Computers in Human Behavior Reports 12 (2023) 100343

Contents lists available at ScienceDirect

Computers in Human Behavior Reports

journal homepage: www.sciencedirect.com/journal/computers-in-human-behavior-reports

How algorithmically curated online environments influence users' political polarization: Results from two experiments with panel data

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ARTICLE INFO

Keywords:
Algorithms
Polarization
Online experiments
Filter bubble
Panel data
Germany

ABSTRACT

Social media platforms are often accused of disproportionally exposing their users to like-minded opinions, thereby fueling political polarization. However, empirical evidence of this causal relationship is inconsistent at best. One reason could be that many previous studies were unable to separate the effects caused by individual exposure to like-minded content from the effects caused by the algorithms themselves. This study presents results from two quasi-experiments in which participants were exposed either to algorithmically selected or randomly selected arguments that were either in line or in contrast with their attitudes on two different topics. The results reveal that exposure to like-minded arguments increased participants' attitude polarization and affective polarization more intensely than exposure to opposing arguments. Yet, contrary to popular expectations, these effects were not amplified by algorithmic selection. Still, for one topic, exposure to algorithmically selected arguments led to slightly stronger attitude polarization than randomly selected arguments.

1. Introduction

Algorithmically curated online environments, such as *Facebook*, *Google News*, and *YouTube*, are changing how people consume information (Newman et al., 2022). On the one hand, algorithms facilitate peoples' access to information that they are interested in (Flaxman et al., 2016). On the other hand, there are concerns that algorithmic curation will influence the political opinions of Internet users (Zuiderveen Borgesius et al., 2016). An often-discussed issue is that algorithms could fuel political polarization of individuals by disproportionally exposing them to like-minded opinions – a phenomenon also known as "filter bubbles" (Pariser, 2011). This political polarization can have negative effects on democracy, for example, by making citizens less satisfied with democracy (Wagner, 2021) or by trying to prevent others from expressing their views (Neumann et al., 2021).

Despite these concerns, little is known about the extent to which navigating algorithmically curated online environments leads to individual political polarization. A recent review on (social) media and polarization shows that most studies have not measured the effects of algorithmic curation on users' political polarization (Kubin & von Sikorski, 2021). Instead, they either analyzed the content of algorithmic curation without measuring its effects on the users (e.g., Flaxman et al., 2016) or used (experimental) survey data to examine the effects of using different (social) media channels on people's polarization without controlling for the algorithmic curation itself (e.g., Ohme, 2021). Furthermore, many studies did not consider and control for the fact that the Internet users can interact with each other.

To tackle these research gaps, we conducted two 2 × 2 between-subjects quasi-experiments that were embedded into a three-wave panel survey. We tested whether and to what extent algorithmically curated online environments foster individuals' attitude polarization (DiMaggio et al., 1996) and affective polarization (Iyengar et al., 2012). We developed an online discussion platform that allowed us to control what information participants were exposed to. Specifically, we

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https://doi.org/10.1016/j.chbr.2023.100343
Received 17 October 2022; Received in revised form 7 September 2023; Accepted 22 October 2023
Available online 29 October 2023

manipulated the direction (like-minded vs. opposing) and selection (algorithmically selected vs. randomly selected) of the arguments that participants were exposed to. For the algorithmic selection, we programmed an algorithm based on collaborative filtering that uses participants' individual preferences and the opinions of other participants to select arguments with which participants are most likely to agree (Brenneis et al., 2020).

The results confirm the findings of previous studies that exposing participants to like-minded arguments fosters their attitude polarization and affective polarization more intensely than exposing them to opposing arguments (e.g., Iyengar et al., 2019; Knobloch-Westerwick et al., 2015). However, these effects were not amplified by the algorithmic selection in both experiments. Nevertheless, in one experiment, exposure to algorithmically selected arguments led to a slightly stronger attitude polarization than exposure to randomly selected arguments. Thus, the study contributes to the research on political polarization and the effects of algorithms in three ways: First, our study is one of the first to generate and implement personalized stimuli that use collaborative filtering to test the effects of algorithmic selection on attitude polarization and affective polarization in controlled experiments (see also Neumann et al., 2021). Second, using panel data, we can simulate the increasing personalization of arguments and test their effects more reliably than in studies that use cross-sectional data. Third, unlike studies that have examined political polarization between Democrats and Republicans in the United States (Kubin & von Sikorski, 2021), our study shows that political polarization can also be found in the (supposedly) less controversial area of food policy in Germany and in a less polarized party system.

2. Literature review

2.1. Online environments and polarization

Iyengar et al. (2012) differentiated the concept of affective polarization from attitude (or ideological) polarization. Attitude polarization refers to a growing distance of political positions, beliefs, or attitudes over time (Dalton, 1987). Affective polarization describes the tendency to which supporters of specific political positions tend to dislike the opponents of these positions or their representatives (e.g., Druckman & Levendusky, 2019; Iyengar et al., 2012).

