User Behavior and Awareness of Filter Bubbles in Social Media

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Abstract. To counter information overflow, social media companies employ recommender algorithms that potentially lead to filter bubbles. This leaves users' newsfeed vulnerable to misinformation and might not provide them with a view of the full spectrum of news. There is research on the reaction of users confronted with filter bubbles and tools to avoid them, but it is not much known about the users' awareness of the phenomenon. We conducted a survey about the usage of Facebook's newsfeed with 140 participants from Germany and identified two user groups with k-means clustering. One group consisting of passive Facebook users was not very aware of the issue, while users of the other group, mainly heavy professional Facebook users were more aware and more inclined to apply avoidance strategies. Especially users who were aware of filter bubbles wished for a tool to counter them. We recommend targeting users of the first group to increase awareness and find out more about the way professionals use Facebook to assist them countering the filter bubble and promoting tools that help them do so.

Keywords: Social media · Filter bubbles · User factors · Professional communication

1 Introduction

Social media has become a dominant factor in everyday communication. Facebook alone had a user base of over 2.2 billion users in 2018. This means that besides private and social communication, also professional communication is to a large extent present in social media channels. Social media, in contrast to traditional media channels, is comprised of user-generated content. Anyone can become a broadcaster in social media. The participation of world wide users has led to an amount of information that no individual user can process, thus making the use of algorithms to filter and recommend content to the users inevitable. One class of algorithms, so-called recommender systems, pick items in accordance with previous user choices and those of similar users. While this approach leads to very accurate recommendations from a users perspective, on a societal

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level recommendations can have critical effects on the flow of information. By recommending items that users are likely to interact with, users are also less likely to receive information that is outside their political alignment, their scope of interest, and in contrast to their held beliefs. This causes problems in professional communication when e.g., decision makers need to get information from a full spectrum of sources. However, little is known about the users awareness of filter bubbles and possible avoidance strategies to combat the negative influence of filter bubbles. To identify whether there are different user groups with different degrees of awareness of the phenomenon, we conducted a study that examines demographics, the big 5 personality traits and the reasons to use Facebook influences as well as the awareness of filter bubbles and the use of possible avoidance strategies. With this information, we clustered the users into two groups showing both different motives to use Facebook and awareness of filter bubbles.

2 Related Work

This chapter will briefly describe the terms filter bubbles, echo chambers and the algorithms that are causing them. Furthermore, strategies to avoid them and to increase users' awareness are discussed.

2.1 Filter Bubbles and Echo chambers

The rise of digital and social media lead to an unprecedented amount of information available to individual users. Virtually anyone can spread news via social media, offering users a broad choice [23]. As there is too much information to consume, users need to choose which sources or channels they use to receive their news.

According to the confirmation bias [18], individuals seek or interpret evidence in ways that are partial to existing beliefs, expectations, or a hypothesis at hand. The cognitive dissonance theory describes the psychological stress an individual experiences when it holds two or more beliefs, ideas or values that contradict each other [11]. To avoid this discomfort, people will always try to keep their views consistent. So when they have the choice, users usually select content that is in accordance with their personal beliefs and opinions while trying to avoid content that contradicts them [3,8].

As there is too much content available in social media, it is close to impossible for a single individual to overview all information and select the relevant ones. To help users with this challenge, social media and news websites use reccomender systems to present a personalized selection of all available information to each user, based on their personal history and interests as well as the content similar users were interested in [21].

The term "filter bubble" was introduced by Pariser [19] to describe the personalization in social media and online searches to an extent where users only see content similar to their history, reducing the diversity to a high degree. While in the real world, people are usually confronted with opinions and facts not strictly in concordance with their views, filter algorithms in online media and social networks are much more likely to produce filter bubbles as they try to show users content similar to what they were previously interested in. The algorithms also favor another distinct phenomenon called echo chambers. Filter bubbles are the result of people not being exposed to all relevant information, possibly by accident. An echo chamber is a structure from which other voices have been actively excluded or discredited [17]. While echo chambers might also benefit from recommender algorithms, this paper focuses on filter bubbles, that might occur without the users noticing. However, sometimes there is no clear distinction between echo chambers and filter bubbles in literature, therefore research concerned with echo chambers might be relevant to understand the effect of filter bubbles.

