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Algorithmic inference, political interest, and exposure to news and politics on Facebook

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ABSTRACT

The visibility of news and politics in a Facebook newsfeed depends on the actions of a diverse set of actors: users, their friends, content publishers such as news organizations, advertisers, and algorithms. The focus of this paper is on untangling the role of this last actor from the others. We ask, how does Facebook algorithmically infer what users are interested in, and how do interest inferences shape news exposure? We weave together survey data and interest categorization data from participants' Facebook accounts to audit the algorithmic interest classification system on Facebook. These data allow us to model the role of algorithmic inference in shaping content exposure. We show that algorithmic 'sorting out' of users has consequences for who is exposed to news and politics on Facebook. People who are algorithmically categorized as interested in news or politics are more likely to attract this kind of content into their feeds – above and beyond their self-reported interest in civic content.

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Introduction

It remains an open question how much power algorithms and the design of platforms have over the individual-level visibility of news and political content on social media. We are not yet certain whether social newsfeeds increase serendipitous encounters with civic content – a happy outcome – or amplify individual preferences, leading to a rich-get-richer model of political content exposure. On Facebook (for example), what becomes visible in the limited real estate of the newsfeed is determined by an entanglement of selection choices made over time by multiple sets of actors, each potentially influencing the other (Thorson & Wells, 2016). These include users' choices about what to 'like' or 'follow,' choices made by friends and followed organizations about what to post, and choices made by politicians and news organizations about whom to target with paid content. All of these selections are in turn mediated by algorithms that rank content for display in the newsfeed.

The purpose of this paper is to untangle the role of algorithmic interest classification processes from other factors that shape the visibility of news and politics on Facebook.

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We seek to understand how users become algorithmically categorized as 'interested' in news and politics, and how that categorization is related to content exposure. Our analytical focus is not on the newsfeed display algorithm itself, but rather on auditing something more fundamental: the algorithms that attempt to classify users based on inferences about their interests (Bowker & Star, 2000; Flyverbom & Murray, 2018). These algorithms draw on measures of 'affinity' for topics that are generated from digital traces of user behavior, such as liking a page or using certain keywords in a post. Via these algorithmic systems, digital traces of user behavior are translated into probabilistic categories that can be used by advertisers for audience targeting and by newsfeed ranking algorithms to ensure that users see 'relevant' content (DeVito, 2017; Juan & Hua, 2012; Kendall & Zhou, 2010).

We show that this algorithmic 'sorting out' of users has consequences for who is exposed to news and politics on Facebook. People who are algorithmically categorized as interested in news or politics are more likely to attract this kind of content into their feeds – above and beyond self-reported interest in civic content. Our findings add nuance to theoretical approaches such as selective or incidental exposure by highlighting the entanglements among individual preferences, digital traces of behavior, and algorithmic inference. On Facebook, individual content selections are, in most instances, temporally divorced from potential future exposure: we do not directly 'choose' what appears in our newsfeed, nor do our friends or the organizations we 'like.' Instead, agency to shape content visibility has shifted to algorithmic interpretations of user preferences and the assemblage of categorization and classification processes required to make users' preferences machine readable and 'ready' to be acted on (Gillespie, 2014; Rieder, 2017).

Our findings are based on a methodological innovation: we combine a survey of young adults with a record of how each participant has been algorithmically classified for sale to advertisers on Facebook. Data about this categorization is available to all Facebook users as part of their profile data. After a process of informed consent, we asked participants to download their own Facebook profile archive and upload relevant files to us. This method, combining self-report data with digital traces of user behavior *and* the results of algorithmic inference based on these data, allows us to investigate the connections among self-reported preferences, algorithmic inference, friends' behavior, and content exposure.