There are good reasons to assume that the use of online media contributes to attitude and affective polarization: Online media facilitate exposing oneself to congruent content and networking with like-minded others (Sunstein, 2018). Research on selective exposure (Knobloch-Westerwick et al., 2020) indicates that people are likely to take advantage of this opportunity, since many people prefer like-minded over opposing information. Exposure to like-minded information, in turn, is likely to contribute to political polarization for at least three reasons (e.g., Stroud, 2010): First, research on group polarization has shown that congruent arguments reinforce people in their preexisting opinions and attitudes (Isenberg, 1986). Second, people desire to make a good impression in front of their peers (Schlenker, 1980). Thus, exposure to like-minded others could exert pressure on people to adapt their own opinions and attitudes to the (perceived) group norm (Litt, 2012). Since these group norms appear to be more extreme online than they are in reality (Bail, 2021), this adaption could ultimately lead to political polarization. Third, like-minded information "shape how viewers see the 'other side' because they powerfully invoke viewers' partisan (social) identities" (Levendusky, 2013a, p. 567), which could lead to a stronger tendency to dislike the outgroup (Iyengar et al., 2012).

In fact, empirical research has shown that exposure to congruent (online) information can strengthen *attitude polarization* (e.g., Kim, 2015; Knobloch-Westerwick et al., 2015; Lück & Nardi, 2019). Taber and Lodge (2006) have revealed several mechanisms behind this reinforcement of prior attitudes: They showed that partisans rated like-minded arguments as more convincing than opposing arguments ("prior attitude effect"; see also, Lord et al., 1979). Moreover, they are more critical against opposing arguments ("disconfirmation bias"). Additionally, partisans tended to search for confirmatory evidence ("confirmation bias"; see also Knobloch-Westerwick et al., 2015). The disconfirmation and confirmation biases reinforced participants' prior attitudes over time, leading to attitude polarization. Although some studies could not find comparable attitude polarization effects of congruent information exposure (e.g., Neumann et al., 2021; Trilling et al., 2017), several other studies have indicated that preexisting attitudes are reinforced by exposure to like-minded information in partisan media (e.g., Kim, 2015; Levendusky, 2013b), news search portals (Knobloch-Westerwick et al., 2015), or online discussions (Lück & Nardi, 2019).

Empirical studies have also shown that exposure to like-minded information can increase *affective polarization*. For example, exposure to like-minded news articles on websites about controversial issues such as abortion reinforced people's negative attitudes toward people with other opinions (Garrett et al., 2014). Other studies have demonstrated that people trust members of the outgroup less (Levendusky, 2013a) or indicate stronger affective polarization (Kim, 2015) after being exposed to congruent media content. Moreover, Stroud (2010) has shown that there is a reciprocal relationship between partisan news media exposure and political polarization. Reasons for the relationship between like-minded media exposure and affective polarization are, among others, the acceptance of like-minded media frames as well as the awareness of one's own position (Tsfati & Nir, 2017). Regarding discussions with like-minded others, research has shown that communicating in homogeneous networks can strengthen people's ingroup identity and thereby contribute to disliking the outgroup, resulting in affective polarization (Halevy et al., 2012; Iyengar et al., 2019). Using a three-wave study and focusing on affective polarization, Hutchens et al. (2019) disentangled these effects, demonstrating that people high in affective polarization primarily engage in discussions with like-minded partners, which then reinforces their affective polarization.

It was hoped that cross-cutting exposure—exposure to opposing information as well as debates with people who hold different opinions—would increase the political tolerance of individuals, thereby also reducing polarization (e.g., Habermas, 1989; Mutz, 2006; Wojcieszak, 2011). Empirical evidence for this thesis is, however, mixed at best. Some studies have indeed indicated that exposure to opposing information (e.g., Kim, 2015; Knobloch-Westerwick et al., 2015) and (anonymous) discussions between members of rival groups (e.g., Combs et al., 2023) can lower attitude and affective polarization and foster deliberation and political compromise. However, the findings of various other studies indicate a backfire effect. People who are exposed to opposing information (e.g., Bail et al., 2018; Garrett et al., 2014; Kim, 2019) or those who encounter disagreement during political discussions (e.g., Marchal, 2022; Wojcieszak, 2011) regularly report or indicate higher attitude and affective polarization than people whose attitudes were shared by other discussants.

Taken together, Kubin and von Sikorski (2021, p. 198) conclude in their recent review on the relationship between (social) media and polarization that "the literature unanimously agrees that exposure to like-minded media increases polarization. However, there is less agreement on the role of counter-attitudinal media in political polarization." Therefore, we hypothesize.

H1). Exposure to like-minded arguments leads to more a) attitude polarization and b) affective polarization than exposure to opposing arguments.

2.2. Algorithmic curation and polarization

In online environments such as social media platforms, news feeds, and sales platforms, users potentially face huge amounts of information. To avoid information overload, improve clarity, provide useful information for each user, and increase time spent on these platforms, these environments have been designed to show personalized content that matches the user's interests (Möller et al., 2018; Schafer et al., 2007). The selection of suitable content for each user is based on recommender systems. One way to achieve meaningful recommendations is through collaborative filtering, a term that describes the prediction of the preferences of a single user by considering the preferences and ratings of other users (Schafer et al., 2007). Many people encounter collaborative filtering systems daily, for example, when they scan their purchase suggestions on e-commerce platforms, recommendations for movies on streaming services, and when they scroll through their social media feeds.

