements that prove them wrong, make that members become entangled within an echo chamber in which no refutation of ideas takes place and continuously slightly more extreme ideas are adopted. This way, opinions and ideas in homogenous groups become exacerbated. This could mean that actual extreme opinions, become more extreme over time.

Friend suggesting algorithms (which suggest similar friends), self-selection of similar friends online, along with user programmability creating the option for making groups and chats online, make that (certain) social media platforms perfect breeding grounds for such homogenous groups. For example Jiang et al. (2021) found that political echo chambers on Twitter are prevalent in the United States, especially for extreme right communities. This phenomenon, along with the filter bubble, can lead to a society that is increasingly segregated along partisan lines (Barberá, 2020).

Filter bubbles

Pariser (2011) identified pre-selected exposure on social media due to algorithms as the earlier described ‘filter bubble’. Due to the algorithm feeding people new information based on previous consuming behavior, people become entangled in these ‘bubbles’. Not only are people continuously exposed to like-minded information, they are also less exposed to cross-cutting information: information that is not similar to the individuals pre-existing opinions (Resnick et al., 2013). This phenomenon is different from the previously described echo chamber. Contrary to the filter bubble, the echo chamber is an (online) group in which the opinions of members are echoed and become more extreme over time. The filter bubble describes how users of (certain) social media networks become exposed to likeminded content and excluded from cross-cutting content through an underlying algorithm. Moreover, the filter bubble is invisible, and one cannot choose to leave the filter bubble.

As has already become clear, Borgesius et al. (2016) stated that there was no warrant for worrying about filter bubbles on social media. However they state that this is only the case when personalization does not pose as a substantial news source. As stated in the introduction of this thesis, the use of social media and subsequently the use of personalized news, increase each year (SCP, 2018). Because of such trends, Spohr (2017) identified that, next to self-selected exposure and echo chambers, filter bubbles can lead to polarization on Facebook.

> "If you are getting all your information off algorithms being sent through phone and it's just reinforcing whatever biases you have, which is the pattern that develops. At a certain point, you just live in a bubble, and that's part of why our politics is so polarized right now. I think it's a solvable problem but I think it's one we have to spend a lot of time thinking about."
> - Barack Obama (Hamedy, 2018, p1).

The link to affective polarization

As has become clear, the pre-selected exposure causing algorithms may have numerous consequences. It can cause that people have homogenous networks on social media -along with their pre-existing homogenous networks. In combination with user programmability, dangers of such homogenous networks are that people become part of homogenous groups and eventually locked into echo chambers in which group opinions are echoed back to them and become stronger. Another consequence of pre-selected exposure can be that people become trapped in a filter bubble, meaning they are continuously exposed to likeminded information.

The consequences of pre-selected exposure have two aspects in common: they limit the amount of cross-cutting content people are exposed to and widen the amount of content that is in agreement with their pre-existing opinions. As has already become clear, these phenomena can lead to a society that is increasingly segregated along partisan lines (Barberá, 2020) thus enhancing polarization (Sphor, 2017; Lee, 2016). Moreover, Cho et al. (2020) found that algorithms select political videos based on participants own search behavior on YouTube, which heightened affective polarization. The nature of the algorithm -recommending content to users based on their previous consuming behavior-implicates a similar relation for other social media. Harel et al. (2020), confirm this finding for Facebook, regarding homogenous enclaves: echo chambers. By analyzing language in the so-called Shadow's Facebook page, they found a process of escalation regarding the members of this page, which had eventually led to affective polarization. As social media use creates pre-selected exposure for users and literature indicates that pre-selected exposure positively influences affective polarization, the following hypothesis is stated:

H3: The impact of social media use on affective polarization can be explained by pre-selected exposure.

Social media as primary news source

As stated in the previous hypothesis, the amount of social media use that can lead to affective polarization. It may be this aspect of using social media more often that would lead to this increase. Borgesius et al. (2016) stated that it is not this aspect of using social media more often. As no such effect was found, they argued that worries regarding filter bubbles are redundant. However, they stated that under the assumption of social media becoming a primary news source, an effect regarding social media use and polarization could be found. Lee et al. (2021) found that using social media as a news source is positively related to affective polarization in both the multi-party system of Japan and the dual-party system of the United States. Therefore, one can assume that the relation between social media use and affective polarization is stronger for people who use social media as primary news source in a multi-party system. Deriving from this point of view, the following hypothesis regarding social media use is stated:

H4: The impact of social media use on affective polarization is stronger for people who use social media as a primary news source.

Left and right identification

According to the social identity theory group categorization leads to in-group favoritism and out-group discrimination (Tajfel et al., 1979). Bäck (2013) translates this theory to conservatives (right-wing) and liberals (left-wing) in the United States. Bäck (2013) finds that both left- and right-wing affiliates display stronger biases when in opposition.

> "… mere perception of belonging to two distinct groups – that is social categorization per se- is sufficient to trigger inter-group discrimination favoring the in-group."- Tajfel et al. (1979, p.56).

In-group favoritism goes hand in hand with out-group discrimination. The question remains whether this mechanism is the same for different groups. Is the relation between social media use and affective polarization stronger or weaker for certain groups? Moreover, is it stronger or weaker in a multiparty system for left- or right-wing groups?

One could argue that left- and right-wing groups experience the same amount of in-group favoritism and out-group discrimination offline as well as online. Yet, as mentioned before, Jiang et al. (2021) found that political echo chambers on Twitter are prevalent in the United States, especially for far-right communities. This finding suggests a difference between the online right- and left-wing groups (in the United States) regarding impact on political echo chambers. Echo chambers were found in both left- and right-wing groups, however right-wing groups tended to connect more to the echo chamber and isolate more form the rest. Therefore left- and right-wing groups may have differences in online behavior, which could lead to different amounts of selective exposure and in turn lead to different amounts of affective polarization. For instance, the more connectivity and isolation by right wing individuals, the less they are exposed to cross-cutting content (non-likeminded content) and the more they are exposed to opinion confirming content compared to those from the left-wing. Reasoning from the notion that selective exposure on social media will lead to more affective polarization, this would mean that the right-wing would become even more polarized than the left-wing.

Whether these facts are generalizable for the Netherlands is not clear. However, Waeterloos et al. (2021) found that, among other things, Belgian adolescents' political ideology influenced their political social media participation. People who identified themselves with the left-wing tended to participate more politically on social media. According to this finding, in a multi-party system left-wing individuals participate more on social media politically. Reasoning from the notion that selective exposure on social media will lead to more affective polarization, this would mean that their political views are more confirmed due to selective exposure compared to right-wing individuals. Thus, left-wing individuals become more affectively polarized as they display stronger negative feelings toward the outgroup compared to right wing individuals.

Whether it is the left-wing or the right-wing that becomes more polarized online, it is nevertheless essential to build on these previous findings. For the reason that (young) left-wing individuals are more likely to politically participate online compared to right-wing individuals in a multi-party system (Waeterloos et al., 2021), the following hypothesis is stated:

H5: The impact of social media use on affective polarization is stronger for people who (strongly) identify themselves with the ideological left wing compared to people who (strongly) identify themselves with the ideological right wing.

Facebook, Instagram and YouTube

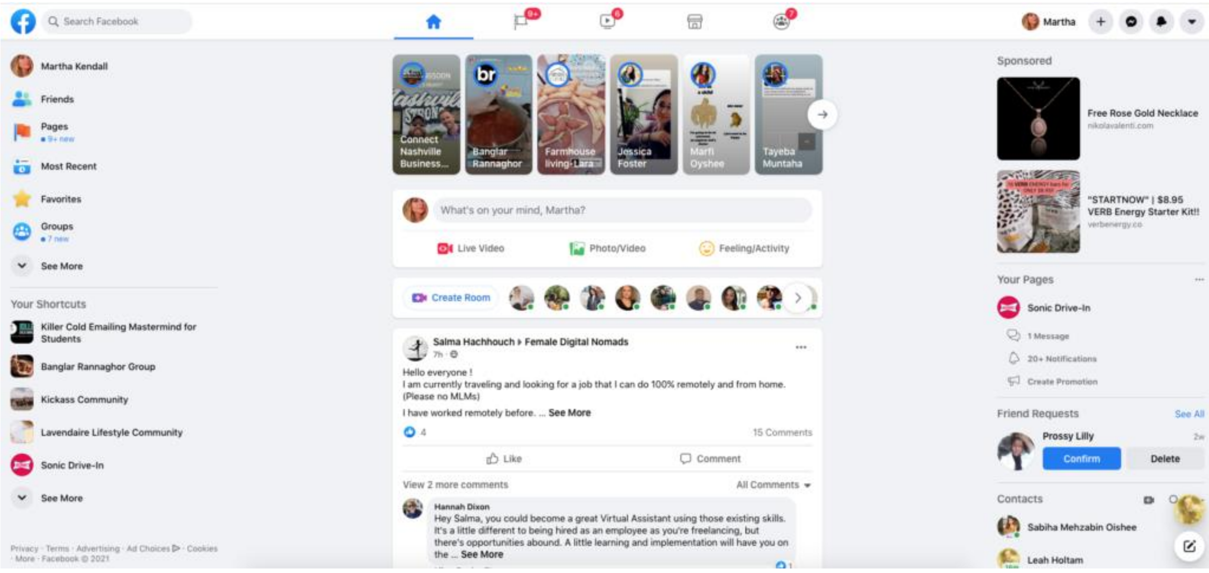
In the previous section of "pre-selected exposure" the example of the EdgeRank algorithm of Facebook in 2012 is discussed. It is important to note that each platform uses a different algorithm. For instance Whittaker et al. (2021) found that YouTube's algorithm prioritizes far-right content after a user has interacted with it. Platforms such as Reddit and Gab showed no signs of amplification of extreme content via recommendations. Due to differences such as these it is important to conduct research regarding social media across different platforms. This research will focus on three different platforms: Facebook, Instagram and YouTube. These platforms are the most popular platforms in the Netherlands in 2019 and at the beginning of 2020 (van der Veen et al., 2020), with the exemption of WhatsApp. The latter platform is a communication platform in which recommended content is not provided to the consumer. For that reason, and manageability of research, only Facebook, Instagram and YouTube are taken into account. If trends continue as in the past few years, these platforms will continue to grow.