Dubois and Blank [10] examined the effect of political interest and media diversity on true echo chambers and concluded that only a small part of the population might be impacted by them. Similarly, a study on the political polarization on Twitter came to the conclusion that the effect of echo chambers in social media may be overestimated [1]. However, previous research has demonstrated that filter bubbles are present in search engines and social media content [9]. While the effect of recommender systems on personalization was rather moderate in Google News [12], another study found empirical evidence for stronger personalization in Facebook's newsfeed [20]. The existence of filter bubble leaves users' newsfeeds vulnerable to systematic misinformation or competitor attacks on information flow.

2.2 Filter Bubble Awareness and Avoidance strategies

So far, only few research has been conducted on the users' awareness of filter bubbles. This information might be relevant as users who are not aware of the filtering mechanisms might not notice that their results possibly do not have the desired diversity [5]. There is a study on how users react when they are confronted with the issue by Nagulendra and Vassileva [16]; they designed a tool to show how filter bubbles work in online peer-to-peer social networks. The visualization increased users awareness and the understanding of the underlying filter algorithms. However, it is still unclear which users actually are aware of the phenomenon. Identifying user groups might help reaching people in their filter bubble for professional communication.

It is possible to burst through the filter bubble, when users understand the mechanisms of the underlying algorithms [21]. According to Bozdag and Hoven [4], there are several digital tools to combat the filter bubble, some by increasing awareness and others by presenting unbiased results. For example, Munson, Lee, and Resnick [15] developed a tool that tracks users' reading behavior to visualize their biases. According to the authors, this increases awareness of the filter bubble because even users who are familiar with the concept actually do not realize that it might apply to themselves to quite a high degree.

The browser add-on Scoopinion[1] follows a similar approach but visualizes the "media footprint" instead of just biases, so users can actually see how frequently they visit different providers of news. Bobble [28], another browser add-on, compares the personalized Google results of a user to those of users world wide. This way, not only awareness is increased, but users are also shown a broader spectrum of results, giving them the opportunity to actually escape the filter bubble. Confronted with a visual comparison of the content a user consumes vs. the content all users in a system consume, users are more inclined to discover new content outside their bubble [13].

There are several ways for users to decrease personalization. Many websites and services use cookies to identify users, deleting them regularly or using the browser's incognito mode makes it harder to track and identify users [14,21]. However, this is not possible for services that require users to log-in, e.g. Facebook. Here, users would need to actively try to like content from various sources to enforce diversity in their newsfeed as recommender algorithms try to match content the user has liked in the past [24].

While there is already some research on the effects of users' awareness and tools to increase it or even escape the filter bubble to some extent, it is unclear how many users are actually aware of the phenomenon. There is even less research to what degree users are using tools and strategies to combat filter bubbles. Research into user characteristics could help develop counter strategies against filter bubble phenomena adapted to the users individual needs.

3 Method

We conducted a survey study with 149 participants in order to measure both user attributes and awareness of filter bubbles. All items were measured on 6-point Likert scales. We used convenience sampling to establish a sample in an online survey. Nine participants who did not complete the survey were removed from the dataset. Apart from demographics we also extensively measured the users' Facebook usage. As an additional characteristic we measured big five personality traits to investigate whether they have an impact on filter bubble awareness and avoidance.

To measure awareness of filter bubbles we used the items *"I have already heard of the filter bubble theory."*, *"I believe the filter bubble exist."*, *"The filter bubble affects me personally."*, *"I take deliberate action against the filter bubble."*. All these items were summarized to the scale *filter bubble awareness* ($r = .65$).

We further measured whether users employed any methods to counter filter bubble effects. To do this, we suggested some methods that require some understanding of how recommender systems work, for example that internet companies could identify users and their interest by cookies and that this can be prevented by using the incognito mode of a browser. In particular, we used the items *"I delete my browser history and cookies."*, *"I use the incognito function*

[1] www.scoopinion.com.

of my browser.", "I click and like different posts to enforce diversity", "I use the 'explore' button in Facebook to get different news.", "I unfollow some of my friends/pages". All of these items were used for the scale *filter bubble avoidance strategies* ($r = .60$).