According to the prominent filter bubble concept (Pariser, 2011), such recommender systems create online environments that tend to hide information from users with which they would potentially disagree. Pariser (2011) argued that people are more likely to interact with like-minded content. Recommender systems would, therefore, more likely present like-minded content to enhance user's experience when navigating online platforms. "As a result, an information environment built on click signals will favor content that supports our existing notions about the world over content that challenges them" (Pariser, 2011, p. 88). Empirical studies, however, have increasingly called into question the assumption that filter bubbles are a major phenomenon (for an overview, see e.g., Bruns, 2019; Zuiderveen Borgesius et al., 2016). Moreover, researchers have argued that exposure to like-minded content on social network sites may not primarily be determined by algorithms, but rather by individual decision-making on what content is actively consumed as well as on networks of friends (Bakshy et al., 2015). Still, Bakshy et al. (2015) and Levy (2021) showed that the Facebook algorithm lowers exposure to opposing views.

Although algorithms potentially increase the degree of like-minded content of people's online environments, the extent to which they contribute to polarization is unclear. Some studies have indicated that social media use reinforces preexisting attitudes and leads to affective polarization (e.g., Lee et al., 2021; Ohme, 2021). Other studies did not confirm these results (e.g., Feezell et al., 2021). After all, it is unclear to what extent algorithmic curation is responsible for these (missing) links, as most previous studies did not focus on or control for the role of algorithmic curation (e.g., Kubin & von Sikorski, 2021). Due to methodological problems resulting from a lack of data access, the algorithms responsible for personalizing online content are therefore still a "black box" for researchers (Stark et al., 2020, p. 23). Thus, empirical studies that experimentally test the effects of algorithmic curation on political polarization are needed. One of the few studies that partly filled this gap was conducted by Cho et al. (2020) in the context of the 2016 U.S. Presidential Elections. The authors demonstrated that exposure to political YouTube videos that were recommended based on users' individual preferences reinforced attitude polarization and affective polarization.

Altogether, it is likely that algorithms can increase and reinforce users' exposure to like-minded content. If the expectations about the influence of exposure to like-minded information on political polarization remain unchanged, then it is likely that algorithms will amplify the presumed effects of like-minded arguments. In contrast, the effects of opposing arguments should not be amplified by the algorithmic selection, as persuasive opposing arguments should be more likely to lead to an understanding of the other side and thus to depolarization than less persuasive opposing arguments. Therefore, we hypothesize.

H2). The expected effects of exposure to like-minded arguments on a) attitude polarization and b) affective polarization are stronger if these arguments were algorithmically selected.

3. Method

3.1. Data collection and sample

To test these hypotheses, a three-wave panel survey was conducted among the German population in 2020 (wave 1: 5–15 August; wave 2: 5–19 October; wave 3: 3–7 December). The German research company *respondi AG* performed the fieldwork. A quota sample was drawn from their online access panel. Representative quotas regarding the German population between 18 and 74 years for gender, age, and education were considered in the sampling of wave 1.

In total, 4792 participants started the questionnaire in wave 1, of which 4004 participants filled out the complete questionnaire and correctly answered a control question ("Please click on 'agree completely'"). A total of 2694 participants completed the questionnaire in wave 2, and 2125 completed the questionnaire in wave 3. The following analyses are based only on a subset of those participants (N = 843) who participated in all three waves.[1]

Compared with data from the Federal Statistical Office of Germany, the sample fairly represents the German population regarding sex (female: sample: 46.6% vs. population: 50.5%), age (sample: M = 48.7 years vs. population: M = 44.5 years), and education (sample: low: 31.1%, medium: 38.6%, high: 30.4% vs. population: low: 36.2%, medium: 30.0%, high: 33.5%).

3.2. Online discussion platform

A quasi-experimental setting was embedded in the questionnaires of waves 2 and 3. The participants were instructed to use an online discussion platform (an instruction video of a similar version of the platform can be viewed here: Brenneis & Mauve, 2020). During the questionnaire, the platform was introduced to the participants as a tool that would help its users to form, change, or reinforce their opinions toward controversial questions in the field of food policy. In wave 2, the question of whether plastic packaging for fresh foods, such as fruits and vegetables, should be allowed or banned in Germany was addressed. The question of whether the cultivation of genetically modified organisms in food production should be allowed or banned in Germany was addressed in wave 3. Both questions were identified based on a pretest.[2]

On the online discussion platform, participants were exposed to six arguments related to the issue at hand. They could rate the arguments, add new arguments, and give explanations for their opinions. The

[1] Because the experiments were embedded in a larger project, there were other experimental factors that are not the focus of this study. Besides the direction and the selection of the arguments, the design of the online discussion platform was also varied (static vs. interactive). In addition, one group of participants did not use the platform. Participants who were exposed to static versions of the discussion platform or did not use the platform were removed from the data set for this study.