In the following section the platforms Facebook, Instagram and YouTube will be explained. Firstly, to get an overview of how these platforms work, their basic appearance will be described. Secondly and lastly, the underlying algorithm of the platform will be explained.

Facebook

The most important feature of Facebook is the previously mentioned 'feed'. This is the starting page on which all posts can be viewed. These posts can range from pages the user has 'followed' to posts of friends on Facebook. Also, these posts can be recommended or promoted (advertisements). Users can ‘follow’ certain pages by liking them. When a user follows a page, posts of this page will appear on their feed. Furthermore, users can interact with posts by clicking on the ‘thumbs up’ logo (‘liking’), commenting on posts or share posts. By doing the latter, the user ‘shares’ the post to the feed of his or her friends. An example of the Facebook feed can be seen in Figure 1 below.

Figure 1: Example of Facebook



Source: Custard (2021).

Next to the feed, users have the option to see only video’s and also have the option to only see posts in groups from which they are member of. They can become member of groups by clicking on ‘become member’.

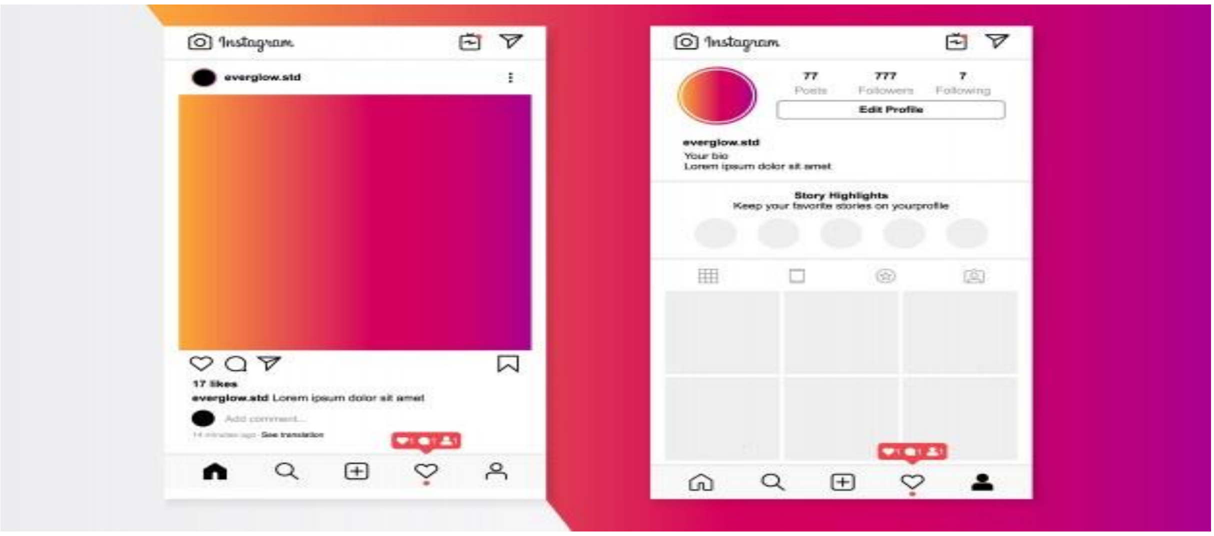
The Washington post (Oremus et al., 2021) summarized how the algorithm of Facebook works in 2021. Most of the documents regarding the algorithm are not publicly available, which aligns with the statement of their secretive nature by Bucher (2012) and van Dijck and Poell (2013). However, by conversating with “Facebook insiders” and scanning available documents the Washington Post is able to give a clear description of the algorithm, which does not differ much from the description of Bucher in 2012.

The top post on a user’s feed is a “prized position based on thousands of data points related to the user and post itself, such as the poster, reactions and comments.” (Oremus et al., 2021, p.4). The position of each post is determined by the algorithm. The algorithm is tailored to each user precisely yet also favors certain behavior and content such as posts that are popular with friends. Due to the human and algorithmic tendency of having homogenous networks, combined with the algorithm prioritizing content, which is popular with friends, it becomes especially likely for more partisan users to become trapped in echo chambers and filter bubbles in which extreme content is prioritized.

Instagram

Comparable to Facebook, Instagram also has a feed on which different content appears (the house icon at the bottom left in Figure 2). Contrary to Facebook, this content is limited to posts of friends and promoted messages (advertisements). Furthermore, users can ‘discover’ posts by clicking on the magnifying glass icon, as can be seen next to the house button in Figure 2. This discover feed shows posts from a wide range of users, changing each time the feed is refreshed by the user. The remaining icons provide the options of making a post, messaging other users, viewing likes and comment and managing one’s profile.

Figure 2: Example of Instagram



Source: https://www.freepik.com/premium-vector/instagram-feed-user-profile-template_4196646.htm

When trying to describe the algorithm of Instagram, again the secretive nature of the algorithm arises (Bucher, 2012; van Dijck and Poell, 2013) as Instagram does not disclose much information about their algorithm. Cotter (2019) describes the user programmability of influencers, people with influence over a certain target audience, and how they try to increase this user programmability by researching the algorithm. Influencers identify increased engagement and the amount of followers as factors that increase visibility of posts (on the feed and in the discover section). Similarly to Facebook this engagement entails the liking and commenting on a post. Furthermore, stagnation of followers and bans of users decrease visibility of posts. Similar to Facebook, Instagram’s algorithm is heavily influenced by engagement. As one influencer stated:

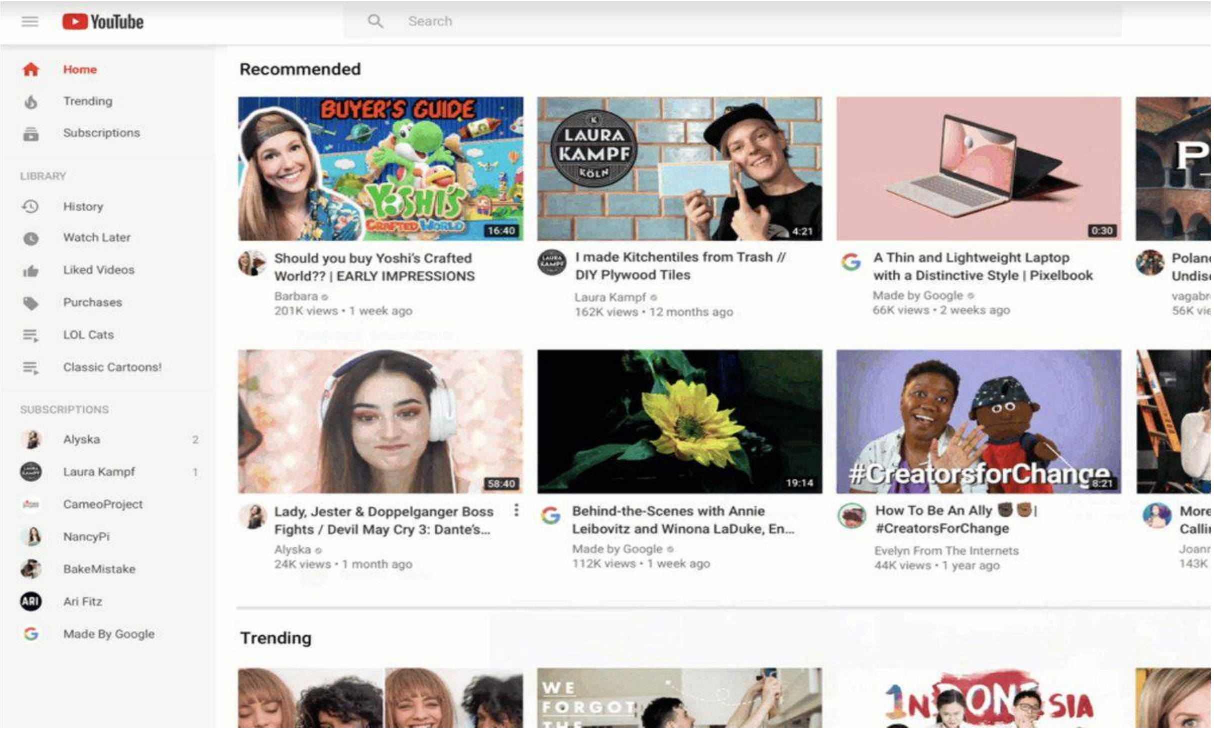
“in order to maximize visibility, you need to get as many of your followers to regularly engage with your posts as you can.” – Influencer (Cotter, 2019, p.903).

One could state that this aspect of the algorithm could, similarly to Facebook, also create the danger of echo chambers especially for more partisan users. There is however, one essential difference compared to Facebook. Where on Facebook users can make friends by clicking on adding them and the befriended person has to ‘accept’ the friendship, the following in Instagram does not have to be mutual. A user on Instagram can follow anyone they wish to follow (in cases of private accounts the user does have to accept the follow request) without the other user having to follow them back. One could argue that in this way it becomes easier for users to follow other users with who they are less connected to compared to other users on Facebook. This would mean that users are less likely to become trapped in an echo chamber. However, due to the nature of the algorithm people are still likely to become trapped in a filter bubble and selectively expose themselves to like-minded content.

YouTube

Contrary to Facebook and Instagram, YouTube offers users to see only videos made by other users. In Figure 3 one can see the front page of YouTube. YouTube offers a wide range of videos with a large number of different categories. Users can ‘subscribe’ to different channels to see the videos which are posted by the subsequent channel. On the bottom left in Figure 3 one can see different ‘subscriptions’ to which the user at hand has subscribed. On the ‘home page’ users get to see recommended videos (based on previous consumption behavior) next to different categories and trending videos. Apart from watching and posting videos, users are able to interact with them (similarly to Facebook and Instagram) by liking and commenting on the videos. Underneath the posted videos users are able to see the number of views and the time that has passed since the video was posted.

Figure 3: Example of YouTube



Source: Alexander (2019).

It is important to note that if a user has created an account on YouTube, previous consuming behavior is recorded for that account. Based on this previous consuming behavior, videos are recommended by the algorithm. These recommended videos account for 60% of all clicks from the home page (Davidson et al., 2010). Ribeiro et al. (2020) found that alt-right channels can be a proxy for more extreme content, as commenting users systematically shifted from commenting on exclusively milder content towards more extreme content. People received minimal criticism on their comments, suggesting the exclusion of cross-cutting content as is described in the echo chamber and filter bubble.