3.1 Statistical Methods

Using the data from the survey we conducted a cluster analysis on the social media usage attributes in order to identify patterns in user behavior. We used the elbow-plot to identify the right amount of different clusters and clustered the users based on their reasons to use Facebook with k-means. Using the resulting clusters we tested the members of clusters for differences in characteristics and filter bubble awareness using analysis of variance (ANOVA). The data was normally distributed for all cases where we tested for correlations, thus we used Pearson correlation. To test for differences between the clusters in ordinal data, Wilcoxon signed-rank test was used. We selected $\alpha = .05$ as the significance level. We report means, standard deviations as well as confidence intervals to characterize the resulting user clusters.

4 Results

4.1 Sample Description

The sample was taken from a previous study published by Burbach et al. [6]. The participants in this sample were on average 25.9 years old ($SD = 7$) and all of them were Facebook users. Exactly 80 participants were female and 61 were male. Education was rather high (83 university degree, 47 Abitur, 11 other) and users were rather open ($M = 4.5$, $SD = 1.07$), conscientious ($M = 4.1$, $SD = 0.88$), extraverted ($M = 4.14$, $SD = 1.1$), and agreeable ($M = 3.81$, $SD = 0.77$). Users on average did not score high on neuroticism ($M = 3.23$, $SD = 1.01$). 55% of the participants reported that they used Facebook at least once per day. However, 65% felt that they use it less often, 33% that the frequency of their usage remains unchanged and only 2% were using it more. Most users prefer to use their smartphone for Facebook ($M = 4.35$, $SD = 1.58$), followed by laptop ($M = 3.08$, $SD = 1.43$). Tablets ($M = 1.60$, $SD = 1.21$) and desktop computers ($M = 1.63$, $SD = 1.27$) were only rarely used.

4.2 Cluster Generation

Cluster analysis was conducted using dendrograms and elbow-plots. These methods help identify how many different clusters yield sufficiently different clusters in the data. As clustering variables we used variables of behavior in individual Facebook use ("professional use", "meeting people", "keeping in touch", "posting", "sharing", "inform others", "express opinion", "passive use").

Both methods indicated that between 2 and 4 clusters yield sufficiently different user groups for a clustering approach. After inspecting usage behaviors for these three cases we decided to rely on two different clusters that are sufficiently different and allow for a meaningful description from the clustering variables.

4.3 Cluster Description

From the two clusters we derived the two cluster definitions using the clustering variables (see Fig. 1). Users in cluster one were generally less active than users in cluster two. This refers to both passive use (reading only ($M = 2.07$, $SD = 1.27$ vs $M = 3.9$, $SD = 1.16$)), active use (sharing ($M = 1.45$, $SD = 0.73$ vs $M = 2.59$, $SD = 1.08$), inform others ($M = 1.26$, $SD = 0.59$ vs $M = 2.51$, $SD = 1.16$), express opinion ($M = 1.09$, $SD = 0.32$ vs $M = 2.1$, $SD = 1.05$) and posting ($M = 1.54$, $SD = 0.88$ vs $M = 2.45$, $SD = 1.02$)), as well as professional use ($M = 1.85$, $SD = 1.28$ vs $M = 3.29$, $SD = 1.5$). In both clusters *keeping in touch* with friends was the highest characterizations of usage behavior, users in both clusters use the social network for that purpose to a similar degree ($M = 4.2$, $SD = 1.4$ vs $M = 4.35$, $SD = 1.22$). Only *passive use* showed similar agreement in cluster 2. Cluster 2 also claimed to have a stronger use of Facebook for meeting new people ($M = 1.51$, $SD = 0.83$ vs $M = 2.1$, $SD = 1.18$).

Cluster 1 had 92 members and cluster 2 had 49. While the number of friends ($p = 0.21$) and groups ($p = 0.97$) did not vary significantly between the two clusters, the Wilcoxon-Mann-Whitney test showed that users in cluster 2 liked more Facebook pages than those in cluster 1 ($p < .001$).