[2] The "respondi AG" also performed the fieldwork of this pretest. The same quotas were implemented as in the main study. In total, 116 participants were asked about the relevance of and their opinion on nine controversial issues regarding food policy in Germany. For the main study, the two issues were selected that participants rated as relevant and where there was a clear difference of opinion among the participants.

participants were told that they were exposed to arguments of other users, but, in fact, they were exposed to arguments that we had collected in advance from various news media reports and that we had tested for their comprehensibility in two additional pretests.[3] We manipulated the direction and the selection of the arguments to which the participants were exposed.

3.3. Experimental factors

The participants were either exposed to (1) arguments favoring a ban on plastic packaging for fresh foods (e.g., "Animals can get caught in discarded plastic packaging and die in pain.") resp. on the cultivation of genetically modified organisms in food production (e.g., "Genetically modified plants can contaminate the genetic material of normal plants.") or to (2) arguments opposing a ban on plastic packaging (e.g., "Food wrapped in plastic is simply much more practical than unwrapped food") resp. the cultivation of genetically modified organisms (e.g., "Genetically modified plants are more resistant to pests and diseases."). Participants' attitudes on both issues were collected in the wave 1, prior to the use the online discussion platform (see Measurements section). By combining participants' attitudes and the direction of the arguments, (1) like-minded and (2) opposing online environments were created. Since the prior attitude could not be randomized but was incorporated in an experimental factor, this experiment, strictly speaking, is a quasi-experiment. The selection of the arguments was either (1) based on a recommendation algorithm or (2) randomly. Thus, the two quasi-experiments in waves 2 and 3 can be described as 2 (online environment) × 2 (selection of arguments) between-subjects design (see Table 1). The experimental groups did not differ in terms of age, gender, education, and their prior attitudes toward plastic packaging and genetically modified organisms.[4]

For the algorithmic selection condition, we created an algorithm that relied on user-based collaborative filtering using the k-nearest neighbors algorithm (Schafer et al., 2007). This algorithm is supposed to select the most likely convincing arguments for each participant. Specifically, arguments were chosen and presented to each participant based on their measured similarity to other users and their preferences for certain arguments. The algorithm worked as follows: The data from the pretests and wave 1 served as initial data to overcome the "cold-start" problem that appears because the algorithm does not have data to make predictions at the beginning (Schafer et al., 2007). In the pretests, 264 participants were exposed to randomly selected arguments favoring or opposing a ban on plastic packaging and genetically modified organisms. The participants were asked to rate these arguments (1 = *very weak argument* to 7 = *very strong argument*). In wave 1 of the panel study, participants were asked whether they were in favor of a ban on plastic packaging resp. genetically modified organisms or whether they are in favor of their continued use. Moreover, they were asked how certain they were in their opinion (1 = *very uncertain* to 7 = *very certain*). The collected opinions of each participant were stored in a weighted argumentation graph, with the arguments being the nodes and the edges being the argument relations (indicating a support or attack relation between the arguments). The value of whether an argument is perceived as persuasive or not determines the weight of the corresponding graph node, and the value of the perceived argument strength forms the weight of the corresponding edge in the graph. To recommend arguments to the participants in wave 2 of our study, we first determined which of the other users were most similar, in terms of their argumentation and opinion, to the participant to whom the algorithm intended to suggest arguments. To measure the similarity between users, we used a pseudo-metric (Brenneis et al., 2020) that works on weighted argumentation graphs, which considers the structure of the underlying argumentation graph to calculate the distance between them. We then averaged the values of these nearest neighbors to predict the value for the user for each argument that they had not seen yet. By collecting more information throughout each wave of our study, it is likely that the algorithm makes more precise predictions of each participant's opinion in wave 3 compared to wave 2. Hence, it is likely that the potential effects of exposure to algorithmically selected arguments increases from wave 2 to wave 3 because the algorithm learned more about the respondents.

Taken together, participants were either exposed to (1) six like-minded or (2) six opposing arguments. The selection of these like-minded or opposing arguments was either (1) based on an algorithm that selected the most likely convincing arguments for each participant or (2) the selection was randomized. Participants that were exposed to algorithmically curated like-minded arguments should evaluate these arguments as more convincing than participants that were exposed to randomly selected like-minded arguments. Similarly, participants that were exposed to algorithmically curated opposing arguments should evaluate these arguments as more convincing than participants that were exposed to randomly selected opposing arguments.

Table 1
Number of participants in the experimental groups.

		Factor 1: Online environment	
		Like-minded	Opposing
Factor 2: Selection of arguments	Random	198/197	221/222
	Algorithm	196/199	228/225

Note. Number of participants in each experimental group; $n_{\text{Plastic packaging}}/n_{\text{Genetically modified organisms}}$.

3.4. Manipulation check

To test whether the respondents correctly identified the direction of the presented arguments, they were asked after using the online platform about the valence of the arguments they had seen from presumably other users (1 = *only arguments opposing a ban on plastic packaging resp. genetically modified organisms*, 3 = *equal number of arguments for both positions* to 5 = *only arguments favoring a ban on plastic packaging resp. genetically modified organisms*). Two ANOVAs using Bonferroni post-hoc tests indicated that the respondents perceived the direction of the presented arguments correctly (see Table 2 for descriptive statistics).

