Google and its ability to manipulate users' decision making from a gender perspective.

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ABSTRACT,
There is a substantial amount of research on the difference in the use of the Internet between men and women, as well as their online behaviour, however there is knowledge lacking on what the role of the medium is in this story. Therefore, this paper provides a deeper understanding of the extent to which personalised search engines, like Google, influence a users' search results and how this has an impact on users' decision making. Furthermore, DuckDuckGo, which does not personalise search results has also been included in this study. This study takes a gender perspective, looking at two topics – jobs and political participation – that still experience a rather conservative division between men and women. An online survey has been conducted with 101 participants, using one sample and independent samples t-tests to analyse the results. This research contributes to the literature by providing in depth knowledge of one specific part of a person's electronic profile. The findings suggest that personalised search engines do provide one-sided views on a topic, making them able to manipulate users' decision making. However, even though it has some impact, gender is only a small part of the equation. Furthermore, even though DuckDuckGo says not to gather personal information the observations done in this study raise questions regarding this statement.

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Personalisation, Google, DuckDuckGo, Gender bias, Jobs, Political Participation.

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1. INTRODUCTION

The volume of information that is available to people is increasing as big data techniques make it possible to store and process data. However, this increasing amount of information makes it almost impossible to find items (Burger, Hirth, Hoûfeld, & Tran-Gia, 2016). To make it easier for people to find personally relevant data, search engines have made it possible for its users to browse the web and find the most relevant web pages for the search terms that they entered in the search bar. The most used and well known search engine is Google (StatCounter, 2016). Google collects data from its users to create electronic profiles to be able to personalise its search results. These profiles can also be called an electronic identification, because people are identified based on the information they have provided to the web. Based on these profiles, the search engine results will differ for users and be ranked according to personal preferences and relevance. According to Hannak et al. (2013) this personalisation may result in a Filter Bubble effect where certain users are not able to see information that the search engines' algorithm deems irrelevant and thus "potentially important results remain hidden" (Hannak et al., 2013). Nguyen et al. (2014) explained the Filter Bubble as "a self-reinforcing pattern of narrowing exposure that reduces user creativity, learning, and connection". (Nguyen, Hui, Harper, Terveen, & Konstan, 2014). Similarly, Burger et al. (2016) have found that the problem with information that is tailored based on a user's profile is, that it reduces the chance to discover new topics or see different views of a topic as a users' profile reflects past activity of the user. Therefore, information shown to the user "is similar to the information consumed in the past" (Burger et al., 2016). Furthermore, the diversity of information exposed to users decreases because of algorithmic filtering and by adapting the online content based on interests and preferences of the user (Helberger, Karppinen, & D'Acunto, 2018).

Based on these findings, there is a possibility that the effect of the Filter Bubble will retrieve search results viewing only one side of a certain topic and therefore the results become biased towards this particular view. When users are not aware of this bias, there is the possibility that a search engine manipulation effect will occur. This manipulation effect has been studied by Epstein and Robertson (2015) and they found that this effect can have an impact on the outcome of elections. Where (almost) all the search results were biased towards one candidate the likelihood to vote for that candidate increased (Epstein & Robertson, 2015). They presume that search engines are powerful means that, without regulation, can be taken advantage of, influencing specific demographic groups (Wijnhoven, 2017).

The Filter Bubble effect appearing in search engines is becoming of increasing concern, which drives the increase in popularity of other search engines that do not produce search results based on personalisation. One example of such a search engine is DuckDuckGo (Hannak et al., 2013). However, the user still experiences the Filter Bubble as something positive. For example, Wijnhoven (2017) found that Google's users were much more satisfied than users of DuckDuckGo, a search engine that does not use personalised data (Wijnhoven, 2017).

The goal of this research is to gain a deeper understanding of the extent that personalised search engines influences a users' search results and how this has an impact on users' decision making. When the search results shown to the user mainly supports one side of a topic, it can be said that search results are biased. This can reinforce or even change a users' view of a certain topic. As these personalised search results are able to influence a user's attitudes and opinions, it can be seen as a manipulation effect. Therefore, this paper aims to measure manipulation by looking at the one-sidedness of Google search results. This leads to the following research question:

To what extent do personalised search engines manipulate users' decision making by providing one-sided views?

To answer this research question, the focus of this article will be on the potential gender bias present in search engines, this is one of many aspects of information about a user taken into account with personalisation (Lopes, Cabral, & Bernardino, 2016). This aspect is introduced below and here the sub question will be introduced as well.

1.1 Gender

Men and Women differ in their search behaviour online. For example, Gallant & Arcand found that, regarding internet shopping, men are more likely to use impersonal online information sources (Gallant & Arcand, 2017). Furthermore, Brandtzaeg, Heim & Karahasanovic (2011) found that for the use of the Internet in general "males are more likely to be Advanced Users than Sporadic Users and more likely to be Entertainment Users than Instrumental Users" (Brandtzæg, Heim, & Karahasanović, 2011). Lastly, Colley & Maltby (2008) analysed the difference between men and women and the areas of the internet that have a big impact on their lives. They found that the differences in impact between men and women "broadly reflects the concerns and motivations associated with men's and women's social roles" in the offline world. Their research supports other findings that the differences between men and women found online will last as long as they are present more generally (Colley & Maltby, 2008).

However, as there is a substantial amount of research regarding the difference in the use of the Internet between men and women, as well as their online behaviour, there is knowledge lacking on what the role of the medium is in this story. Hargittai & Shafer (2006) suggest that the supply-side of content - due to its structure and presentation - is in itself male-biased (Hargittai & Shafer, 2006). However, to be able to make this claim more research should be done. This leads to the following sub-question, which this research tries to answer:

To what extent do personalised search engines manipulate users' decision making by providing one-sided views based on their gender?

2. THEORY

This section will provide more in-depth information that is at the basis of this study. First it will go into more detail about Google and it explains why their practices are of growing concern. Then it will set out the concerns regarding gender inequalities and the hypotheses related to the research question. Lastly, it will explain more about the search engine DuckDuckGo, which results in two additional hypotheses.