The genders were balanced in the first cluster, in the second one there were only 14 male participants (29%). As the vast majority of the complete sample was highly educated, there were no differences between the clusters in that regard. There were no significant differences between the clusters for any of the Big Five personality traits (openness: $p = 0.108$, extraversion: $p = 0.684$, conscientiousness: $p = 0.194$, agreeableness: $p = 0.552$, neuroticism: $p = 0.616$).

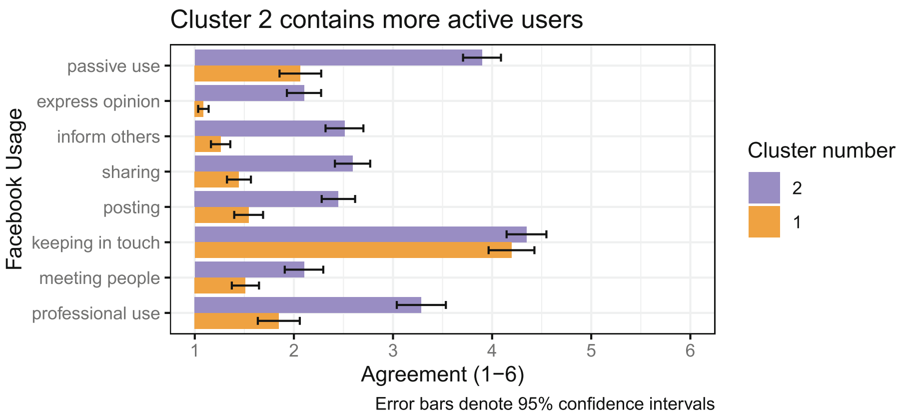

Fig. 1. Differences in users between clusters.

4.4 Awareness of Filter Bubbles

Next, we were interested in determining whether differences exist between both clusters regarding filter bubble awareness and possible avoidance strategies.

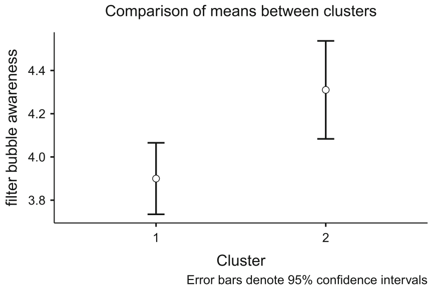

Fig. 2. Differences in users between clusters regarding filter bubble awareness.

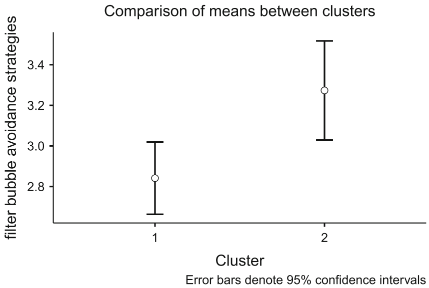

Fig. 3. Differences in users between clusters regarding avoidance strategies.

When we look at filter bubble awareness, we see that cluster 1—the passive users—show lower awareness of the phenomenon ($M = 3.9,\ SD = 0.89$ vs $M = 4.31,\ SD = 0.61$). This difference is significant in a one-way ANOVA ($F(1{,}139) = 8.36$, $p = .004$, see also Fig. 2).

A similar result can be seen for the presence of avoidance strategies regarding filter bubbles. Here, a difference is significant in a one-way ANOVA ($F(1{,}139) = 8.0$, $p = .005$, see also Fig. 3), showing also more strategies of avoidance in cluster 2 ($M = 2.84,\ SD = 0.87$ vs $M = 3.27,\ SD = 0.85$). There were no significant gender differences for both filter bubble awareness and filter bubble avoidance strategies. Also, the awareness of filter bubbles does not seem to have an influence on whether or not users apply avoidance strategies ($r(139) = .01$, $p = .227$).

4.5 Applied Avoidance strategies

Overall, the participants did not make particularly intensive use of any of the strategies to burst the filter bubble. Users in cluster 2 were generally more inclined to apply avoidance strategies, but there were differences which strategies were used in particular (see also Fig. 4).