To check whether the collaborative filtering algorithm selects more convincing arguments than the random mode, respondents were asked during the usage of the online platform whether they rated the presented arguments as convincing (=1) or not convincing (=0). The number of convincing arguments was summed up. Participants exposed to arguments selected by the collaborative filtering algorithm rated more arguments as convincing than those exposed with arguments that were randomly selected (Table 3). However, *t*-tests indicate that the difference was only significant in wave 3, $t(840) = -2.32$, $p = .021$, but not in

[3] Again, the "respondi AG" performed the fieldwork of the pretests. The same quotas were implemented as in the main study. In total, 264 participants were randomly exposed to arguments favoring a ban on plastic packaging resp. genetically modified organisms and to arguments opposing a ban on plastic packaging resp. genetically modified organisms. They were asked whether the arguments were for or against a ban on plastic packaging resp. genetically modified organisms, and how convincing they arguments are. Building on the results of the second pretest, the arguments were adjusted and tested again in the third pretest. For the main study, the arguments whose direction was clear to the participants were selected. Moreover, care was taken to ensure that the arguments for each direction were perceived as having similar overall strength.

[4] Gender: plastic packaging: $X^2(3, N = 843) = 1.33$, $p = .723$; genetically modified organisms: $X^2(3, N = 843) = 1.80$, $p = .615$; age: plastic packaging: $F(3, 839) = 0.36$, $p = .785$; genetically modified organisms: $F(3, 839) = 0.78$, $p = .504$; education: plastic packaging: $H(3) = 0.97$, $p = .808$; genetically modified organisms: $H(3) = 4.94$, $p = .177$; prior attitude (dichotomous): plastic packaging: $X^2(3, N = 843) = 2.52$, $p = .572$; genetically modified organisms: $X^2(3, N = 843) = 1.22$, $p = .749$.

Table 2
Manipulation check: Direction of arguments.

Experimental setting	Plastic packaging		Genetically modified organisms	
	Mean	SD	Mean	SD
Favoring a ban (random)	4.33[a]	0.93	3.98[a]	1.05
Favoring a ban (algorithm)	4.25[a]	1.00	4.05[a]	0.98
Opposing a ban (random)	2.72[b]	1.16	2.18[b]	1.10
Opposing a ban (algorithm)	2.86[b]	1.34	2.17[b]	1.15

Note. Plastic packaging: $F(3, 839) = 124.44$, $p < .001$; Genetically modified organisms: ANOVA: $F(3, 839) = 206.40$, $p < .001$; mean values with different small capitals in the same column differ significantly (Bonferroni; $p < .001$).

Table 3
Manipulation check: Selection of arguments.

	Plastic packaging			Genetically modified organisms		
	Algorithm	Random	t	Algorithm	Random	t
Total	3.41 (2.36)	3.27 (2.20)	t (840) = −0.93, p = .351	3.34 (2.03)	3.02 (2.04)	t (840) = −2.32, p = .021
Like-minded environment	5.18 (1.44)	4.65 (1.58)	t (392) = −3.46, p = .001	4.56 (1.49)	4.22 (1.42)	t (394) = −2.36, p = .009
Opposing environment	1.89 (1.88)	2.03 (1.91)	t (446) = 0.77, p = .222	2.27 (1.84)	1.95 (1.91)	t (444) = −1.78, p = .038

Note. Average number of convincing arguments; means and standard deviation (in parentheses).

wave 2, t (840) = −0.93, p = .351. Table 3 shows that the algorithm performed well in wave 2 for participants in like-minded environments but not for those in opposing environments. One reason for the non-significant t-test could be that the algorithm still had too little information about the participants in wave 2.[5]

3.5. Measurements

3.5.1. Prior attitude toward plastic packaging and genetically modified organisms

Participants' prior attitudes toward plastic packaging and genetically modified organisms are relevant to determine whether they were exposed on the online platform to attitudinally congruent or attitudinally incongruent arguments. Participants' prior attitudes toward a ban on plastic packaging were measured in wave 1. They were asked whether plastic packaging for fresh foods such as fruits and vegetables should be banned or allowed in Germany. In total, 79.7% of the respondents were in favor of a ban, and 20.3% were in favor of the permission.

In wave 2, participants were asked whether the cultivation of genetically modified organisms to produce food should be (a) banned or (b) allowed in Germany. More respondents were in favor of a ban (73.8%) than for the permission (26.2%).

3.5.2. Attitude polarization

After using the online platform, the participants were asked to indicate how they evaluated a ban on plastic packaging (wave 2) or genetically modified organisms, respectively (wave 3). Participants were asked to indicate how they evaluate a ban on plastic packaging for fresh foods: very stupid/very smart, very irresponsible/very responsible, very meaningless/very meaningful, very bad/very good, very useless/very useful, and very disadvantageous/very advantageous (Ajzen, 1991; semantic differentials, 7-point-scales). The items were then averaged (plastic packaging: $M = 5.57$, $SD = 1.75$, $\alpha = 0.98$; genetically modified organisms: $M = 4.95$, $SD = 1.93$, $\alpha = 0.98$). Thus, there is a high attitude polarization if the values are as small or as large as possible. In preparation for the analyses, the data were recoded so that the larger the value, the larger the attitude polarization (plastic packaging: $M = 1.50$, $SD = 1.80$; genetically modified organisms: $M = 1.03$, $SD = 1.89$). For this purpose, the center of the scale (=4) was subtracted from the attitudes of those respondents favoring the ban on plastic packaging or genetically modified organisms, respectively, and the attitudes of those respondents who opposed the ban on plastic packaging or genetically modified organisms, respectively, were subtracted by the center of the scale (=4).