Moreover, Whittaker et al. (2021) found that accounts that interact with far-right content are twice as likely to be exposed to extreme content, with multiple finding suggesting that such interactions will be amplified in the future.

Differences in polarization

The previous findings indicate that there are several differences between these platforms. For one, Instagram differs from Facebook in that users do not have to follow other users back, which makes the entanglement in an echo chamber possibly less likely whilst other mechanisms seem equally likely. Furthermore, no clear expectations can be derived from such different platforms from which the algorithms are relatively secret. Therefore, to be able to establish possible differences in platforms in the impact of social media use on polarization, the former expectation leads to the statement of the following hypothesis:

H6: The effect between social media use and polarization is weaker for Instagram compared to YouTube and Facebook.

3. METHODS

The main research question *How does the use of social media relate to affective polarization in the Netherlands?* describes a relation between two variables. In order to research this relation, possible options of methods have been considered. Benefits of quantitative methods outweighed those of qualitative methods. Nordbrandt (2021) already established a relation between social media use and affective polarization with a different measurement of affective polarization: sympathizing with political parties. Therefore, the relation between social media use and affective polarization has not been researched among the population Netherlands regarding the definition of affective polarization as having negative feelings toward the outgroup. As this relation is yet to be established, quantitative methods was chosen for exploring this relation as compared to exploring depth of the relation when using qualitative methods. Quantitative methods offer the best options for reliably and validly establishing the direction of the relation for the population of the Netherlands and the concepts that influence it.

Survey and dataset

In order to answer the research questions empirically, a survey was conducted among 270 people living in the Netherlands with a minimum age of 18 using Qualtrics. As questions regarded political preference and voting, the minimum age of 18 was adopted as this is the minimum voting age in the Netherlands. The survey was spread through personal social media channels on Facebook and LinkedIn. Questions were asked not in English yet in Dutch in order to avoid an unnecessary language barrier for respondents who do not or hardly speak English. The survey can be found in Appendix A.

After conducting the survey the data was transferred to SPSS in order to analyze the results. These results showed that the research population was not representative for the Dutch population, specifically regarding the variables of education and age. In order to get a more representative research population, a weighing was added to the SPSS dataset regarding education. Percentages regarding educational level (highest accomplished level) of the actual Dutch population were compared to the research population. By doing so, factors were calculated regarding the difference between the two populations. By adding these factors to the syntax of the SPSS dataset (Appendix B), some cases came to weigh more than others and the survey became representative to the Dutch population regarding educational level. A weighing of age was considered. However, not all ages are represented in the dataset. For this reason data became unrepresentable after adding the weight factors regarding age. For this reason age was not weighed.

The disadvantage of weighing the dataset is that some respondents' opinions weigh more than others, giving a distorted view of the reality of the dataset. Moreover, not all opinions in the Dutch population may be the same as to those opinions that are weighed more or weighed less. However, weighing the dataset does provide a theoretical representation of the Dutch population, which is of essence when researching that specific population. As stated before, when researching a population it is of essence that findings can be generalized to that population. By weighing the data, findings are more generalizable. Considering these advantages and disadvantages, the choice was made to weigh the dataset.

When theoretically expecting network homogeneity on social media, it is of importance to 'burst the bubble' in order to get a clear representation of the Dutch population. As the survey was spread through personal networks, there is an overrepresentation of students from Nijmegen. In order to retrieve a more reliable representation of Dutch society, next to weighing the data, the survey was also spread on politically oriented Facebook groups for receiving more right-wing oriented response. The Facebook groups included: Ja21 and PVV.

Control variables

As a means of enhancing internal validity, certain control variables are added to control for external effects on polarization. Some variables other than the included ones can be of influence on the analyses. By controlling for these other concepts, it can be determined whether they can explain the researched relation. The variables included must be exogenous from the independent variable. Moreover, they may be likely to influence the dependent variable. For instance, one's educational level could be of influence on the amount affective polarization, since more highly educated people may have more cognitive ability to become aware of the mechanisms that cause affective polarization. Additionally, age might influence the level of affective polarization as older people are more likely to be influenced by polarized clickbait (Munger et al., 2020). Lastly, sex might influence affective polarization, as women might be more affectively polarized than men (Ondercin et al, 2021). For these reasons, educational level, age and sex are added to the analyses as control variables. The questions asked within the survey regarding these variables were:

- *What is your sex? (Male, female, other, I do not wish to say).*
- *What is your highest attained educational level? (Elementary school, VMBO/MBO1/AVO junior high school, HAVO/VWO/MBO2/MBO3/MBO4, HBO/WO bachelor, WO Master/doctorate).*
- *What is your age?*

The options regarding educational level were chosen according to the options stated by CBS (2021).

Missing data

In some instances, respondents filled in half of the survey or less. These respondents have been removed from the dataset. Furthermore, some respondents had missing data on a maximum of one question. For these missing values, the average of the question was assigned to their response. Out of 270 initial responses, 208 were considered for analyses.

Variables

To test the stated hypothesis, different questions were asked to the respondents regarding social media use and polarization. Answers were transferred to SPSS and for each question a variable was made with syntax. The syntax can be found in Appendix B.

The first questions in the survey regarded the consent and anonymity. Respondents were asked if they are 18 years of age or older and if they agree with the terms as stated in Appendix A. Follow-up questions were asked to add the previously discussed control variables to the analyses (sex, age and educational level).

To test the first hypothesis the concepts of 'social media use' and 'affective polarization' needed to be made measurable. Respondents were firstly asked if they used social media (*Do you use social media? (yes/no)* (Appendix A, question 8)). If answered yes, following questions regarded the number of minutes per day respondents spent on social media (*Could you give an indication of how many time you spent on social media a day in minutes? Please fill in a whole number.* (Appendix A, question 9)). Answers ranged from 2 to 360 minutes a day. The reason why measuring the number of minutes per day was chosen, was to get a clear overview of how much social media potentially influenced respondents' day to day lives. Respondents were also asked whether they used Facebook, Instagram or YouTube (*Which of the following platforms do you use? (Instagram/YouTube/Facebook)* (Appendix A, question 10)).

For the measurement of affective polarization respondents were asked whether they feel deterrence of people with other political views, whether they have negative feelings regarding people with other political views and whether they have aggressive feelings regarding people with other political views (*Could you indicate to what extent you agree with the following statement? I experience dislike/negative feelings/aggressive feelings toward people with different political preferences. (totally not agree/not agree/not agree or disagree/agree/totally agree)* (Appendix A, questions 30, 31, 32)). The choice was made for multiple questions regarding negative feelings toward the outgroup. The reason for this choice was to increase the reliability regarding the measurement of affective polarization. Respondents could choose (for all three questions) if they totally disagreed, disagreed, neither disagreed nor agreed, agreed or totally agreed. The reason for these options was to be able create a 5 point Likert scale. The three questions were eventually converted to this Likert scale ranging from 0 (totally disagree) to 5 (totally agree) regarding the mean scores on all three questions. A reliability test showed a reliable Cronbach's Alpha (.834), meaning these three variables are closely related. Furthermore, a factor analysis was conducted to see if these three variables all measured the same dimension. When analyzing the communalities and factor scores, it showed all three variables measured the same dimension. Thus, the scale measures what it should measure: affective polarization.

In order to operationalize self-selected exposure, people were asked if they totally did not agree ranged to if they totally did agree with the following statement: "I click on articles/messages/videos on social media that agree with my political preferences" (Appendix A, question 14). By formulating the statement in this way ("that agree with my political preferences") the definition of self-selected exposure can be measured. This question was made into a dichotomous variable by recoding the options from agree to totally agree to "experienced self-selected exposure" to "no experienced self-selected exposure". Note that this variable measures experienced self-selected exposure. As this may not give a complete view on whether self-selective exposure indeed occurs, a small experiment was conducted during the survey.

Four different Facebook posts of far/radical left wing and right wing groups (Pegida, Erkenbrand, Volks Communistische Partij Nederland and GroenFront!) were added to the survey. Respondents were asked on which of the four posts they would most likely click (*On which of the following articles would you most likely click? (when choosing pay attention to the content of the message and not the graphical look) (article 1/article 2/article 3/article 4)* (Appendix A, question 13)). The names of the groups who posted them were hidden so respondents would not be deterred or attracted by the names of the groups. Moreover, respondents would click on the posts based on their content. Two posts regarded (extreme) left-wing content and two post regarded (extreme) right-wing content. A new variable was made that compared the political preferences of the respondents to their choice of post. It was coded 0 (no self-selected exposure) 1 (right self-selected exposure) and 2 (left self-selected exposure). After that a new dichotomous variable was added that described the difference between 0 (no self-selected exposure) and 1 (self-selected exposure).

Respondents were asked which of three social media channels they used (Facebook, Instagram, YouTube) (*Which of the following social media channels do you use? (Instagram/Facebook/YouTube)* (Appendix A, question 10)). When selected, for each channel the question was asked whether they experienced seeing content based on their previous consumption behavior and their political standpoints (*Could you indicate to what extent you agree with the following statement? I see suggested articles/messages on Instagram/Facebook/YouTube that agree with my political preferences/my previous consumption behavior (totally not agree/not agree/not agree or disagree/agree/totally agree)* (Appendix A, questions 19, 21, 23, 25, 27)). Based on these two aspects, experienced pre-selected exposure could be measured. Again, respondents could choose the options ranging from "totally not agree", to "totally agree". All questions regarding the different platforms were made into a single variable. This was realized by firstly making a Likert scale. In doing so, the reliability and the amount of dimensions were tested. The Cronbach's Alpha was .772 and considered reliable. Factor analysis showed all variables measured the same dimension. After making the Likert scale, the variable was made dichotomous with 0 meaning "no experienced pre-selected exposure" and 1 meaning "experienced pre-selected exposure".

Additionally respondents were asked whether they used social media as a primary news source (*Could you indicate to what extent you agree with the following statement? I use Instagram/Facebook/YouTube as a primary news source (totally not agree/not agree/not agree or disagree/agree/totally agree)* (Appendix A, questions 13,14,15)), in order to test hypothesis 4: *The impact of social media use on affective polarization is stronger for people who use social media as a primary news source*. A new variable was made regarding using social media as a primary news source. Respondents who do use social media as a primary news source were coded as 1 and respondents who do not were coded as 0.