2.1 Google

Search engines are a popular tool when searching for information on the Internet, however most users do not have an idea how they work and the consequences of the algorithms that are used (Pan et al., 2007). In the case of Google, they apply two ways of ranking the results:

1. They apply a page ranking algorithm which measures the number of in-links of a document with others, to retrieve "the relative popularity of recalled documents."
2. The Google algorithm uses a search query as input to search for "data from the Google index". This is the part where personalisation occurs, besides the information that can be found in someone's account.

Here personalisation occurs, because the search rankings that result from a query are used as new input for the algorithm, so it can learn. Thus, the behaviour of the user on the Google search engine is also used as a part of your personal profile (Wijnhoven, 2017).

Ranking the search results can lead to a ranking bias, because users are by a great extent influenced by the order of the search results, instead of "the actual relevance of the abstracts" (Pan et al., 2007). Epstein et al. (2017) found that the primacy effects – showing better recall and higher evaluation for results in the beginning of a list – "have a particularly strong influence during online search". Moreover, a bigger concern is that personalisation practices in combination with ordering results makes it almost impossible to detect ranking bias (Epstein, Robertson, Lazer, & Wilson, 2017).

2.2 Gender inequalities

To answer the research question, it is first needed to find areas where there is an inequality experienced between men and women. According to the United Nations Development Program (UNDP), there are still significant inequalities between women and men in Europe and the region of Central Asia, "particularly when it comes to jobs and income, political participation, access to resources and services, and the distribution of unpaid domestic and care work". Similarly, gender stereotypes are prevalent, hindering women's access to opportunities. Furthermore, men are more likely to gain promotion "to top management positions and prestigious leadership roles" than women. Moreover, women are more likely to have insecure jobs, no contract or regular salary, or part-time jobs (United Nations Development Programme, 2018). For this research we have decided to focus on the areas: jobs and political participation. These areas are explained in more detail in the following sections.

2.2.1 Jobs

As according to Scherer (2004) the "labour market entry and a successful transition from school to work are of crucial importance for subsequent career chances and risks" (Scherer, 2004), it is a good start to look at the possibly different opportunities that are presented towards men and women when searching for their first job. Defloor, van Ootegem & Verhofstadt (2015) found that the quality of a person's first job is largely dependent on personal effort, although circumstances, for example gender, do have a considerable influence on these efforts. This would therefore suggest that a difference between jobs between men and women is due to a difference in effort spent between men and women when searching for their first job. However, they analysed the quality of someone's first job using an equality of opportunity framework (Defloor, Van Ootegem, & Verhofstadt, 2015). Equality of opportunity means that "outcomes experienced by a population depend only on factors for which persons can be considered to be responsible" (Roemer & Trannoy, 2015). And as according to Nikolaou (2014) people are increasingly searching for jobs online (Nikolaou, 2014), the Filter Bubble effect can disturb this equal opportunity. As Pariser (2011) pointed out, the Filter Bubble not only reflects a person's identity but it also shows the options a person has. Some options will be shown while others would be hidden, giving the Filter Bubble the ability to influence a person's decision making (Pariser, 2011). For example, University students will see personalised results while searching for job vacancies, while Higher Vocational Education students will never become aware of these vacancies.

Following these previous studies, this part of the study will focus on the reinforcement of current stereotypes in the job market. To do this it is necessary to have a classification of which types of jobs are typically seen as male related jobs and which are female related. Figure 1 below illustrates a list of various occupations, classifying them as male-dominated, mixed or female-dominated based on data from 12 EU countries.

Occupation	Number of countries where the occupation is		
	Male-dominated	Mixed	Female-dominated
Armed forces	10	0	0
Legislators, senior officials and managers	7	5	0
Corporate managers	8	4	0
Managers of small enterprises	5	7	0
Physical, mathematical and engineering science professionals	12	0	0
Life science and health professionals	0	7	5
Teaching professionals	0	2	10
Other professionals	0	11	1
Physical and engineering science associate professionals	11	1	0
Life science and health associate professionals	0	0	12
Teaching associate professionals	0	2	8
Other associate professionals	0	10	2
Office clerks	0	0	12
Customer services clerks	0	0	12
Personal and protective services workers	0	2	10
Models, salespersons and demonstrators	0	1	11
Skilled agricultural and fishery workers	8	4	0
Extraction and building trades workers	12	0	0
Metal, machinery and related trades workers	12	0	0
Precision, handicraft, craft printing and Related trades workers	5	7	0
Other craft and related trades workers	5	7	0
Stationary-plant and related operators	11	1	0
Machine operators and assemblers	5	6	1
Drivers and mobile plant operators	12	0	0
Sales and services elementary occupations	0	0	12
Agricultural, fishery and related labourers	3	6	2
Labourers in mining, construction, manufacturing and transport	12	0	0

Figure 1. (Bettio, Verashchagina, Mairhuber, & Kanjuo-Mrčela, 2009)

Furthermore, regarding working sectors, "women make up almost 80% of those employed in health and social work, over 70% of those employed in education and over 60% of those working in retailing". In contrast, only 8% of those employed in construction and 14% of those in land transport are women. This pattern is visible throughout all the Member States of the EU. In all of these Member States women were more frequently present in "secretarial, clerical and sales jobs and as nurses or teachers", while men were more frequently "employed as craft and related trades workers and as machine operators" (European Communities, 2008).

Having an idea about which occupations more frequently employ women or men makes it possible to formulate the hypotheses. Thus, the hypotheses are as follows:

H1: Women are mainly shown vacancies for female related jobs in their Google search results.

H2: Men are mainly shown vacancies for male related jobs in their Google search results.