3.5.3. Affective polarization

An established way to measure affective polarization is to ask respondents how well various traits describe different groups (Iyengar et al., 2012). Therefore, after using the online platform, participants were asked how well various positive and negative traits describe (a) people favoring a ban on plastic packaging for fresh foods or the cultivation of genetically modified organisms, respectively, and (b) people opposing a ban on plastic packaging for fresh foods or the cultivation of genetically modified organisms, respectively (1 = *not good at all* to 5 = *very good*). Positive traits included intelligence, open-mindedness, honesty, and selflessness. Negative traits included selfishness, narrow-mindedness, hypocrisy, and meanness. Both positive and negative traits were averaged (plastic packaging: positive traits regarding (a): $\alpha = 0.77$, negative traits regarding (a): $\alpha = 0.85$, positive traits regarding (b): $\alpha = 0.78$, negative traits regarding (b): $\alpha = 0.89$; genetically modified organisms: positive traits regarding (a): $\alpha = 0.72$, negative traits regarding (a): $\alpha = 0.87$, positive traits regarding (b): $\alpha = 0.82$, negative traits regarding (b): $\alpha = 0.89$). Net ratings were created by subtracting negative traits from positive ones. Subsequently, an affective polarization scale was calculated by subtracting the net rating of the out-group from the net-rating of the in-group (plastic packaging: $M = 1.80$, $SD = 2.75$; genetically modified organisms: $M = 1.46$, $SD = 2.39$).

4. Results

To test whether exposure to like-minded online environments leads to more (a) attitude polarization and (b) affective polarization than exposure to opposing environments (H1), and to test whether the expected effects are stronger in algorithmically curated online environments than in randomly generated online environments (H2), four between-subject ANCOVAs were conducted. The online environment (like-minded vs. opposing), the selection of arguments (algorithm vs. random), and their interaction served as independent variables. Attitude polarization and affective polarization were used as dependent variables. Participants' prior attitudes regarding plastic packaging or genetically modified organisms were used as covariates.

The results regarding plastic packaging show that exposure to like-minded arguments ($M = 1.68$, $SD = 1.78$) leads to a higher attitude polarization than exposure to opposing arguments ($M = 1.35$, $SD = 1.81$), $F(1, 838) = 10.48$, $p = .001$ (Table 4). Attitude polarization was

[5] The non-significant difference reduces the internal validity of the experiment in wave 2. However, the difference is in the expected direction. Furthermore, the actual influence of the algorithmic curation may not have been detected in wave 2 because the manipulation check was too imprecise. Participants could only rate arguments as convincing or not convincing. Thus, analyses are nevertheless conducted with the data of wave 2 that consider the experimental factor "selection of arguments" in order to test the hypotheses, although the results regarding this experimental factor should be taken with caution.

Table 4
ANCOVA test of between-subject effects for attitude polarization and affective polarization regarding plastic packaging by direction of arguments, selection of arguments, their interaction, and prior attitude (n = 843).

	Attitude Polarization				Affective Polarization			
	df	*F*	*p*	η^2	*df*	*F*	*p*	η^2
Adjusted model	4	61.10	<.001	.23	4	23.97	<.001	.10
Direction of arguments	1	10.48	.001	.01	1	10.95	<.001	.01
Selection of arguments	1	0.11	.738	.00	1	1.16	.281	.00
Direction of arguments × selection of arguments	1	0.42	.518	.00	1	0.83	.364	.00
Prior attitude (1 = favoring a ban)	1	233.20	<.001	.22	1	82.22	<.001	.09

Note. Attitude Polarization: $R^2_{adj} = 0.22$; Affective Polarization: $R^2_{adj} = 0.10$.

not influenced by the selection of arguments, $F(1, 838) = 0.11$, $p = .738$, and its interaction with the direction of arguments, $F(1, 843) = 0.42$, $p = .518$. The prior attitudes of the respondents, however, affected attitude polarization, $F(1, 843) = 223.20$, $p < .001$. Respondents favoring the ban on plastic packaging ($M = 1.93$, $SD = 1.52$) indicated stronger attitude polarization than those opposing the ban ($M = -0.15$, $SD = 1.86$). Thus, in the context of plastic packaging, H1a is confirmed; H2a is rejected.

For the topic of plastic packaging, participants' exposure to like-minded or opposing arguments also impacted their affective polarization, $F(1, 839) = 10.95$, $p < .001$ (Table 4). Participants who were exposed to like-minded arguments ($M = 2.11$, $SD = 2.75$) indicated stronger affective polarization than those who were exposed to opposing arguments ($M = 1.53$, $SD = 2.72$). The selection of arguments, $F(1, 839) = 1.16$, $p = .281$, and its interaction with the direction of arguments, $F(1, 839) = 0.83$, $p = .364$, did not have a significant influence on affective polarization. However, respondents' prior attitudes influenced affective polarization, $F(1, 839) = 82.22$, $p < .001$. Respondents favoring the ban on plastic packaging ($M = 2.21$, $SD = 2.66$) indicated stronger affective polarization than those opposing the ban ($M = 0.18$, $SD = 2.47$). Taken together, H1a and H1b were confirmed in the context of plastic packaging, and H2a and H2b were rejected.