For testing hypothesis 5: *The impact of social media use on affective polarization is stronger for people who (strongly) identify themselves with the ideological left wing compared to people who (strongly) identify themselves with the ideological right wing,* respondents were asked where they would place themselves on the political spectrum from left to right, in order to measure their political orientations

(*On which part of the political spectrum would you place yourself? (Far left/left/left-middle/middle/right-middle/right/far right)* (Appendix A, question 28)). Respondents could choose from ‘middle’ ‘middle-left’ ‘left’ and ‘far left’ (the same concept applied regarding the right wing). Two dichotomous variables needed to be made. This was done by converting the variables regarding polarization (left and right wing orientation) into dichotomous variables. Two variables were created with 0 meaning not left or meaning not right wing and 1 meaning left wing or meaning right wing.

Lastly, for hypothesis 6, three different dichotomous variables were made. They regarded the use of Facebook, Instagram and YouTube, with 0 meaning a respondent did not use the platform and 1 meaning a respondent did use the platform.

Note how some questions are left out of the analyses. When setting up the survey, a slightly different research set up was established. Therefore, some questions are not considered in the analyses and the data preparation. For transparency, they are however still described in Appendix A, as this was the complete survey respondents was answered by respondents.

4. ANALYSES

In order to test the hypothesis linear regression analyses are conducted. The reason for choosing this form of analysis is that it offers not only the option of establishing the correlation and direction of the relation between the independent and dependent variables, it also determines the strength of the relation between the two. More specific, univariate linear regression will be conducted as the relation describes one independent variable. For testing the hypothesis with regression analyses certain assumptions for the data must be met. These include the normal distribution, linearity and homoscedasticity.

Normal distribution

It is important for data to be normally distributed. Should this not be the case, results of the analyses may not be valid. The normal distribution of the residues of the variables will not be assessed. The central limit theorem states that a large sample (>30) is likely to be normally distributed. Due to the sample size (208) one can assume that the data is normally distributed.

Linearity

In order to test hypothesis 1 the data must meet the assumption of linearity. Linearity is tested in order to establish whether the variables are both linear. Should this not be the case, conducting a linear regression is not possible. A linearity test showed that the independent variable -social media use- and dependent variable -affective polarization- are not significantly linear as can be seen in Table 1.

Table 1: linearity test

		Affective polarization
Social media use * polarization	linearity	**-2447,390**
	Deviation from linearity	**88394,402**

***sig. <.05 ** sig. <.01 *** sig. <.001 Source: Dataset thesis selective exposure (N208)**

For this reason both the independent variable and the dependent variable are transformed by inverting the variables. This is done by dividing 1 through the variable. In doing so, the cases of the dependent variable come to lie closer together. Additionally, after transforming the independent variable and conducting a linearity test, a significant linearity between the independent and dependent variable can be observed in Table 2. The reason for choosing for inversion instead of other transformations such as logarithmic transformation, another way to restore linearity, is that the inversion of the variable shows for a better interpretation of the results. Namely, inversion gives a result in the analyses that has to be interpreted merely the other way around. Interpretation of logarithmic transformation requires knowing the natural logarithm of the independent variable.

Table 2: linearity test

		Affective polarization
Social media use inverted * affective polarization inverted	linearity	**,079*** **
	Deviation from linearity	**,326*** **

***sig. <.05 ** sig. <.01 *** sig. <.001 Source: Dataset thesis selective exposure (N208)**

Homoscedasticity

After the transformation, homoscedasticity is tested. The principle of homoscedasticity means that the values of the residues of the variance from social media use in minutes are all equal. The principle of heteroscedasticity states the opposite, namely that these residues of variance are different. The striving is having homoscedastic residues and not heteroscedastic. The consequence of heteroscedasticity would be that the significance of the tested hypothesis would be wrong and results may not be accurate. In order to test whether social media use is homoscedastic, an UNIANOVA test is conducted. By comparing the significance of the standard error and the robust standard error, as can be seen in Table 3, homoscedasticity or heteroscedasticity can be observed. The levels of significance are nearly the same. This means the independent variable of social media use is homoscedastic and a regression analyses can be conducted.

Table 3: UNIANOVA homoscedasticity test

Variable	Std. Error	Sig.	Robust Std. Error	Sig.
Intercept	,097	<,001	,103	<,001
Socia media use in minutes	,264	<,001	,135	<,001
Sexe	,032	,010	,032	,011
Age	,001	,078	,001	,077
Educational level	,015	,645	,016	,670

Source: Dataset thesis selective exposure (N208)

Pearson correlation

Before conducting a regression analysis, it is important to get an indication of the relation between the independent and dependent variable. By using the Pearson correlation test, correlations between the independent and dependent variable can be interpreted. The difference with regression analyses is that this is a correlation that merely indicates whether or not there is a relation between the two variables and the possible direction of the relation.

Table 4 describes the Pearson correlation. As can be seen, a significant negative relation between social media use and affective polarization is indicated. A regression analyses will expose more about this relation.

Table 4: Correlations

		Affective polarization
Social media use in minutes	Pearson Correlation	-,289***

*sig. <.05 ** sig. <.01 *** sig. <.001 Source: Dataset thesis selective exposure (N208)

Regression analyses

In the first model (Model 1, Table 5) the direct relation between social media use and affective polarization is tested. The following hypothesis (1) was stated: *The use of social media leads to more affective polarization.* Transformation of the variables means they are inverted. A higher score on social media use in minutes means spending less minutes on social media. Similarly, for affective polarization: the higher the score on affective polarization, the less affectively polarized the respondent is. In Model 1, a strong negative effect can be observed. The B-coefficient of -1,220*** means that a higher score on social media use in minutes means a lower score on affective polarization under the control of sex, age and highest attained educational level. Based on the inversion of the variables, this means the less a respondent uses social media in minutes a day, the more affectively polarized that respondent is. Contrariwise, using more social media in minutes a day, will lead to less affective polarization. Coding and data preparation were both checked due to this unexpected finding. No miscoding or other mistakes were found that could influence this result. Based on this finding, hypothesis 1: *The use of social media leads to more affective polarization* is rejected. Instead, a new hypothesis must be stated: *The use of social media leads to less affective polarization.*

Table 5: Regression analyses

	Model 1		Model 2		Model 3	
	B-coefficient	SE	B-coefficient	SE	B-coefficient	SE
Constant	,665***	,090	,738***	,088	,805***	,092
Social media use in minutes	-1,220***	,243	-1,057***	,236	-,985***	,236
Sex	-,058	,030	-,043	,029	-,038	,029
Age	,001	,001	,002	,001	,001	,001
Highest attained educational level	-,001	,016	-,005	,016	-,012	,016
Self-selected exposure			-,144***	,033	,-123***	-,034
Pre-Selected exposure					-,078*	-,035
Adjusted R squared	**,117**		**,192**		**,212**	

***sig. <.05 ** sig. <.01 *** sig. <.001 Source: Dataset thesis selective exposure (N208)**

Self-selected exposure

The opposite effect was found regarding the first hypothesis. Therefore hypothesis 1 was rejected and new hypothesis, *The use of social media leads to less affective polarization,* was adopted. To test hypothesis 2, *The relation between social media use on affective polarization can be explained by self-selected exposure* the variable of self-selected exposure was added in Model 2. A difference between the B-coefficient of social media use in minutes in Model 1 and Model 2 is observed. Where the effect was -,1220*** in Model 1, in Model 2 the effect is -,1057***. Moreover, the adjusted R-squared rises from 11,7% in Model 1 to 19,2% in Model 2, meaning the total amount of explained variance of the predictors has increased. This indicates that the effect between social media use and affective polarization can be partially explained by self-selected exposure. Additionally, a positive effect between social media use in minutes and affective polarization can be observed. Respondents who experience self-selected exposure are more likely to become affectively polarized (B-coefficient: -,144***). In addition, when conducting a regression analysis regarding social media use and self-selected exposure, a B-coefficiënt of 1,129* is observed. Meaning that respondents who use social media less frequent are more likely to experience self-selected exposure. Due to the finding that self-selected exposure can explain the relation between social media use and polarization, hypothesis 2, *The relation between social media use on affective polarization can be explained by self-selected exposure,* is confirmed.

Pre-selected exposure

To test hypothesis 3, *The impact of social media use on affective polarization can be explained by pre-selected exposure,* pre-selected exposure was added in Model 3. A difference between the B-coefficient of social media use in minutes in Model 2 and in Model 3 can be observed. The coefficient decreases from -,1057*** to -,985***. Additionally, the R-squared increases from 19,2% to 21,2%, meaning an increase in total explained variance. This indicates that pre-selected exposure partially explains the relation between social media use and affective polarization. As can be observed, pre-selected exposure has a weak positive impact on affective polarization (-,078*). Respondents who experience pre-selected exposure are more likely to become affectively polarized. Additionally, when conducting a regression analysis regarding social media use and pre-selected exposure, a B-coefficiënt of ,930 * is observed., which indicates that respondents who use social media less frequent are more likely to experience pre-selected exposure. Due to the finding that pre-selected exposure partially mediates between social media use in minutes and affective polarization, hypothesis 3, *The impact of social media use on affective polarization can be explained by pre-selected exposure,* is confirmed.

Primary news source

To test hypothesis 4: *The impact of social media use on affective polarization is stronger for people who use social media as a primary news source,* the interaction term *social media use* primary news source* and the interaction variable *primary news source* of using social media as a primary news source were added to the model. In Table 6, Model 4 there is no observed effect between the interaction term of using social media as a primary news source and the main effect between the independent and dependent variables. There is no difference between respondents who use social media as a primary news source compared to respondents who don’t. Therefore, hypothesis 4 is rejected.

Left- and right-wing identification

For testing hypothesis 5: *The impact of social media use on affective polarization is stronger for people who (strongly) identify themselves with the ideological left wing compared to people who (strongly) identify themselves with the ideological right wing,* an interaction term was added to the model. In Table 6, Model 5 one can see that the term *social media use * left wing identification* and the interaction variable *left wing identification* are added. The B-coefficient is not significant. This means that there is no difference in impact between social media use and affective polarization for people who (strongly) identify themselves with the ideologically left wing compared to the ideologically right wing. Therefore hypothesis 5 will be rejected.