2.2.2 *Political Participation*

The gender gap occurring in political structures is likely caused by the promotion of men and the hindering of women (Turcinskaite-Balciuniene & Balciunas, 2016). According to Eurostat (2008), the participation of women in politics across Europe has increased over time. However, their presence in important "positions of power and influence is still far below that of men". Moreover, regarding women in government, they frequently have the responsibility over lower level ministries e.g. the ones regarding "social and cultural activities and infrastructure", while men frequently have the responsibility over higher level ministries such as the ones that have "to do with economy or basic functions (such as foreign and internal affairs, defence and justice)" *(European Communities, 2008)*. Cabeza-García, Del Brio & Oscanoa-Victorio (2018) found similar differences between men and women regarding political participation. They found evidence that "participation in bodies of power and institutions is predominantly masculine, whereas voluntary associations, organizations, and "informal" community politics tend to be led by women". Moreover, in the data used in this study the number of women in governments was only 16% over 127 countries and not one of the women "was in a top parliamentary management post". Furthermore, the women that did have a post in "local, municipal, or national government" occupied posts with a more social and cultural nature and thus with less political importance (Cabeza-García, Del Brio, & Oscanoa-Victorio, 2018). Brandtzaeg (2017) studied the difference between men and women in expressions of civic engagement on Facebook and he found that millennial women more often engage with posts "related to children and the environment when compared to men of the same age". Moreover, he concluded that patterns in the offline world regarding the differences among men and women in civic engagement were reproduced and reinforced on Facebook rather than equalized (Brandtzaeg, 2017).

Moreover, Pfanzelt & Spies (2018) studied the difference between young German men and women regarding political participation. They distinguished between three types of political participation, namely: institutional, non-institutional and expressive. The first one "covers long-established activities, which mainly address the state via participation in elections or actively running for or holding office". Non-institutional participation refers to protest activities e.g. boycotts, and expressive participation "includes activities primarily giving voice to the political aims and intentions of citizens." The internet is a main medium for expressive participation. They found that young men are more likely to participate in institutional and expressive forms, while "young women tend toward non-institutional, protest-oriented activities" (Pfanzelt & Spies, 2018).

As explained above women are more likely to engage in certain practices regarding politics while men in other, which could possibly be reinforced through personalisation techniques used by Google. Furthermore, the practices that women engage in are mainly ones with a lesser political importance than the ones men engage in. This leads to the following hypotheses:

H1: Women are mainly shown political involvement opportunities for positions of low power and influence.

H2: Men are mainly shown political involvement opportunities for positions of high power and influence.

2.3 DuckDuckGo

We will also do the same research for the alternative search engine DuckDuckGo (DDG), which is said to not gather personal data from its users for its results (Hannak et al., 2013). Instead, DDG bases their search results on expert advice. This means that they focus only on the search term and "its semantics and what an expert would recommend to access" (Wijnhoven, 2017). However, there is a negative side to this "keyword based web search method" as search queries can have different meanings in different contexts (Mala & Lobiyal, 2016). For example, the keyword 'code' will refer to something related to metadata for an IT specialist, while it will refer to a set of rules for a lawyer. Thus, considering the method used by DDG it is expected that search results for every individual user will be the same. This leads to the following hypotheses:

H1: There is no gender bias in the vacancies shown on DuckDuckGo to men and women.

H2: There is no gender bias in the political involvement opportunities shown on DuckDuckGo to men and women.

3. TERMINOLOGY

Before moving to the research design and findings some terms used in this study need clarification.

First of all, it should be clear what is meant with organic search results, as these are the search results that are analysed in this study. The same classification as used by Höchstötter & Lewandowski (2009) has been used in this study, which describes organic search results as "results from Web Crawl. "Objective hits" not influenced by direct payments" (Höchstötter & Lewandowski, 2009). Thus, these are the results that appear after the advertisements (if any are shown), but it also excludes images, related questions and the like.

Moreover, it is needed to set out what this study considered to be included in a user profile and what not. For this study it has been assumed that a user's profile not only includes the information stored on a user's account but also their online behaviour, which includes their (search) history and their cookies stored on their computer and so on. Furthermore, also the IP-address and location is considered to be part of a user's profile.

4. METHODOLOGY

4.1 Research method

In order to answer the research question presented in the above section an online survey has been conducted. A survey is by default an obtrusive and verbal data collection method (Dooley, 2009). This means that participants of the survey will be aware of the fact that data about them is collected and the means by which this is collected is done by using words. Furthermore, in this research all questions are the same for each participant and further questions are not influenced by earlier answered questions. Thus the questions in the survey are standardised. The units of observation are students from around the world most of which are located in the Netherlands. However, the units of observation are not the same as the units of analysis. Answering the research question will tell something about search engines and not the individual that participates in the survey. In this research the two search engines Google and DuckDuckGo have been used. Therefore, the units of analysis are the search engines Google and DuckDuckGo.

To be able to conduct a survey that asks relevant questions the construct that will be measured needs to be clear. The construct in this research will be manipulation, which is set in the context of search engines and how they are able to manipulate their users through the search results that they provide. A good example of how we would determine if users are manipulated is the research done by Epstein and Robertson (2015). Epstein and Robertson found out that elections can be manipulated by (almost) only showing results of one candidate and no information about others (Epstein & Robertson, 2015). We have used this research to define the manipulation effect in search results. This means that for this research manipulation is defined as 'the illustration of search results that (almost) only show one perspective of the information asked for by the search query'.

4.2 Search queries

Regarding the gender issues participants of the survey are asked to type in two search queries into the Google search engine and the same two into the DuckDuckGo search engine. These two search queries are 'job openings near me' and 'how to become involved in politics'. These two search queries are based on the literature about the gender gap in occupations and political participation as set out in the theory section above. Moreover, the search query for the job openings is a frequently used search query when people search for a job according to Google Trends (Google, sd).

One of the search queries has been formulated as a question and one as a statement. Therefore, besides the possible gender bias, measured with these search queries it could also give interesting insights regarding the formulation of search queries.

4.3 Data collection

To be able to measure the construct of manipulation the survey consisted of five separate parts.