The most common strategy was to delete cookies and browser history which was applied by both cluster 1 \$$M = 3.98,\ SD = 1.46$) and cluster 2 ($M = 4.24$, $SD = 1.33$) rather frequently. Other strategies that were applied by users of both clusters are to unfollow certain friends or pages in order to increase diversity in the Facebook newsfeed (Cluster 1: $M = 3.24,\ SD = 1.61$, Cluster 2: $M = 3.63$, $SD = 1.48$) as well as the use of the browser's incognito mode that does not store any data like cookies and history beyond the current session (Cluster 1: $M = 3.11$, $SD = 1.61$, Cluster 2: $M = 3.24,\ SD = 1.41$). Neither cluster made much use of the explore button in Facebook (Cluster 1: $M = 1.92$, $SD = 1.22$, Cluster 2: $M = 2.35$, $SD = 1.2$). Users in cluster 1 ($M = 1.96$, $SD = 1$) did not deliberately like and click various posts to enforce diversity in their news feed while the second group was more inclined to apply this strategy ($M = 2.9$, $SD = 1.49$)).

Most users wish for a tool to that shows them different topics, opinions and ideas ($M = 4.00$, $SD = 1.28$). The desire for such a tool is associated with the awareness of filter bubbles ($r(139) = 0.19$, $p = .021$). As users in cluster 2 are generally more aware of filter bubbles they were more interested in a tool ($M = 4.44$, $SD = 1.10$) than users in cluster 1 ($M = 3.76$, $SD = 1.30$). The difference between the groups is significant in a one-way ANOVA ($F(1,139) = 9.89$, $p = .002$).

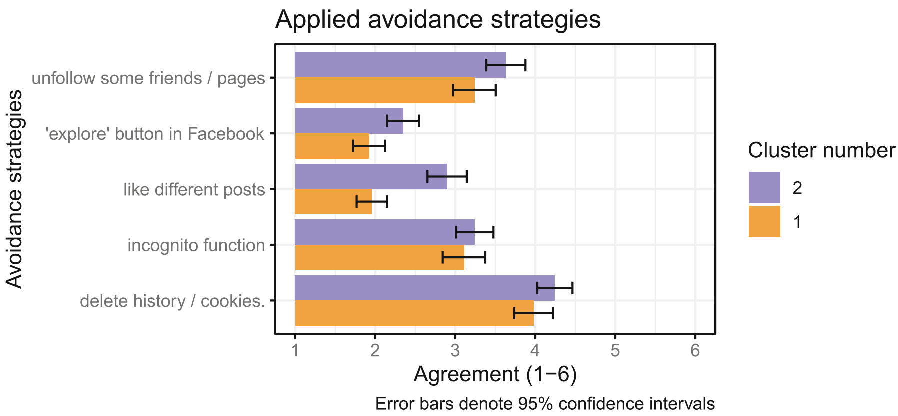

Fig. 4. Differences between clusters in applied avoidance strategies.

5 Discussion

The results presented in the previous section suggest that the awareness of filter bubbles in general is rather high. However, there are severe differences between users, therefore it is worth taking a closer look on how different user types differ in terms of awareness and avoidance strategies in order to burst the filter bubble.

Awareness of filter bubbles is associated with both professional and heavy Facebook use. However, these variables do not correlate with avoidance strategies, therefore it is important to look at all the user factors to understand why people try to avoid the bubble. In order to do so, we identified two types of users that show differences in user behavior on Facebook. These differences relate to both private and professional use of social media. The first type uses Facebook passively to keep in touch for private purposes for the most part. In contrast, the second type does not only use Facebook much more, but also posts, shares and informs others to a much higher degree. Facebook is used professionally by many of these users. The heavy users of the second type seem to be more aware of filter bubble problems in social media and are also more inclined to apply strategies to counter them. Higher awareness alone does not lead to the application of strategies to avoid the bubbles, therefore other user factors in the cluster might play a role. One of them could be the professional use of Facebook, which is much more common in the second group. The professional necessity to get a broader view of the spectrum of opinions on one hand, and the need to reach people from outside their filter bubbles on the other might force users to think about the bubbles and how to overcome problems related to them. Our survey did not cover the nature of the professional Facebook use, but it might be worth looking into for further research for a better understanding why professionals are more aware of the phenomenon.