The results regarding the topic of genetically modified organisms reveal that exposure to different arguments did not significantly affect attitude polarization, $F(1, 838) = 2.96$, $p = .086$ (Table 5). Participants who were exposed to like-minded arguments ($M = 1.13$, $SD = 1.93$) indicated similar attitude polarization to those who were exposed to opposing arguments ($M = 0.94$, $SD = 1.86$). In contrast, the selection mode of arguments impacted attitude polarization, $F(1, 838) = 4.99$, $p = .026$. Participants who were exposed to algorithmically selected arguments ($M = 1.15$, $SD = 1.86$) indicated slightly stronger attitude polarization than those who were exposed to randomly selected arguments ($M = 0.90$, $SD = 1.91$). However, there was no interaction effect between the direction and the selection of arguments, $F(1, 838) = 0.00$, $p = .996$. Participants favoring the ban on genetically modified organisms ($M = 1.34$, $SD = 1.84$) indicated stronger attitude polarization than those who opposed the ban ($M = 0.15$, $SD = 1.76$), $F(1, 838) = 71.38$, $p < .001$. In the context of genetically modified organisms, H1a and H2a were rejected.

Table 5
ANCOVA test of between-subject effects for attitude polarization and affective polarization regarding genetically modified organisms by direction of arguments, selection of arguments, their interaction, and prior attitude (n = 843).

	Attitude Polarization				Affective Polarization			
	df	*F*	*p*	η^2	*df*	*F*	*p*	η^2
Adjusted model	4	19.45	<.001	.09	4	5.80	<.001	.03
Direction of arguments	1	2.96	.086	.00	1	10.25	.001	.01
Selection of arguments	1	4.99	.026	.01	1	1.88	.171	.00
Direction of arguments × selection of arguments	1	0.00	.996	.00	1	0.37	.545	.00
Prior attitude (1 = favoring a ban)	1	71.38	<.001	.08	1	11.29	<.001	.01

Note. Attitude Polarization: $R^2_{adj} = 0.08$; Affective Polarization: $R^2_{adj} = 0.02$.

For the issue regarding genetically modified organisms, affective polarization was influenced by exposure to different arguments, $F(1, 838) = 10.25$, $p = .001$. Respondents who were exposed to like-minded arguments ($M = 1.73$, $SD = 2.27$) indicated stronger affective polarization than those who were exposed to opposing arguments ($M = 1.22$, $SD = 2.47$). The selection of arguments, $F(1, 838) = 1.88$, $p = .171$, and its interaction with the direction of arguments, $F(1, 838) = 0.37$, $p = .545$, did not affect affective polarization. Again, respondents favoring a ban on genetically modified organisms ($M = 1.62$, $SD = 2.43$) indicated stronger affective polarization than those opposing such a ban ($M = 1.02$, $SD = 2.22$), $F(1, 838) = 11.29$, $p < .001$. In the context of genetically modified organisms, H1b was confirmed and H2b was rejected.

5. Discussion

This study investigated to what extent the exposure to differently curated online environments impacts people's political polarization. Based on theoretical assumptions that like-minded and algorithmically curated online environments fuel political polarization (Pariser, 2011; Sunstein, 2018), two quasi-experiments embedded in a three-wave panel study were conducted. An online discussion platform developed specifically for the experiments served as a stimulus. Participants were asked to discuss two controversial food policy issues on the platform, namely whether plastic packaging for fresh foods (wave 2) and the cultivation of genetically modified organisms in food production (wave 3) should be allowed or banned in Germany. The direction and selection of arguments presented on the online discussion platform were manipulated. Participants were exposed either to arguments that were in line or in contrast with their prior attitudes toward the two issues. The arguments were selected either randomly or by an algorithm based on collaborative filtering that selected the arguments that the individual participants were most likely to agree with.

On the one hand, the results of the quasi-experiments largely support the hypothesis that being exposed to like-minded arguments leads to more political polarization than exposure to opposing arguments. In the context of plastic packaging, this proves to be true for both attitude polarization and affective polarization, whereas in the context of genetically modified organisms, this only applies to affective polarization but not for attitude polarization. We can only speculate why the effects differ between the two contexts; overall, the question of whether the cultivation of genetically modified organisms should be banned seems to be less polarizing in Germany than the question of whether plastic packaging should be banned (see 3.5 Measurements). One reason could be that people come more frequently into contact with plastic packaging than with genetically modified organisms, making the issue more salient. Moreover, many arguments for plastic packaging are mainly practical (e.g., light weight, robust), while some of the arguments for the cultivation of genetically modified organisms are much more far-reaching (e.g., more efficient way of producing food, which is important considering continued human overpopulation).

On the other hand, the results did not confirm the hypothesis that algorithmic selection amplifies the effects of exposure to likeminded arguments on political polarization. In both contexts, the interaction term between the direction and the selection of arguments did not significantly affect attitude polarization and affective polarization.