The first part of the survey asked questions to determine the suitability of a respondent. This part is explained in more detail in the next section: 'Participants'. The second part of the survey asked general questions regarding demographics and behaviour on the Google search engine of the respondent, for example age, educational level and the language mostly used to conduct Google searches. The third and the fourth part of the survey asked the respondent to upload screenshots of their first 6 organic search results appearing when searching for 'job openings near me' and 'how to become involved in politics'. The third part asked this for the Google search engine while the fourth part asked to do this on DuckDuckGo. The last part asked questions that were related to the search queries the respondents had to type in. These questions were asked to be able to determine to which extent a personal profile influences the search results shown to a user as well as how much Google actually knows about its users. An example of such a question is the extent of political involvement of a respondent, ranging from not involved to very involved.

To gather enough respondents, the link of the survey has been shared on the personal Facebook of the researcher and in multiple group pages. Furthermore, it has been shared in multiple WhatsApp group chats as well. Lastly, to speed up the data collection, the link was printed and handed to people working at university together with some candy as an incentive. Giving out candy as an incentive has been chosen, because it has been proven that a small incentive would increase the response rate for web-based surveys, but it was not so valuable that it could have affected a person's responses. It was also not in any way related to the study and therefore it only encouraged people to respond but it could not have any effect on the answers given to the survey questions (Cobanoglu & Cobanoglu, 2003).

4.4 Participants

The survey received 144 respondents, however not all of these respondents could be used due to certain requirements set for this research. One of these requirements is related to the removal of cookies. Therefore, respondents were asked when they removed their cookies for the last time. "A cookie is a small piece of data sent from the website and stored on the user's browser that is sent back to the website every time the user returns" (Coey & Bailey, 2016). Thus, a cookie is set on a person's browser when this person visits a website for the first time and when this person returns to the website, this website is able to identify this person and his/her preferences. Furthermore, the information stored on the cookies are used to create a user's profile (Jegatheesan, 2013). More and more people use the internet on a daily basis. According to a survey of Statista (2018) 83% of respondents from Germany and 89% of respondents from the United Kingdom use the internet daily (Statista, 2017). Furthermore, Perrin & Jiang (2018) found that around 88% of Americans aged 18-29 go online at least daily (Perrin & Jiang, 2014). This has led to the decision of including all respondents that removed their cookies two weeks or later, as the frequent use of the internet and the instant installation of cookies gives Google a good impression of the users profile in these two weeks.

Other requirements included the use of a personal computer or laptop instead of a phone, being 18 or older and the use of Google as main search engine. This left 101 respondents that were suitable for this study.

Of these 101 participants 52% are male and 48% are female. All of the participants are students following a higher vocational education, bachelor or master. The age ranges from 18 till 29 years old, with most participants falling in the range of 20 till 23 years old. Lastly, the three most occurring nationalities are Dutch (60.8%), Mexican (8.8%) and German (7.8%).

4.5 Data analysis

To be able to analyse the data collected in a systematic matter, a coding scheme is designed. This coding scheme will determine if the results are indeed one-sided for the particular gender according to the theory.

The data analysis in this research is a directed content analysis, because this research has started with an explanation of theories related to the research question and from this the coding scheme has followed. The codes are mainly defined before doing the data analysis but has been altered a bit during the analysis (Hsieh & Shannon, 2005).

Only the first four search results have been analysed, as the sixth result was not always visible on all screenshots. Moreover, to be able to detect one-sidedness an equal amount of results is needed, thus therefore also the 5th result has not been taken into account in this study. The points given to a screenshot range from -6 "only male biased search results are shown" and 6 "only female biased search results are shown". The first two results have been given extra weight (-2 for male-biased and 2 for female-biased), as according to Dillahunt, Brooks & Gulati (2015) people generally believe that the top results are presented first (Dillahunt, Brooks, & Gulati, 2015). The third and the fourth result are given either -1, for male-biased, or 1 for female-biased. This way this study also takes ranking bias into account. The detailed coding scheme can be found in Appendix 1.

After all the data has been coded it has been analysed with the statistical program 'Statistical Package for the Social Sciences' (SPSS). One sample- and independent samples t-tests are conducted to test the hypotheses. These tests have been chosen because to test the hypotheses proposed this study wants to compare the means. Furthermore, the independent samples t-test has been chosen because two means have to be compared, namely the one for male and for female, which are independent of each other (Van der Kaap, 2015). However, these tests require the data to be normally distributed and therefore for all four variables ('Jobs Google', 'Politics Google', 'Jobs DDG', 'Politics DDG') a Shapiro Wilk test has been conducted to test for normality. Unfortunately, for all four variables the outcome suggests that they are not normally distributed ($p < 0.000$). However, as the sample size is large enough and the shape of the histogram do suggest the data to be fairly normal the tests are still used (Van der Kaap, 2016). To say that a result is significant an alpha of 0.05 has been used.

4.6 Reliability

The coding has been done by two persons individually to be able to check if the search results could be categorised correctly using this coding scheme. In other words, the coding scheme has been tested for reliability. The coding scheme includes independent categories that are mutually exclusive. Therefore, results can only be categorised into one category. The two coders were the researcher and another researcher working on the same kind of project but looking at it from a different perspective. The second coder got the document with the coding scheme, as included in appendix 1, before coding. Additionally, questions about the coding could be asked before starting the coding process. The test used to test for reliability has been Krippendorff's alpha, which tests for inter coder reliability. This test has been used as it includes all the criteria for a good measure of reliability. Moreover, it is suitable for ratio data which the data of this study appears to be (Hayes & Krippendorff, 2007). Ratio data is data that can be classified, has an order with equal intervals and an absolute zero point. With the scores assigned to the screenshots a meaning is given to the data, an order is established ranging from -6 fully male-biased to 6 fully female-biased, the intervals are of equal distance and there is an absolute zero point as assigning a 0 means that there is no bias (Van der Kaap, 2015). Before checking for reliability the results of coding for Google and DuckDuckGo have been combined per category. This has been done because the same coding scheme has been used for 'Jobs Google' and 'Jobs DDG' as well as for 'Politics Google' and 'Politics DDG'. For both categories Krippendorff's alpha were higher than 0.67, namely α= 0.7682 for 'Jobs' and α = 0.7725 for 'Politics', which means that the coding scheme for both Political Participation and Jobs were reliable (De Swert, 2012). The reliability scores can be found in appendix 2.