Some users seem to be familiar with strategies to avoid filter bubbles like the deletion of cookies and browser history. In general though, avoidance strategies are not very common and users seem to be unaware of how to escape the filter bubble phenomenon. Many of them express the wish for a tool helping them do so, especially when they are more aware of the phenomenon. This indicates that even those people who are aware of the problems and like to overcome them in many cases do not have the required knowledge or motivation to do so. Here, communication strategies can be developed that help users understand how the underlying algorithms work in a first step. Making people aware of the issue and its causes might increase the wish for tools to overcome the problem. In fact, research presented in Sect. 2 suggests that users who are confronted with the problem are much more likely to burst their bubble.

In a second step solutions on how to overcome the pitfalls of personalization in social media and web-applications could be promoted. As some of the current mechanisms to counter the filter bubble require some technical knowledge it might be necessary to bundle them in tools that are easy to use for users without technical background. For example, it requires several clicks through some submenus to delete cookies and browser history. As this option is not very easy to find and it can be annoying to repeat the process frequently, it could help to promote a browser extension that does it with one click or even automatically. Of course some of the tools that were introduced earlier could provide the user with a broader view of the spectrum of news without requiring any background knowledge. Unfortunately, they usually only work for one specific service like Google or Facebook, so users would need to utilize multiple tools and techniques to effectively combat filter bubbles.

Another improvement that might help users to understand the cause end effects of filter bubbles is transparency of services. For example, Facebook's explore button uses a recommender system that might not increase diversity in content. On the contrary, it recommends content based on the users interest, hence it is very likely that the users only see similar content that affirms their opinions. Software companies might not be willing to disclose information about their algorithms as they are a crucial part of their business model, but there are some third party solutions that demonstrate the way the algorithms work to some extent. Some of them were also mentioned in Sect. 2. As many users of social media and other online services might not be familiar with them, it is important to promote these, especially to professional communicators and decision makers who rely on social media for information gathering.

6 Conclusion

In our exploratory study, we found that many users already know about the filter bubble. The application of the k-means clustering algorithm helped us to identify two different user types. The first type uses Facebook mainly passively and to stay in touch with private contacts, while the second type makes heavier use of Facebook and shares, posts and likes content to a higher degree. The users of the second group also use Facebook for professional reasons. Both the awareness of filter bubbles and the application of avoidance strategies is higher among the heavy, professional users. Higher awareness alone does not encourage users to apply strategies to avoid filter bubbles, so the question opposes why users of the second group are not only more aware, but are also more likely to try to counter the filter bubble. A possible explanation is their professional use of social networks, which requires them to reach people in their bubbles. For further research, it might be interesting to look how they use Facebook in particular to further understand why users try to escape the filter bubble. For the first group, the question remains on how to reach them and increase awareness of the phenomenon.

While not all users might want to burst their filter bubble, especially among those who are aware of it, there are many who would like to have a tool to avoid it. This shows that the current technical solutions to do so are either not sufficient or not known to many users.

We recommend to develop communication strategies to inform those users in the first group about the underlying algorithms of recommendations in social networks and their consequences to increase awareness of filter bubbles among all users, especially the ones who do not use Facebook that much.

In a second step, existing and tools techniques to avoid filter bubbles should be promoted to users. Additionally, it might be necessary to design new user interfaces to simplify the process. More transparent communication on behalf of social networks how their recommender algorithms work could further increase the users' understanding of the problem, but might not be desired by the social networks.

For the private passive users, the question remains whether they really want to burst their filter bubbles. The expression of desire for a tool to do so does not mean that the users would prefer the unbiased presentation of content that includes opposing opinions. For the heavy professional users who actually need a view of the full spectrum of information in order to make decisions, we suggest further research on how they use Facebook in particular. This knowledge might help to develop strategies to communicate effective methods assisting the professional users to get a broader view of social media content.

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