Facebook, YouTube and Instagram

Hypothesis 6: *The effect between social media use and polarization is weaker for Instagram compared to YouTube and Facebook* was tested by adding the interaction term of *social media use* Instagram use* and the interaction variable *Instagram use.* As one can see in Table 6, Model 6, the B-coefficient of *social media use * Instagra*m use is not significant. Meaning that there is no difference in impact between social media use and affective polarization between Instagram, YouTube and Facebook. Therefore hypothesis 6 is rejected.

Table 6: Regression analyses models 4 and 5

	Model 4		**Model 5**		**Model 6**	
	B-coefficient	SE	B-coefficient	SE	B-coefficient	SE
Constant	,815***	0,090	,823***	,089	,695***	,101
Social media use in minutes	-1,154***	,248	-1,126***	,250	-,139	,865
Sex	-,039	,028	-,026	,029	-,037	,029
Age	,001	,001	,001	,001	,002	,001
Highest attained educational level	-,010	,015	-,007	,015	-,011	,015
Self-selected exposure	-,145***	,034	-,125**	,035	-,100**	,036
Pre-Selected exposure	-,060	,035	-,064	,035	-,051	,035
Social media use* primary news source	1,296	,694	1,149	,691	1,533*	,697
Primary news source	-,199**	,064	-,190**	,063	-,195**	,063
Social media use * left wing identification			-,513	1,132	-1,111	1,276
Left wing identification			-,077	,044	-,070	,045
Social media use* Instagram use					-1,683	,908
Instagram use					,125**	,047
Adjusted R squared	**,253**		**,273**		**,289**	

***sig. <.05 ** sig. <.01 *** sig. <.001 Source: Dataset thesis selective exposure (N208)**

5. CONCLUSION

It was found that the use of social media negatively influences the amount of affective polarization. In other words when a respondent uses social media more frequently, compared to not using social media, that respondent is less likely to be affectively polarized (i.e. have negative feelings toward the outgroup). This finding has answered the first research question (*To what extent relates using social media more frequently on a daily basis, when compared to using social media less frequently on a daily basis, to more affective polarization?*). Additionally, it contradicts the formulated theory and hypothesis on social media use leading to more affective polarization. Therefore, a new hypothesis was formulated: *The use of social media leads to less affective polarization.* For further answering the research question: *How does the use of social media relate to affective polarization in the Netherlands?* we must look into the remaining findings of this research and see how the other sub-questions can be answered.

Regarding self-selected exposure, the formulated theory states that more social media use will lead to more self-selected exposure which in turn leads to more affective polarization. Based on the findings of Baksy et al. (2015) and Trilling et al. (2017) it was expected that the more a person uses social media, the more limited that person is to cross-cutting content due to the self-selection of information on social media. Due to this limitation, an increased chance of affective polarization was expected (Stroud, 2010; Trilling et al., 2017; Tsfati and Chotiner, 2016). After the formulation of the new hypothesis, other hypothesis were tested. It was found that self-selected exposure partially explains the relation between social media use and affective polarization. Meaning that using social media less often, leads to more self-selected exposure, which in turn leads to more affective polarization. Due to this finding, the stated theory can partially be confirmed. The part where self-selected exposure leads to more affective polarization is found and confirmed. However, the part where using more social media leads to more self-selected exposure is not found. Moreover, the relation is negative instead of positive. The second sub-question (*To what extent explains self-selected exposure the relationship between social media use and affective polarization?*) can be answered. The relationship between social media use and affective polarization can be partially explained by self-selected exposure.

With regard to pre-selected exposure, a similar expectation was formulated based on the stated theory. Algorithms on social media can lead to more affective polarization in different ways. They can lead to homophilic networks, echo chambers and filter bubbles. Each can lead to affective polarization by limiting the amount of cross-cutting content people are exposed to. This can in turn lead to a society that is increasingly segregated along partisan lines (Barberá, 2020) and (affective) polarization (Cho et al, 2020; Harel et al, 2020; Sphor, 2017; Lee, 2016). Findings in this research indicate that using social media more often will lead to less pre-selected exposure, but using less social media will lead to more pre-selected exposure. Additionally, more pre-selected exposure will lead to more affective polarization. Regarding these findings, the theory stating that more social media use leads to more pre-selected exposure is be rejected. Moreover, this relation should be negative. Furthermore, what can be confirmed is that pre-selected exposure does lead to more affective polarization. The third sub-question (*To what extent explains pre-selected exposure the relationship between social media use and affective polarization?*) can be answered. Pre-selected exposure can partially explain the relation between social media use and affective polarization.

Findings of Lee et al. (2021) indicated that the use of social media as a primary news source in a multi-party system will lead to more affective polarization. Based on this finding, it was expected that the relation between social media use and affective polarization would be stronger for those respondents who use social media as a primary news source. Findings in this research indicate that there is no such relation. The fourth sub-question (*To what extent differs the relationship between social media use and affective polarization for people who use social media as a primary news source and people who do not use social media as a primary news source?*) can be answered. Regression analysis has shown that the relation between social media use and affective polarization is not different for people who use social media as a primary news source compared to people who do not use social media as a primary news source.

Based on the findings of Waeterloos et al. (2021), it was expected that younger left-wing people are more likely to actively to participate on social media. In doing so, they are more likely to experience self-selected exposure and pre-selected exposure, leading to more affective polarization. Therefore it was expected that the effect between social media use and affective polarization is stronger for people identifying themselves as left wing compared to people who identify themselves as right wing. Findings in this research indicate that there is no such relation. No effect was found regarding the interaction of left-and right wing groups regarding the relation between social media use and polarization, therefore the fifth sub-question (*To what extent differs the relationship between social media use and affective polarization for people who strongly identify themselves with the ideological left wing and those who identify themselves with the ideological right wing?*) can be answered. The relation between social media use and affective polarization is not different for respondents who identify themselves with the ideological left wing compared to the ideological right wing.

By analyzing the differences between the social media platforms Facebook, Instagram and YouTube it was expected that the relation between social media use and affective polarization is stronger for people who use Instagram. Namely because less likelihood of homophily on Instagram was expected. Findings indicate that there is no such relation. There seems to be no difference in the relation between social media use and affective polarization between the platforms of Facebook, Instagram and YouTube. For the sixth and final sub-question (*To what extent differs the relationship between social media use and affective polarization for people who use Facebook, Instagram or YouTube?*) one can state that the relationship between social media use and affective polarization is not different for the platforms Facebook, Instagram and YouTube.

Due to worries about the use of social media in the Netherlands and a continuous increase in its use, the following research question was stated: *How does the use of social media relate to affective polarization in the Netherlands?* After elucidating theories on social media use, (affective) polarization and possible mediating and interacting factors, regression analyses of the survey (Dataset thesis selective exposure, N208) showed that using social media less often will lead to more affective polarization. Moreover, using social media less often will lead to more self-selected and pre-selected exposure, which in turn lead to more affective polarization.

6. DISCUSSION

This research has contributed to previous research by implicating a new measure of affective polarization, by taking into account both self-selected exposure and pre-selected exposure, measuring differences between platforms, taking social media as a primary news source into account and making the distinction between partisan groups regarding the left and right wing. Next to the contributions to previous research, this research also has its shortcomings. For one the sample size and the weighing make for improvement in the future.

Due to using a new measure of affective polarization, possibly more accurate measures can be made for affective polarization in future research. By including questions regarding both dislike, negative feelings and aggressive feelings, a statistically reliant measurement of affective polarization has been found. Factor analyses showed a relatively high reliability level and the measurement of one dimension: affective polarization. As has been stated, Nordbrandt (2021) used a different, more basic measure of affective polarization. One of the reasons for such different outcomes in this research as compared to that of Nordbrandt (2021) may be this difference in measurement.

Both self-selected exposure and pre-selected exposure have been taken into account in this research. It was found that these concepts do in fact explain the relation between social media use and affective polarization. However not as expected. As the relation between social media use and affective polarization is of negative sort, using social media less often partially leads to more self- and pre-selected exposure, which in turn lead to more affective polarization.

As was expected in the theoretical section, more social media use will lead to more self-selected and pre-selected exposure. An explanation of finding the opposite (less social media use will lead to more self-selected and pre-selected exposure) might be found in Sears and Freedman (1967). As stated before, they found most people seem to be disproportionately exposed to communications that agree with their pre-existing opinions, however under some conditions, such as being heavily involved in a certain topic, people might also prefer information that contradicts their opinions. It might be that respondents who use social media more often, are heavily involved in (a wide range of) topics. If this is the case, and with the statement of Sears and Freedman (1967) in mind, this would mean that these respondents prefer that information that contradicts their opinions -cross-cutting content-, explaining the finding that less social media use would lead to more self-selected exposure. For future research a captivating topic would be to research whether this is in fact the case. Namely, it could be that due to using social media more often, people become more heavily involved in certain topics, which in turn would lead to exposure to more cross cutting content (read: less self-selected exposure) and less affective polarization. Contrariwise, using social media less often could lead to being less heavily involved in topics, making that people become less exposed to cross-cutting content (read: more self-selected exposure) and more affective polarization.

This explanation however, merely supports the finding that less social media use leads to more self-selected exposure. An explanation for pre-selected exposure could be found in the nature of the algorithm. As has been discussed in the stated theory, algorithms on social media platforms use previous consumption behavior to suggest further content for its user. One could reason, as was done in this research, that using social media more often provides the algorithm with more information to suggest similar content as was previously consumed, leading to being less exposed to cross-cutting content. However one could also argue, based on the findings of this research, that using social media more often, could provide an algorithm with more information to suggest more content on the same topic, making that the user is more heavily involved in that topic. Thus the user would be exposed to cross-cutting content regarding the same topic (read: less pre-selected exposure) with the consequence of becoming less affectively polarized. Opposite to this, using less social media would provide the algorithm with less information of the platform's user, providing that user with a wider range and less in depth knowledge about certain topics, leading them to become less exposed to cross-cutting content (read: more pre-selected exposure) with in turn would lead to more affective polarization. Therefore, for future research, more in-depth analysis should be conducted regarding the interaction between user and algorithm. This will provide more insight as into why using social media less often will lead to more affective polarization.

In order to gain insight regarding the use of social media and the effect on affective polarization, it is of importance to make a distinction between respondents who do use social media and those who do not. By making such a distinction, elaboration on whether using less social media leads to more affective polarization as compared to using none at all and using more social media can be realized.