5. RESULTS

In this section the results of this study are presented per search query.

5.1 Jobs Google

Before testing the hypotheses, a one sample t-test has been conducted to test if there is a bias towards either side. The results differ significantly from 0 (one sample t test = 6.286, df=96, $p < 0.000$), meaning that the search results for 'job openings near me' are in general biased towards one side as 0 means neutral results. This general bias is in the direction of female-dominated jobs as the average score of the screenshots is 1.36.

Testing the first two hypotheses leads to answering the question if there is a difference between vacancies shown to women and men. With the coding scheme used in this study the expectation will be that women will have a significantly higher score than men. When conducting an independent samples t-test support has been found for the first hypothesis: 'women are mainly shown vacancies for female related jobs in their Google search results' (independent samples t-test = -1.845. df=81.795, p=0.0345).

Surprisingly, the mean score of men is 0.98, which also implies that on average men were shown more female-dominated jobs instead of male-dominated jobs. Nevertheless, before being able to say with evidence that the second hypothesis is not supported a one sample t-test only for men has been conducted. The results shown to men are indeed significantly different than 0 (one sample t-test = 3.951, df=50, $p < 0.000$). This means that they are shown one-sided views on the search query 'job openings near me', however it was not in the expected direction. Therefore, the second hypothesis is not supported. The detailed output of SPSS for these tests can be found in appendix 3.

5.2 Political participation Google

Here, the same structure as for 'Jobs Google' has been followed. Thus, starting with a one sample t-test to determine if there is actually a bias to be found in the search results for the search query 'how to become involved in politics'. The test found that the results differ significantly from 0 (one sample t-test = -6.872, df = 92, $p < 0.000$), meaning that the search results were generally biased towards one side as 0 means neutral results. The general bias was in the direction of political positions with high power and influence, as the mean is -1.89.

To be able to test the two hypotheses related to the political participation the following question has to be answered: Is there a difference between positions shown to women and men? Following the coding scheme used in this study the expectation will be that men have significantly lower scores than women. The test did not find significant differences between men and women (independent samples t-test = 1.498, df=91, p=0.069). Therefore, both the hypotheses are not supported. Even more surprisingly, women had a mean score -2.30 while men had an average score of 1.48. This means that the average search results of women were more biased toward positions of high power and influence than the one from men, which is the opposite of what we expected. The detailed SPSS output can be found in appendix 4.

5.3 Jobs DuckDuckGo

For this section to be able to test the hypothesis a one sample t-test should be enough, as the hypothesis suggests that there will be no gender bias in the search results shown, thus they should not differ significantly from 0. However, conducting the one sample t-test the outcome shows a significant difference from 0, which means that there is a certain general bias to be found in the search results (one sample t-test = -2.816, df=93, p=0.006). When looking at the average score of this sample it shows that the direction of this bias is towards male-dominated vacancies, as the mean is -0.26.

This outcome could still suggest an absence of a bias based on gender; however further tests are required to prove this. Therefore, also for this hypothesis an independent samples t-test has been conducted. The hypothesis could still be true if the difference between male and female is not significant, as this will mean that although there is a general bias towards one side it is not because of being either male or female. The test did not show significant results and therefore support for the hypothesis has been found (independent samples t-test = -0.055, df=92, p=0.478). The detailed SPSS output can be found in appendix 5.

Even though the tests supported the hypothesis of this study, some surprising observations have been made regarding the search results shown. First of all, a great number of participants received search results mentioning vacancies for teen jobs. This could be of concern as the participants were all young adults and thus this could suggest that DuckDuckGo knows certain personal details about you even though they say they do not. Furthermore, the ranking of search results was not the same for all participants. As people generally believe that the top results are presented first (Dillahunt et al., 2015), this could raise questions regarding the neutrality of DuckDuckGo. In appendix 6 examples of these observations are shown.

5.4 Political participation DuckDuckGo

For the last search query of this study, again, only the one sample t-test could be enough to test the hypothesis. The hypothesis suggests that there is no gender bias present in the search results regarding political participation. Therefore, the scores given to the screenshots should not differ significantly from 0, as 0 means neutral results. The outcome of the test supports this hypothesis and thus there is no general bias present in searching 'how to become involved in politics' on DuckDuckGo (one sample t-test = 1.000, df=90, p=0,320). There is no need to conduct an independent samples t-test here, because when there is no general bias found there is also no possibility to find a bias based on the gender of a participant. The detailed SPSS output can be found in appendix 7.

For this search query there were also some surprising observations. First of all, we found that the ranking of search results was not the same for all participants which is similar to the finding of the search query 'job openings near me' on DuckDuckGo. Having observed a ranking bias for both of the search queries on DuckDuckGo raises the concern regarding the neutrality of DDG. Furthermore, for quite some participants one of the search results suggested to get involved with campus politics. As all of the participants were students suggesting this kind of involvement raises concern about the knowledge DDG has about a person's online profile. In appendix 8 examples of these observations are shown.

6. DISCUSSION & CONCLUSION

In this section the findings are discussed and they are compared with the theory. Furthermore, the contribution and managerial implications of this study are discussed shortly. Afterwards, the limitations of this study are reviewed and a direction for future research has been proposed. Lastly, the research question has been answered.

6.1 Discussion

In this study we found that men were also shown more female-dominated jobs, on average, for the search query 'job openings near me'. This was not in line with the expectations, however there could be various explanations for this. One of such an explanation is that the employment of students is seen as a "flexible source of labour". Student employment includes any form of paid work during the academic year or during summer (Baert, Rotsaert, Verhaest, & Omey, 2015). As in this study, flexible work has been seen as an aspect of a female job following the findings of the UNDP (United Nations Development Programme, 2018), this could have underestimated the findings for 'Jobs Google', as it possibly gave male participants higher scores than necessary. Moreover, as this study has been conducted around the time people will be searching for summer jobs, it could have influenced the results even more than any other time of the year. This is because the search results are also based on earlier searches (Burger et al., 2016) and it would be likely that some participants have been searching for summer jobs around the time of this study.