However, as the manipulation check failed with respect to the experimental factor "selection of arguments" in wave 2, the non-significant effects of the algorithmic selection on political polarization should be treated with caution. Since the manipulation check was successful in wave 3, there is some evidence that the algorithm had too little information about the participants in wave 2 to select those arguments that were most likely to be convincing to the individual participants. Nevertheless, we cannot observe an interaction effect in wave 3 either, but only a main effect of the algorithm: Participants exposed to algorithmically selected arguments in the context of genetically modified organisms developed a slightly stronger attitude polarization than participants exposed to randomly selected arguments. Since the effect occurs independently of the direction of the arguments, an online environment with persuasive arguments—regardless of whether they support one's own opinion or not—seems to solidify one's attitudes. Another explanation could be that participants pay less attention to the direction of arguments, as long as they evaluate them positively. However, since we can only speculate at this point, further studies are needed that focus on the impact of algorithmically curated online environments. Building on the failed manipulation check in wave 2, longitudinal panel studies should also investigate how much information the algorithms need to select information that fits the user's attitudes.

Furthermore, the results show that the prior attitudes toward plastic packaging and genetically modified organisms strongly shape attitude polarization and affective polarization. Participants favoring the ban on plastic packaging or genetically modified organisms indicated a stronger attitude polarization and affective polarization than those who opposed the ban. One explanation for this result could be that Germans who oppose plastic packaging and genetically modified organisms have a stronger social identity as "environmentalists" than Germans who favor both. A stronger social identity, in turn, is closely related to greater political polarization (Iyengar et al., 2012). However, since environmental debates in some countries are more ideological and controversial than in Germany, it is questionable whether these results can be transferred to other national contexts. For example, opponents of environmental protection measures in the United States have likely developed a stronger collective social identity than opponents of these measures in Germany (Dunlap et al., 2016). Further cross-country comparative studies are needed to investigate which political debates in which countries promote polarization.

This study has limitations besides the failed manipulation check in wave 2. First, whereas individuals in most cases can choose between different online environments, the participants of the present study were forced to be exposed to specific like-minded or opposing online environments. As there is some evidence that forced exposure has different effects on polarization than self-selective exposure (e.g., Arceneaux & Johnson, 2013), additional studies are needed that allow participants to choose between different online environments to increase the external validity of the experiments. Second, the discussion platform was unfamiliar to participants. While this was necessary to control the impact of the algorithmic selection, it has the disadvantage that participants may behave differently in familiar or real online environments. Third, we focused only on participants in one country and only on controversial food policy issues. It is unclear to what extent the results can be generalized to other contexts, policy fields, and countries. This is also evident for the algorithm used in the study. It is unclear how other algorithms perform and how much they contribute to polarization. Fifth, because we did not integrate a "placebo" discussion on another topic in our design, we cannot show whether mere exposure to topic-related arguments contributes to polarization compared to exposure to off-topic arguments.

Despite these limitations, the results have several implications. First, the study shows that exposure to arguments selected algorithmically can slightly influence attitude polarization, at least for one issue. Algorithms thus contribute to polarization, even if the effects are extremely small, especially in contrast to the effect of the direction of the arguments. However, the fact that algorithms have a (small) effect can also be seen as a normatively positive result. After all, this could be seen as another reason to develop algorithms that make online environments more balanced, which might help to lower polarization. Moreover, it is noteworthy that the polarization effect of the algorithm seems to be issue-dependent. Platform providers and researchers should be sensitized to this. It would be useful to identify such sensitive topics in order to provide more balanced online environments with the help of algorithms. Second, even though algorithmic curation is of increasing importance in online environments, empirical studies rarely attempt to capture this curation. Thus, from a methodological perspective, it is particularly noteworthy that a personalized stimulus was developed within this study using a learning algorithm to measure the impact of personalized content on political polarization. The algorithmic adaption of stimuli in experimental settings has great potential to better understand the impact of algorithmic curation and should be further developed in the future. Third, the study has demonstrated that a party affiliation is not a necessary condition for (affective) polarization. It is sufficient that individuals identify themselves with opinion-based groups on controversial issues. This was also evident during the Brexit referendum (Hobolt et al., 2021) and regarding the efforts to mitigate the spread of COVID-19 (Neumann et al., 2021). Especially in multiparty systems, where polarization can rarely be broken down to the conflict between two political parties, this is an important finding that expands our understanding of polarized societies.

6. Conclusion

The debate about whether social media and algorithms contribute to polarization is receiving a lot of public and academic attention. Yet there are few studies that attempt to identify the specific effects caused by algorithms. Relying on two quasi-experiments, our results show that algorithmic curation can have an impact on political polarization, but the effect is very small compared to other factors, such as the general direction of the selected arguments or people's prior attitudes. Thus, the study demystifies the dangers of algorithms to some extent. However, further studies are needed to assess the impact of algorithmically selected information in other contexts and with other algorithms.

Funding

This work was founded by the Jürgen Manchot Foundation [Manchot Research Group "Decision-Making with the Help of Artificial Intelligence"].

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data is available on request from the corresponding author.

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