One of the shortcomings in this research, next to the shortcoming as discussed in the methods section regarding overrepresentation, is the relative small sample size. By weighing the data for educational level it was attempted to tackle this shortcoming. As the data was also not representable for age, it was also attempted to weigh the data according to age. However this was not possible, as not all ages were represented in the data. One of the positive notes regarding these shortcomings is that the control variables age and education did not influence the researched relations as appeared from the analyses. However, should the sample size have been larger and more representative for the Dutch population, different outcomes might have been found. In short, the data was not fully representative for the Dutch population regarding age and educational level. However, weighing the data catered in making it more representable.

The questions in the survey have some adequate aspects regarding reliability and validity. Additionally some aspects are less adequate. For one, after performing factor analysis and a reliability test, the measurement of affective polarization has proven to be reliable. In addition, the measurement of self-selected exposure contributes to the validity of this research due to the measurement of the concept by both experienced self-selected exposure and by conducting a small experiment. The concept that has come short in terms of validity is pre-selected exposure.

Where self-selected exposure was measured as an experience and along an experiment, pre-selected exposure was measured merely by respondents' experiences. For instance, respondents were asked whether they see content on social media platforms that agree with their own political preferences and that agree with their previous consumption behavior. In doing so, experienced pre-selected exposure is measured as opposed to factual pre-selected exposure. As has become clear in this research, the human mind can trick itself merely by seeing content that it agrees with. By measuring experienced pre-selected exposure, it could be so that respondents who are aware of algorithmic influence on social media platforms also experience more pre-selected exposure than those respondents who do not. Most important, it does not give an actual representation of pre-selected exposure, merely an indication. In terms of validity this concept does not accurately measure what it should measure. For future research it is recommended that factual pre-selected exposure is researched, in order to receive a more clear view of its effect on affective polarization.

The issue of social desirable answers may have occurred when asking for people political preferences. By formulating the answers as 'far left' and 'far right' instead of formulating them as 'extreme left' and 'extreme right', it was attempted to tackle the issue. People may give more social desirable answers when confronted with terms such as 'extreme left' or 'extreme right'. Results showed that mostly the far right was underrepresented. This may be due to the issue of social desirability, however it may also have been the case due to a too leftist sample.

Not all questions asked in the survey have been used in this research, because of a change in the set up of the research. This had no implications for this research in terms of concepts that were missing. It may have influenced the survey by it being longer than necessary. Many responses were deleted (62) as the survey answers were not complete. Therefore, some respondents may have continued their answers should the survey have been shorter. As the survey was only five minutes, this does not seem likely. Overall the survey questions have measured what they were deemed to measure with the exception of pre-selected exposure. Moreover the survey could have been shorter which in some cases could have led to more response.

An underlit aspect of social media use and affective polarization in this research is the term ‘user programmability’ as stated in the theoretical section. As has become clear, this aspect of users’ influence on algorithm can have consequences for affective polarization. For one, the study of Kramer et al. (2014) showed how Facebook was able to manipulate users’ emotions. Furthermore, the Trump presidential campaign in 2016 made clear that advertisement targeting could possibly influence events as big as elections. Findings in this research indicate that (experienced) pre-selected exposure can lead to affective polarization. Programmers’ influence on algorithms has shown its potential on elections and human emotions. In this age of hybrid warfare, methods such as these can be used to disrupt a specific country or population. Algorithms can be used to for instance, spread instability through propaganda and misinformation. For this reason, it is important for future research to elaborate on the role of user programmability, its specific role in the relation between social media use and affective polarization and the dangers that come with it, rather than merely taking it into account.

An important note for future research would be to research, next to selective exposure, selective avoidance. As we as human beings are each different, social media might impact us also different. Using corneal eye tracking software, Bode et al. (2017) found that among the least interested in politics, the earlier the post was deemed political, the faster one skips it. Therefore, for some people the notion might apply that more social media use will lead to less selective exposure. For others it might apply that more use of social media will lead to more selective exposure. By taking into account peoples differences (such as involvement in politics) and selective avoidance, different effects on affective polarization may be found for different people. Additionally, future research should differentiate between certain amounts of using social media as a news source. This research merely explored the use as an amount and as primary news source. Future research should innovate by adding social media as a secondary news source in order to gain more insight in the nature of social media use. In order to understand the implications of social media use and affective polarization, it may be essential to emphasize these differences.

7. POLICY IMPLICATIONS

Next to the need for future research based on the findings and shortcomings of this research, it is of importance to further elaborate on how these findings can have implications for policy regarding the subject.

Firstly, as described in the discussion section, the aspect of user programmability can have numerous implications for societies and affective polarization within them. Recent events have shown how warfare nowadays is fought both offline and online. Russia's attack on Ukraine has led to a major discrepancy in information flow toward Russia, Ukraine and Western states such as the Netherlands. Where Ukraine and Western states receive content regarding the developments of the war, Russia has limited access on social media such as Facebook (Troianovski, 2022). User programmability of social media's algorithms show how not only access to diverse information can be limited or individuals can be influenced, it also shows how individuals can be silenced. Moreover, user programmability allows foreign actors to spread misinformation on social media in specific countries (Arayankalam, J., & Krishnan, S., 2021). As this research has shown, (experienced) pre-selected exposure can lead to affective polarization. Should a foreign actor with the agenda of disrupting a population or country exploit such relationship, they may be able to disrupt that population. For instance, French intelligence agencies investigated possible Russian influence on the yellow jacket protests in 2018 which disrupted the French nation (Telegraaf, 2018).

In order to tackle the issue of affective polarization that can come along with user programmability, it is of essence to make sources as transparent as possible on social media. For instance disclaimers can be placed by the moderators of a specific social media platform, stating the actor creating the content may have a hidden agenda. In doing so, it prevents people from assuming that information as a truth. Moreover, such disclaimers could be used to counter the spread of misinformation in general. For instance, these disclaimers could state that these messages have not been fact checked. Placing such disclaimers non-automatically would prove to be immensely labor intensive. Therefore digital tools and algorithms could be applied to provide these disclaimers. With regard to the assumption that disclaimers on social media can counter misinformation, or at the least inform users about the danger of misinformation in the content they read, Dutch policy should consider implicating laws that require social media platforms in the Netherlands to place such disclaimers on messages that cannot be fact checked. At the very least as a general message should be placed on the social media platform itself.

Next to the spread of misinformation, self-selected and pre-selected exposure have proven to partially lead to affective polarization through mechanisms such as filter bubbles, echo chambers and homophily. In order to counter the negative effects (affective polarization) different tools and algorithms have been created. Studies such as that of Bozdag, E., & Van Den Hoven, J. (2015) and Amrollahi, A. (2021) show how online tools can and specific algorithms can be used to tackle problems such as the filter bubble. An example of such a tool is Scoopinion as stated in Bozdag, E., & Van Den Hoven, J. (2015). Scoopinion is a browser add-on that tracks (social media) sites and stories the user reads on those sites. It provides a visual summary of the users' reading habits in order to increase the users' autonomy and stimulate reading more diversly.

In order to counter both self- and pre-selected exposure among the Dutch population, these tools can be used. Next to this study, other studies have also shown alarming micro and macro effects of social media use. The reality that self- and pre-selected exposure can lead to affective polarization indicate that measures should be taken. First and most important, people should be made aware of the underlying algorithms and human mechanisms that occur when using social media. Especially future generations should be made aware of the dangers of social media and the digital landscape. People should learn how personalized certain platforms can be, in order for them to realize the influence it can have on them. One way of implicating such awareness is to obligate social media lessons on elementary and high schools. Moreover, in order to reach older generations, the Dutch government should offer such lessons for free. The target audiences can be reached by advertising on social media itself.

Furthermore, the digital landscape in which social media platforms are situated, is a rapid and ever changing landscape. Algorithms have been developed to be self-learning and are constantly updated which makes it difficult for research to keep up with it. As has become clear in the theoretical section, there is low transparency to none at all regarding these algorithms. Social media platforms legally own these algorithms. They are not obligated to make them transparent for their audiences. It is the responsibility of the owners of these algorithms to provide researchers with as much insight as possible. As for now these algorithms with their constantly changing nature are not often subjected to any form of ethical or critical review (Bucher, 2012; van Dijck and Poell, 2013). Given the vast amount of influence these algorithms have on different populations it is essential for them to be subjected to critical review. Moreover, the reality states that these algorithms can influence people's emotions and wellbeing. By not making them transparent in order for them to be subjected to the necessary research, ethical boundaries are crossed.

For commercial goals, owners of these algorithms are less likely to give full insight in to how their platforms work. Legislation should be adopted regarding the necessary transparency of these algorithms. To meet with owners' agendas this legislation should instated be with the goal of gaining insight and providing necessary changes to the algorithms. Therefore, only researchers and government should be able to access them. In this regard the agendas of the owners are met and harmful mechanisms can be countered.

"A world constructed from the familiar is the world in which there's nothing to learn."

— Eli Pariser (2011).

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Appendix A.

Survey: Thesis selective exposure

Start of Block: Introductie

Vraag 1 Welkom bij mijn vragenlijst over selective exposure op social media. De vragenlijst zal ongeveer 5 minuten duren. U bent volledig anoniem en uw gegevens zullen uitsluitend gebruikt worden voor wetenschappelijk onderzoek volgens de richtlijnen die door de Radboud Universiteit zijn vastgesteld. Daarnaast is deelname geheel vrijwillig. U hebt het recht om u ten alle tijden terug te trekken uit het onderzoek (zonder opgave van reden). In dit geval zullen uw gegevens worden verwijderd.

Mocht u vragen hebben over het onderzoek, het eindproduct graag ontvangen of uzelf terug willen trekken uit het onderzoek, kunt u mailen naar t.langhout@student.ru.nl

Bent u boven de 18 jaar en gaat u akkoord met deze voorwaarden?

◯ ja (1)

◯ nee (2)

Skip To: End of Survey If Vraag 1 = nee

Wat is uw geslacht? Wat is uw geslacht?

◯ Man (1)

◯ Vrouw (2)

◯ Anders (3)

◯ Wil ik niet zeggen (4)

Vraag 3 Wat is uw leeftijd?

____

Vraag 4 Wat is uw hoogst voltooide opleiding?