Even though, the results for the search query 'job openings near me' are likely influenced by more factors than taken into account in this study, researchers have found that a person's first job after school matters for their future career (Scherer, 2004). Therefore, the significant difference between the vacancies shown to men and women in this study is still of concern regarding the gap in higher positions (Broadbridge & Fielden, 2015). Especially because it is plausible that the gap will be even greater in reality than has been found in this study as the scores for male participants are probably underestimated.

Additionally, regarding the political participation results for Google the result of the tests did not support the hypotheses proposed in this study. However, the general bias towards male-biased results could prove the theory of Hargittai & Shafer (2006). They suggest that the supply side of content – due to its structure and presentation – is in itself male-biased (Hargittai & Shafer, 2006).

Lastly, although it was not explicitly tested in this study, the observations done in the search results for DuckDuckGo suggests a disagreement with the common believe that DDG does not use a person's personal data (Hannak et al., 2013). As in the abstracts or title of the search results 'teen' or 'campus' is mentioned and as all the participants were students it suggests a knowledge of the users age and educational level (appendix 8). Furthermore, the ranking of results is also different among different persons which should not be the case when considering the design of DDG. This is in line with the findings of Wijnhoven (2017), as he found "differences within the top *k* list" for the search term 'Brexit' in DDG (Wijnhoven, 2017). However, there is also a possibility that not DDG themselves manipulate the search results with the use of personal profiles but that the biased search results are a consequence of the information market. This phenomenon can be "attributed to algorithm-guided dynamics driven by market forces". This means that algorithms itself can prefer certain websites above others without human interventions (Epstein & Robertson, 2015). For example, Höchstötter & Lewandowski (2009) found that some websites (as Wikipedia) are preferred in comparison to other websites as well as websites using optimization techniques (Höchstötter & Lewandowski, 2009). Thus, the popularity of a website also plays a role in the ranking position of a search result.

6.2 Contribution

This study contributes to the ever growing literature about the filter bubble. This study increased the knowledge about the filter bubble by going into more depth of one specific part of a person's electronic profile, namely gender. Furthermore, it did this by including two topics that still experience a rather conservative division between men and women. Therefore, it also contributes to finding possible solutions for this division.

Additionally, this research can have a social contribution as well. It can help people become aware when searching online. However, more than research is needed to not let people become influenced by the biased results, as earlier research found that even the ones that were aware of a bias still acted in the predicted directions (Epstein & Robertson, 2015).

Lastly, this research also shed some light on the increasing concern about online services that use electronic profiles. As this study increases this concern it should contribute to alternative ways of providing online services, with a minimum amount of personal information used or even without any personalisation.

6.2.1 Managerial implications

The most important implication for managers relates to the findings for 'Jobs Google'. It could make managers rethink their keywords and the design of job vacancies, keeping in mind that Google shows certain results to certain user profiles. This could help target the right people for a certain job. Even more importantly it could help managers increase the female interest for a vacancy related to a male-dominated vacancy. In the end companies can use this knowledge to increase the number of female workers in their company by targeting them more efficiently.

6.3 Limitations

One of the limitations of this study is related to the carry-over effect as explained by Hannak et al. (2013). This effect occurs because searches conducted in the same session can be influenced by each other. For example, when a user searches for query A, followed by search query B, B could be influenced by search query A. It has been found that this effect disappears after waiting 10 minutes between subsequent searches (Hannak et al., 2013). In this study, this kind of noise has not been taken into account, however it could have influenced the results. As the survey is used by other researchers the participants had to type in additional search queries to the ones used in this study. Moreover, the search queries used in this study were the last two of the six search queries that participants had to fill in. Furthermore, two preceding search queries were related to politics this could have underestimated the results for political participation, as Google could have shown participants search results based on their earlier searches instead of their profile.

Another limitation is the distribution of the data for 'Politics Google'. The tests used in this study assume that the data is normally distributed (Rasch, Kubinger, & Moder, 2011) and this assumption is not fully met as the data for 'Politics Google' is slightly skewed to the right. This is shown in a histogram in appendix 9. However, following the nearly normal condition the tests were still safe to use as the sample sizes were larger than 40 (Van der Kaap, 2016).

Additionally, as the search queries entered by the participants are in English, the findings can only give assumptions for other languages. This should be taken into account when extending the results to other languages.

6.4 Future research

There are a lot of future research opportunities following this study. First of all, it would be interesting to perform the same study regarding the job vacancies on Google for junior managers. This could then test if the higher likelihood of men being promoted "to top management positions and prestigious leadership roles" (United Nations Development Programme, 2018) is reinforced by a significant difference in the search results shown to men and women by Google. Secondly, it would also be interesting to replicate this study to a job vacancy site similar to indeed.com or monsterboard.com, to test if these are also showing biased results following the gender of a user.

Additionally, even though the findings in this study did not find a gender bias regarding the political participation search query on Google, the results could still favour male users. As the search results are found to be biased towards men in general and some are very obvious targeted toward male users, for example one link that was shown quite often was called artofmanliness.com, it could keep women from clicking on these results and thus the opportunity of exploring the information in these kind of search results is lost. These kind of search results could then also keep existing gaps in political participation instead of equalize them. However, the kind of clicking behaviour speculated here should be explored in future research.

Furthermore, this study made some observations that would suggest that it is possible for DDG to have knowledge about a person's electronic profile and uses this to provide search results. Although, these observations could also possibly be explained by the influence of market forces on the algorithms. Therefore, there should be more research done on the search engine DuckDuckGo instead of assuming they do not personalise the search results of their users because they say so. Moreover, exploring the impact of market forces on the algorithms used by search engines would be interesting for further research.

Another direction for future research could be the study of possible solutions to the problem of bias in search results caused by (among other things) personalisation practices. Sweeney (2013) studied unwanted bias in advertising on Google and found that technology could be built to differentiate between wanted and unwanted bias. This technology needs to encompass four elements: it should be able to identify the affected groups, specify which advertisements to evaluate, determine an advertisements sentiment, and it should test for harmful impact (Sweeney, 2013). However, as this study solely takes advertisements into account further research should test if something similar could also be implemented regarding the organic search results. Moreover, Wijnhoven & Brinkhuis (2015) did research on the use of an information triangulator on the Internet among college students. They found that information triangulation makes opinions more moderated especially because alternative views shown increase (Wijnhoven & Brinkhuis, 2015). However, further research on this should be conducted to be able to say something about the use of information triangulation in relation to user profiling.

Moreover, this study has only taken into account the organic search results. However, Google and DuckDuckGo also show advertisements relating to a search query. It would therefore be interesting to do a similar study but then looking at the advertisements instead of the organic search results.

Lastly, English was not the native language of all participants and therefore some of the participants normally conduct searches in another language. There could be a possibility that this could also have an influence on the difference in search results among the participants. Nevertheless, more research on the impact of language on search results should be conducted to say something about this effect.

6.5 Conclusion

This research has tried to answer the proposed research question by conducting an online survey as well as reading articles of others on the topic. Only for three out of the six hypotheses we found significant support. The most remarkable result has been found for women searching for 'job openings near me' on Google. This was significantly different from the search results shown to men and therefore results for this search query are able to manipulate the decision making of women regarding job search. However, men were also shown significant different results from 0 which means that these results were also able to manipulate the decision making of men. Although, this manipulation was not in the expected direction. Nevertheless, it was still significant lower than women's results. Moreover, for the political participation search query on Google, the bias was not explicitly based on the gender of the users but there was a general bias favouring male users. This can still have an impact on decision making processes, however future research should be done to provide evidence for this.

Most surprisingly, the results for 'Jobs DDG' also had a significant difference from zero. Although, not based on the gender of a user as the difference between men and women were not significant, there was still a general bias towards male-dominated occupations. Furthermore, there were differences in the ranking of the search results found for DDG, as well as the results targeting a particular group, namely teens and students. Thus, even though DDG says not to gather personal information the observations done in this study raise some questions with this statement.

To conclude, personalised search engines do provide one-sided views on a topic, making them able to manipulate users' decision making. However, even though it has some impact, gender is only a small part of the equation.

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APPENDIX.

1. Coding scheme.

Jobs

When is it one-sided for women?:

When there is a vacancy mentioned in either the header, abstract or link of the search result that relates to a part-time job, insecure contract, and/or the following female dominated occupations:

- Teaching professionals
- Life science and health associate professionals
- Teaching associate professionals
- Office clerks
- Customer services clerks
- Personal and protective services (e.g. security) workers
- Models, salespersons and demonstrators
- Sales and services elementary occupations

Furthermore, when it is explicitly mentioned that the vacancy is for a woman than it is also showing a one-sided results.

When is it one-sided for men?:

When there is a vacancy mentioned in either the header, abstract or link of the search result that relates to a full-time job, and/or the following male dominated occupations:

- Armed forces

- Legislators, senior officials and managers
- Corporate managers
- Physical, mathematical and engineering science professionals
- Physical and engineering science associate professionals
- Skilled agricultural and fishery workers
- Extraction and building trades workers
- Metal, machinery and related trades workers
- Stationary-plant and related operators
- Drivers and mobile plant operators
- Labourers in mining, construction, manufacturing and transport

Furthermore, when it is explicitly mentioned that the vacancy is for a man than it is also showing a one-sided result.

! If a part time or full time job is mentioned in the results as well as occupations, occupations are determining the bias, however if e.g. two female dominated occupations are mentioned and 1 male + full-time then neutral!

! If the occupation(s) does not relate to some in the above lists than it's neutral!

! When there are more occupations mentioned and two relate to male and two to female e.g. then also neutral (0)!

! When the screenshot cannot be used, use code 999!

<u>Coding system:</u>

Content of search result	**Code**
First result mentions male dominated occupation(s)	-2
2nd result mentions male dominated occupation(s)	-2
3rd result mentions male dominated occupation(s)	-1
4rd result mentions male dominated occupation(s)	-1
First result mentions female dominated occupation(s)	2
2nd result mentions female dominated occupation(s)	2
3rd result mentions female dominated occupation(s)	1
4rd result mentions female dominated occupation(s)	1
When no occupations are mentioned in the results	0

Political Participation.

<u>When is it one-sided for women?:</u>

When the search result mention in either the header, abstract or link, relate to examples of low power and influence positions regarding politics e.g.:

- Regarding social and cultural activities
- Infrastructure
- Children
- Environment
- Indirect involvement (e.g. school board, voting)

As well as if it somewhere mentions explicitly female/woman etc.

<u>When is it one-sided for men?:</u>

When the search result mention in either the header, abstract or link, relate to high power and influence positions regarding politics e.g.:

- Regarding economics
- Foreign and internal affairs
- Defence and justice
- Direct involvement (e.g. run for office, get in touch with politicians)

As well as if somewhere it mentions explicitly male/man etc.

<u>Coding system:</u>

Content of search result	Code
First result mentions high power and influence position(s)	-2
2nd result mentions high power and influence position(s)	-2
3rd result mentions high power and influence position(s)	-1
4rd result mentions high power and influence position(s)	-1
First result mentions low power and influence position(s)	2
2nd result mentions low power and influence position(s)	2
3rd result mentions low power and influence position(s)	1
4rd result mentions low power and influence position(s)	1
No particular position(s) of power and influence are mentioned	0

! If the position(s) does not relate to some in the above lists than it's neutral!

! When there are more positions mentioned and two relate to male and two to female e.g. then also neutral (0)!

! When the screenshot cannot be used, use code 999!