- ○ Basisonderwijs (basisschool) (1)
- ○ VMBO/MBO1/AVO onderbouw (onderbouw voortgezet onderwijs) (2)
- ○ HAVO/VWO/MBO 2/MBO 3/MBO 4 (3)
- ○ HBO/WO bachelor (associate degree, de hbo- en wo-bachelors en 4-jarige hbo-opleidingen) (4)
- ○ WO master, doctor (dit omvat wo-masters en wo-doctorsopleidingen) (5)

Vraag 5 Heeft u een partner?

- ○ Ja (1)
- ○ Nee (2)
- ○ Wil ik niet zeggen (3)

Vraag 6 Wat is uw bruto inkomen per maand in euro's? (vul enkel een getal in of "wil ik niet zeggen")

____

Vraag 7 In welke stad of in welk dorp woont u?

____

End of Block: Introductie

Start of Block: Social media gebruik

Vraag 8 Gebruikt u social media?

○ Ja (1)

○ Nee (2)

Skip To: End of Block If Vraag 8 = Nee

Vraag 9 Kunt u aangeven hoeveel tijd u gemiddeld besteed aan social media in minuten per dag? Vul a.u.b. een heel getal in

____

Vraag 10 Welk van de volgende platforms gebruikt u?

▢ Instagram (1)

▢ YouTube (2)

▢ Facebook (3)

Vraag 11 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik ben sinds de COVID-19 pandemie vaker social media gaan gebruiken

- ◯ helemaal oneens (1)
- ◯ oneens (2)
- ◯ niet eens/oneens (3)
- ◯ eens (4)
- ◯ helemaal eens (5)

Vraag 12 In hoeverre bent u het eens met de coronamaatregelen die zijn ingesteld door het kabinet in 2020/2021?

- ◯ helemaal oneens (1)
- ◯ oneens (2)
- ◯ niet eens/oneens (3)
- ◯ eens (4)
- ◯ helemaal eens (5)

Display This Question:

If Vraag 10 = Facebook

Vraag 13 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik gebruik artikelen op Facebook als primaire nieuwsbron

- ◯ Helemaal oneens (1)
- ◯ Oneens (2)
- ◯ niet eens/oneens (3)
- ◯ eens (4)
- ◯ helemaal eens (5)

Display This Question:

If Vraag 10 = Instagram

Vraag 14 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik gebruik artikelen op Instagram als primaire nieuwsbron

- ◯ helemaal oneens (1)
- ◯ oneens (2)
- ◯ niet eens/oneens (3)
- ◯ eens (4)
- ◯ helemaal eens (5)

Display This Question:

If Vraag 10 = YouTube

Vraag 15 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik gebruik video's op YouTube als primaire nieuwsbron

- ○ helemaal oneens (1)
- ○ oneens (2)
- ○ niet eens/oneens (3)
- ○ eens (4)
- ○ helemaal eens (5)

End of Block: Social media gebruik

Start of Block: Self selected personalization

Vraag 13 Op welk van de volgende artikelen zou u het meest waarschijnlijk klikken? (Let bij het kiezen op de inhoud van de tekst en niet op de grafische weergave)

- ○ Artikel 1 (1)
- ○ Artikel 2 (2)
- ○ Artikel 3 (3)
- ○ Artikel 4 (4)

Vraag 14
Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik klik op artikelen/berichten/video's op social media die overeen komen met **mijn eigen** politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Vraag 15
Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?
Ik klik op artikelen/berichten/video's op social media die overeen komen met **een andere dan mijn eigen** politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

End of Block: Self selected personalization

Start of Block: Pre-selected personalization

Display This Question:

If Vraag 10 = Facebook

Vraag 16 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Facebook die **niet** overeenkomen met mijn eigen politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = Facebook

Vraag 17 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Facebook die **wel** overeenkomen met mijn eigen politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = Facebook

Vraag 18 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Facebook die **niet** overeenkomen met mijn voorgaande consumptiegedrag op Facebook

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = Facebook

Vraag 19 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Facebook die **wel** overeenkomen met mijn voorgaande consumptiegedrag op Facebook

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = Instagram

Vraag 20 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Instagram die **niet** overeenkomen met mijn politieke voorkeur

- ◯ helemaal oneens (1)
- ◯ oneens (2)
- ◯ niet eens/oneens (3)
- ◯ eens (4)
- ◯ helemaal eens (5)

Display This Question:

If Vraag 10 = Instagram

Vraag 21 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Instagram die **wel** overeenkomen met mijn politieke voorkeur

- ◯ helemaal oneens (1)
- ◯ oneens (2)
- ◯ niet eens/oneens (3)
- ◯ eens (4)
- ◯ helemaal eens (5)

Display This Question:

If Vraag 10 = Instagram

Vraag 22 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Instagram die **niet** overeenkomen met mijn voorgaande consumptiegedrag op Instagram

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = Instagram

Vraag 23 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde artikelen/berichten tegen op Instagram die **wel** overeenkomen met mijn voorgaande consumptiegedrag op Instagram

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = YouTube

Vraag 24 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde video's tegen op YouTube die **niet** overeenkomen met mijn politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = YouTube

Vraag 25 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde video's tegen op YouTube die **wel** overeenkomen met mijn politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = YouTube

Vraag 26 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde video's tegen op YouTube die **niet** overeenkomen met mijn voorgaande consumptiegedrag op YouTube

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

Display This Question:

If Vraag 10 = YouTube

Vraag 27 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling? Ik kom voorgestelde video's tegen op YouTube die **wel** overeenkomen met mijn voorgaande consumptiegedrag op YouTube

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

End of Block: Pre-selected personalization

Start of Block: Block 4

Vraag 28 Op welk deel van het politiek spectrum (links/rechts) zou u zichzelf plaatsen?

- ver links (1)
- links (2)
- linksmidden (3)
- midden (4)
- rechtsmidden (5)
- rechts (6)
- ver rechts (7)

Vraag 29 Op welke politieke partij heeft u voor de verkiezingen van 2021 gestemd?

- ◯ VVD (Volkspartij voor Vrijheid en Democratie) (1)
- ◯ D66 (Democraten 66) (2)
- ◯ PVV (Partij voor de Vrijheid) (3)
- ◯ CDA (Christen-Democratisch Appèl) (4)
- ◯ SP (Socialistische Partij) (5)
- ◯ PvdA (Partij van de Arbeid) (6)
- ◯ GL (GroenLinks) (7)
- ◯ PvdD (Partij voor de Dieren) (8)
- ◯ CU (ChristenUnie) (9)
- ◯ FvD (Forum voor Democratie) (10)
- ◯ Volt (11)
- ◯ JA21 (JuisteAntwoord21) (12)
- ◯ SGP (Staatkundig Gereformeerde Partij) (13)
- ◯ DENK (14)
- ◯ BBB (BoerBurgerBeweging) (15)
- ◯ BIJ1 (16)
- ◯ 50+ (50 PLUS) (17)
- ◯ Geen (18)
- ◯ Anders namelijk: (19) ____
- ◯ Wil ik niet zeggen (20)

Vraag 30 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik ervaar afkeer van mensen met een andere politieke voorkeur

- ○ helemaal oneens (1)
- ○ oneens (2)
- ○ niet eens/oneens (3)
- ○ eens (4)
- ○ helemaal eens (5)

Vraag 31 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik ervaar negatieve gevoelens jegens mensen met een andere politieke voorkeur

- ○ helemaal oneens (1)
- ○ oneens (2)
- ○ niet eens/oneens (3)
- ○ eens (4)
- ○ helemaal eens (5)

Vraag 32 Kunt u aangeven in hoeverre u het eens bent met de volgende stelling?

Ik ervaar agressieve gevoelens jegens mensen met een andere politieke voorkeur

- helemaal oneens (1)
- oneens (2)
- niet eens/oneens (3)
- eens (4)
- helemaal eens (5)

End of Block: Block 4

Appendix B.

Syntax dataset: thesis social media use and affective polarization

```
* Encoding: UTF-8.


*weging opleiding, geslacht en leeftijd.

freq vraag_4.

freq vraag_3.

recode vraag_3 (sysmis=44) (else=copy) into leeftijd.

freq Wat_is_uw_geslacht_.

recode Wat_is_uw_geslacht_ (3=1) (4=1) (else=copy) into geslacht.

freq geslacht.


freq vraag_4.


recode vraag_4 (1=1) (2=2) (3=3) (4=4) (5=5) (else=1) into Opleiding.

freq Opleiding.



NPAR TESTS

  /CHISQUARE=vraag_4

  /EXPECTED= 0.09256187 0.2002627 0.3673441 0.2048251 0.1191069

  /MIsSING ANALYSIS.


if (vraag_4=1) opleiding_w= 0.09256187/0.00473934.

if (vraag_4=2) opleiding_w= 0.2002627/0.01421801.
```

if (vraag_4=3) opleiding_w= 0.3673441/0.29383886.

if (vraag_4=4) opleiding_w= 0.2048251/0.47393365.

if (vraag_4=5) opleiding_w= 0.1191069/0.21327014.

freq opleiding_w.

WEIGHT BY opleiding_w.

weight off.

*socialmedia gebruik in minuten.

freq vraag_9.

RENAME VARIABLES vraag_9=SocialMM.

variable labels SocialMM 'social media gebruik in minuten'.

freq socialmm.

recode socialmm (sysmis=89.76) (else=copy) into socialmmm.

freq socialmmm.