2. Krippendorff's alpha for inter coder reliability.

```
KALPHA judges = JobsJeanna RebeccaJobs/level = 2/0 = 1/boot = 10000
```

Matrix

```
Run MATRIX procedure:

Krippendorff's Alpha Reliability Estimate


             Alpha      Units    Obsrvrs      Pairs
Ordinal      .7682   204.0000     2.0000   204.0000

Judges used in these computations:
 JobsJean RebeccaJ

Examine output for SPSS errors and do not interpret if any are found

------ END MATRIX -----
```

```
KALPHA judges = PoliticsJeanna PoliticsRebecca/level = 2/0 = 1/boot = 10000.
```

Matrix

```
Run MATRIX procedure:

Krippendorff's Alpha Reliability Estimate


             Alpha      Units    Obsrvrs      Pairs
Ordinal      .7725   204.0000     2.0000   204.0000

Judges used in these computations:
 Politics Politi_1

Examine output for SPSS errors and do not interpret if any are found

------ END MATRIX -----
```

3. SPSS output Jobs Google.

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
job openings near me Google	97	1.36	2.132	.216

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
job openings near me Google	6.286	96	.000	1.361	.93	1.79

Independent samples t-test

T-Test

Group Statistics

	What gender do you identify with?	N	Mean	Std. Deviation	Std. Error Mean
job openings near me Google	Male	51	.98	1.772	.248
	Female	46	1.78	2.421	.357

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
job openings near me Google	Equal variances assumed	7.757	.006	-1.875	95	.064	-.802	.428	-1.652	.047
	Equal variances not assumed			-1.845	81.795	.069	-.802	.435	-1.667	.063

One sample t-test only male participants included:

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
job openings near me Google	51	.98	1.772	.248

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
job openings near me Google	3.951	50	.000	.980	.48	1.48

4. SPSS output Political participation Google.

One sample t-test:

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
how to become involved in politics Google	93	-1.89	2.656	.275

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
how to become involved in politics Google	-6.872	92	.000	-1.892	-2.44	-1.35

Independent samples t-test

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
how to become involved in politics Google	Equal variances assumed	2.421	.123	1.498	91	.138	.820	.547	-.267	1.906
	Equal variances not assumed			1.497	90.667	.138	.820	.547	-.268	1.907

T-Test

Group Statistics

	What gender do you identify with?	N	Mean	Std. Deviation	Std. Error Mean
how to become involved in politics Google	Male	46	-1.48	2.689	.397
	Female	47	-2.30	2.587	.377

5. SPSS output Jobs DuckDuckGo

One sample t-test:

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
job openings near me DDG	94	-.26	.879	.091

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
job openings near me DDG	-2.816	93	.006	-.255	-.44	-.08

Independent samples t-test

T-Test

Group Statistics

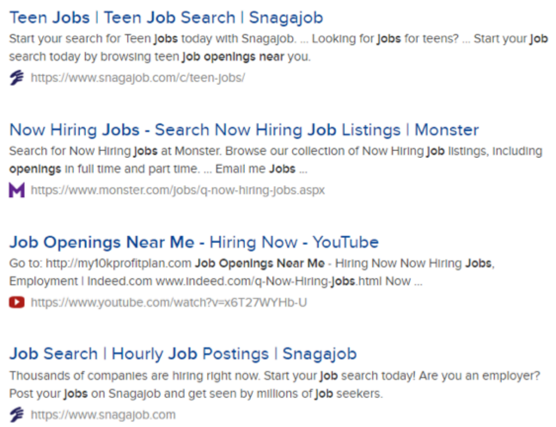
	What gender do you identify with?	N	Mean	Std. Deviation	Std. Error Mean
job openings near me DDG	Male	50	-.26	.899	.127
	Female	44	-.25	.866	.131

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
job openings near me DDG	Equal variances assumed	.006	.939	-.055	92	.956	-.010	.183	-.373	.353
	Equal variances not assumed			-.055	91.232	.956	-.010	.182	-.372	.352

6. Example of the surprising observations Jobs DDG.

#37



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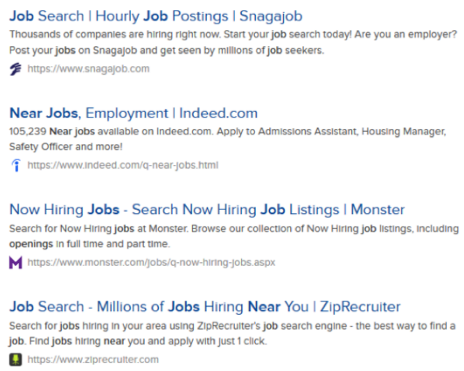
#52



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7. SPSS output political participation DuckDuckGo

T-Test

One-Sample Statistics

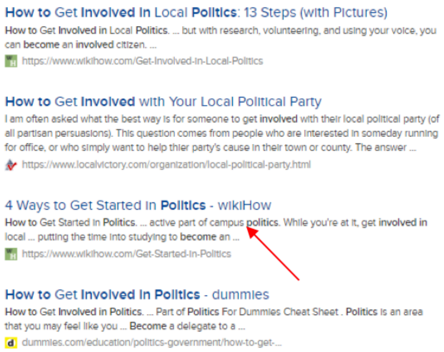
	N	Mean	Std. Deviation	Std. Error Mean
how to become involved in politics DDG	91	.03	.314	.033

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
how to become involved in politics DDG	1.000	90	.320	.033	-.03	.10

8. Example of the surprising observations Political participation DDG

#15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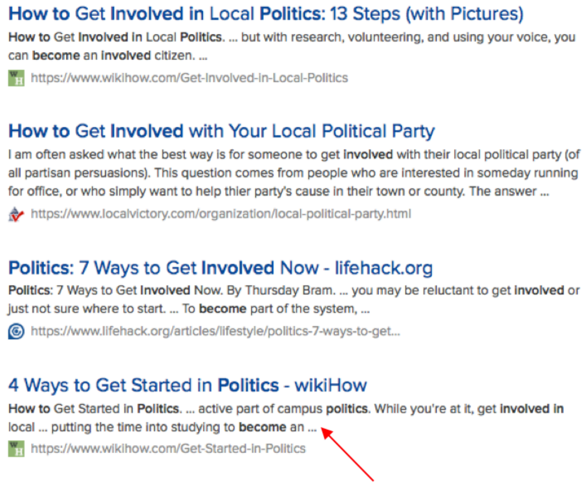
#7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9. Histogram Political participation Google

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