*Social media primaire nieuwsbron.

freq vraag_13 vraag_14 vraag_15.

recode vraag_13 vraag_14 vraag_15 (1=0) (2=0) (3=0) (4=1) (5=2) into vraag_13R vraag_14R vraag_15R.

value labels vraag_13R vraag_14R vraag_15R 0 'oneens/nieteensoneens' 1 'eens' 2 'helemaal eens'.

```
compute PMNB=  sum.1( vraag_13R, vraag_14R, vraag_15R).

recode PMNB (2=1) (sysmis=0) (Else=copy) into primairenieuwsbron.

freq primairenieuwsbron.

value labels primairenieuwsbron 0 'niet' 1 'wel'.



*affectieve polarisatie.

freq A_Vraag_30 vraag_28 vraag_31 vraag_32.


FACTOR

  /VARIABLES A_Vraag_30 vraag_28 vraag_31 vraag_32

  /MISSING LISTWISE

  /ANALYSIS A_Vraag_30 vraag_28 vraag_31 vraag_32

  /PRINT INITIAL CORRELATION EXTRACTION ROTATION

  /PLOT EIGEN

  /CRITERIA MINEIGEN(1) ITERATE(25)

  /EXTRACTION PAF

  /CRITERIA ITERATE(25) DELTA(0)

  /ROTATION VARIMAX

  /SAVE REG(ALL)

  /METHOD=CORRELATION

  /format sort blanc(0.30).



RELIABILITY
```

```
  /VARIABLES=A_Vraag_30 vraag_31 vraag_32
  /FORMAT=LABELS
  /SCALE(ALPHA)=ALL/MODEL=ALPHA
  /STATISTICS=SCALE CORR
  /SUMMARY=TOTAL .

compute indpol= mean.3(A_Vraag_30, vraag_31, vraag_32).
value labels indpol 0 'geen afkeer'  3 'matige tot geen afkeer' 4 'afkeer' 5 'sterke afkeer'.
freq indpol.

*variabele links.
compute linkseidentificatie= vraag_28.
if vraag_28=1 linkseidentificatie=3.
if vraag_28=2 linkseidentificatie=2.
if vraag_28=3 linkseidentificatie=1.
IF vraag_28 gt 3 linkseidentificatie=0.
freq linkseidentificatie.
Value labels linkseidentificatie 0 'niet links' 1 'linksmidden' 2 'links' 3 'ver links'.

*variabele rechts.
compute rechtseidentificatie= vraag_28.
if vraag_28=7 rechtseidentificatie=3.
if vraag_28=6 rechtseidentificatie=2.
if vraag_28=5 rechtseidentificatie=1.
```

IF vraag_28 lt 5 rechtseidentificatie=0.

freq rechtseidentificatie.

Value labels rechtseidentificatie 0 'niet rechts' 1 'rechtsmidden' 2 'rechts' 3 'ver rechts'.

*dummyariabele sterk links.

recode linkseidentificatie (3=1) (2=1) (1=0) (sysmis=0) (else=copy) into sterklinks.

value labels sterklinks 0 'niet sterk links' 1 'sterk links'.

freq sterklinks linkseidentificatie.

*dummyariabele sterk rechts.

recode rechtseidentificatie (3=1) (2=1) (1=0) (sysmis=0) (else=copy) into sterkrechts.

value labels sterkrechts 0 'niet rechts' 1 'sterk rechts'.

freq sterkrechts rechtseidentificatie.

recode rechtseidentificatie (3=0) (2=0) (1=0) (sysmis=1) (else=copy) into missingidentificatie.

value labels missingidentificatie 0 'niet missing' 1 'missing'.

freq missingidentificatie rechtseidentificatie.

*self selected exposure.

freq Vraag_13.0.

value labels Vraag_13.0 1 'rechts erkenbrand' 2 'links groenfront' 3 'rechts pegida' 4 'links VCP'.

compute selfselectedexposure=0.

if rechtseidentificatie gt 0 and vraag_13.0=1 or vraag_13.0=3 selfselectedexposure=1.

```
if linkseidentificatie gt 0 and vraag_13.0=2 or vraag_13.0=4 selfselectedexposure=2.

value labels selfselectedexposure 0 'geen exposure' 1 'exposure rechts' 2 'exposure links'.

freq selfselectedexposure.


recode selfselectedexposure (1=1) (2=1) (else=copy) into selfselectedexposure_dich.

 value labels selfselectedexposure_dich 0 'geen exposure' 1 'wel self selected exposure'.

freq selfselectedexposure_dich.


* experienced self selective exposure.

freq vraag_14.0 vraag_15.0.

recode vraag_14.0 (1 thru 3=0) (4 thru 5=1) (else=copy) into exselfselect_alg.

value labels exselfselect_alg 0 'geen ervaren exposure' 1 'ervaren exposure'.

freq exselfselect_alg.


*experienced pre-selected exposure.

freq vraag_17 vraag_19 A_vraag_21 A_Vraag_23 Vraag_25 Vraag_27.



RELIABILITY

  /VARIABLES=vraag_17 vraag_19 A_vraag_21 A_Vraag_23 Vraag_25 Vraag_27

  /FORMAT=LABELS

  /SCALE(ALPHA)=ALL/MODEL=ALPHA

  /STATISTICS=SCALE CORR

  /SUMMARY=TOTAL .
```

```
FACTOR
  /VARIABLES vraag_17 vraag_19 A_vraag_21 A_Vraag_23 Vraag_25 Vraag_27
  /MISSING LISTWISE
  /ANALYSIS vraag_17 vraag_19 A_vraag_21 A_Vraag_23 Vraag_25 Vraag_27
  /PRINT INITIAL CORRELATION EXTRACTION ROTATION
  /PLOT EIGEN
  /CRITERIA MINEIGEN(1) ITERATE(25)
  /EXTRACTION PAF
  /CRITERIA ITERATE(25) DELTA(0)
  /ROTATION VARIMAX
  /SAVE REG(ALL)
  /METHOD=CORRELATION
  /format sort blanc(0.30).


compute preselectedexp= mean.1( vraag_17, vraag_19, A_vraag_21, A_Vraag_23, Vraag_25,
        Vraag_27).
freq preselectedexp.
recode preselectedexp (1 thru 3.5=0) (3.5 thru 5=1) (sysmis=0) into preselectedexp_dich.
freq preselectedexp_dich.
value labels preselectedexp_dich 0 'geen pre-selected exposure' 1 'wel pre-selected exposure'.


recode preselectedexp_dich (sysmis=1) (else=0) into preselectedexp_missing.
freq preselectedexp_missing preselectedexp_dich.


freq Wat_is_uw_geslacht_.
```

```
*dummies FB IG YT.

*Facebook.

recode Vraag_10_3 (1=1) (else=0) into FBuse.

value labels FBuse 0 'geen facebook' 1 'wel faceook'.

freq FBuse.


*Instagram.

recode Vraag_10_1 (1=1) (else=0) into IGuse.

value labels IGuse 0 'geen instagran' 1 'wel instagram'.

freq IGuse.


*Youtube.

recode Vraag_10_2 (1=1) (else=0) into YTuse.

value labels YTuse 0 'geen youtube' 1 'wel youtube'.

freq YTuse.


freq Vraag_13

Vraag_14

Vraag_15.

freq socialmmm.


*lineariteitstoets.

MEANS TABLES=socialmmmsq BY indpolsq

  /CELLS=MEAN COUNT STDDEV
```

```
  /STATISTICS LINEARITY.

recode socialmmm (0=89.76) (else=copy) into socialmedia.

compute socialmmmsq=1/socialmedia.
compute indpolsq=1/indpol.

MEANS TABLES=socialmedia BY indpol
  /CELLS=MEAN COUNT STDDEV
  /STATISTICS LINEARITY.

freq socialmmmsq socialmedia indpol.

*Heteroscedasticiteit.
UNIANOVA indpolsq WITH socialmmmsq Wat_is_uw_geslacht_ leeftijd Vraag_4
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /PRINT MBP WHITE F BP PARAMETER
  /CRITERIA=ALPHA(.05)
  /ROBUST=HC3
  /DESIGN= socialmmmsq Wat_is_uw_geslacht_ leeftijd Vraag_4.

*analyse.
correlations socialmmmsq with indpolsq.
```

```
REGRESSION

  /MISSING LISTWISE

  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL

  /CRITERIA=PIN(.05) POUT(.10)

  /NOORIGIN

  /DEPENDENT indpolsq

  /METHOD=ENTER socialmmmsq

  /METHOD=ENTER Wat_is_uw_geslacht_ leeftijd Vraag_4.



freq missingsocialmediagebruik primairenieuwsbronmissing.


REGRESSION

/DESCRIPTIVES N

 /DEPENDENT INDPOLsq

 /METHOD=ENTER socialmmmsq

 /METHOD=ENTER socialmmmsq  Wat_is_uw_geslacht_  Leeftijd vraag_4.
```

***mediatie self-selected exposure.**

```
REGRESSION

/DESCRIPTIVES N

 /DEPENDENT indpolsq

 /METHOD=ENTER socialmmmsq
```

/METHOD=ENTER Wat_is_uw_geslacht_ Leeftijd vraag_4 selfselectedexposure_dich.

***mediatie pre-selected exposure.**

REGRESSION

/DESCRIPTIVES N

/DEPENDENT indpolsq

/METHOD=ENTER socialmmmsq

/METHOD=ENTER socialmmmsq Wat_is_uw_geslacht_ Leeftijd vraag_4 selfselectedexposure_dich preselectedexp_dich.

***primairenieuwsbron.**

compute Socialmediagebruik_pmnb=socialmmmsq*primairenieuwsbron.

REGRESSION

/DESCRIPTIVES N

/DEPENDENT indpolsq

/METHOD=ENTER socialmmmsq

/METHOD=ENTER socialmmmsq Wat_is_uw_geslacht_ Leeftijd vraag_4 selfselectedexposure_dich preselectedexp_dich Socialmediagebruik_pmnb primairenieuwsbron.

***interactie links rechs.**

compute socialmediagebruik_links=socialmmmsq*sterklinks.

REGRESSION

/DESCRIPTIVES N

/DEPENDENT indpolsq

```
/METHOD=ENTER socialmmmsq

/METHOD=ENTER socialmmmsq  Wat_is_uw_geslacht_ Leeftijd vraag_4 selfselectedexposure_dich
        preselectedexp_dich Socialmediagebruik_pmnb primairenieuwsbron
        socialmediagebruik_links sterklinks.
```

***interactie socialmediakanalen.**

```
compute socialmediagebruik_IGuse= socialmmmsq*IGuse.

REGRESSION

/DESCRIPTIVES N

/DEPENDENT indpolsq

/METHOD=ENTER socialmmmsq

/METHOD=ENTER socialmmmsq  Wat_is_uw_geslacht_ Leeftijd vraag_4 selfselectedexposure_dich
        preselectedexp_dich Socialmediagebruik_pmnb

 primairenieuwsbron socialmediagebruik_links sterklinks socialmediagebruik_IGuse IGuse.

freq indpol veelsocialmediagebruik IGuse socialmmm YTuse IGuse FBuse Wat_is_uw_geslacht_
        preselectedexp_dich selfselectedexposure_dich rechtseidentificatie linkseidentificatie
        primairenieuwsbron.

CORRELATIONS

 /VARIABLES=indpolsq socialmmmSq

 /PRINT=TWOTAIL NOSIG FULL

 /MISSING=PAIRWISE.
```