Literature review

Inferring user interests

Algorithmic categorization of what users are interested in is fundamental to the Facebook platform. Facebook needs to know about users' interests (e.g., 'gardening' or 'Marvel') to ensure that users see relevant content in their newsfeeds and also to provide advertisers with the ability to target based on interest categories. Based on a content analysis of Facebook's public documents, DeVito (2017) characterized users' interests as one of the top two 'algorithmic values' of the system (the other being friend relationships). DeVito found that 'explicit user interests and implicit user preferences are deeply tied into multiple algorithmic systems, including the News Feed' (p. 766; see also Cotter, Cho, & Rader, 2017; Kendall & Zhou, 2010; Lada, Li, & Ding, 2017; Mosseri, 2017; Zhou & Moreels, 2012).

As evidenced by close reading of Facebook's patent applications, *algorithmic inference* of user interests posed an early challenge for Facebook. Not all users declared their interests on their profiles, limiting Facebook's ability to provide advertisers with enhanced targeting capabilities (Kendall et al., 2009, p. 4). One after another, from 2009 onward, Facebook patents describe the evolving use of machine learning to infer users' interests probabilistically from user behavior and friends' behaviors on the site (e.g., Kendall et al., 2009; Kendall & Zhou, 2010; Rajaram, Wu, Yan, & Kanter, 2014; Zhou & Moreels, 2012). A patent by Zhou and Moreels (2012, p. 6) described an 'interest inference module' that infers user interests via machine learning algorithms based on users' connections (friends) and behavior (such as pages users liked, searches they performed, content they engaged with), and the keywords they used in their Facebook posts. Rajaram and Sanaratna (2013) outlined a dynamic model for estimating 'interest intensity' for a given topic or product. Another patent application addressed how 'organic' (non-paid) stories can be ranked for display in the newsfeed, in part by drawing connections between inferred user interest categories and 'affinity rankings' for particular stories available for display in the newsfeed (Hegeman, Ge, Gubin, & Amit, 2014, p. 7).

Facebook's algorithmic inference systems are optimized to support the company's revenue goals. They are designed to learn which features of users' data (a) create interest classifications that produce sales for advertisers and (b) maintain user engagement on the newsfeed. As such, algorithmic inference of user interests is an 'interested reading' of digital trace data (Rieder, 2017). As we will show, an important but little discussed consequence of this sorting process is the impact on individual exposure to news and political content. Although algorithmic classification of user interests has been addressed in discussions of advertising targeting on Facebook (e.g., Angwin, Varner, & Tobin, 2017), its possible connection to exposure to news feed content has not yet been explored.

Inferred political interest and content exposure

A large and growing body of literature has documented the importance of political interest as a predictor of individual-level exposure to news and political content. Our current era has been characterized as a high-choice media environment, providing more options for media selection than the low-choice, broadcast era (e.g., Bimber, 2003; Prior, 2007; Van Aelst et al., 2017). Individual preferences are increasingly strong predictors of media exposure: People with higher levels of political interest are more likely to use news, and the power of political interest to predict news consumption has grown over time (Lecheler & de Vreese, 2017; Prior, 2007; Strömbäck, Djerf-Pierre, & Shehata, 2013). Political interest is a more important predictor of political content exposure than selective exposure motivated by partisanship (Skovsgaard, Shehata, & Strömbäck, 2016).

On social media platforms like Facebook, however, users have somewhat less control over content exposure than on other media. Power over information visibility is distributed among individual preferences, friends, strategic communicators, journalists, and algorithms, diffusing the power of any one actor to shape or limit exposure (Chadwick, 2013; Thorson & Wells, 2016). A user may 'like' the public page of a news organization, but not everything the news organization posts will appear in the user's feed. Whether a post from a news organization does appear or not depends on how it has been ranked by the newsfeed algorithm for that user. A similar dynamic shapes the visibility of friends' posts. Algorithmic ranking and classification systems mediate the relationship between user preferences and content exposure.

Therefore, we propose that, in the context of algorithmically curated platforms, we need to analyze not only a *direct* relationship between political interest and exposure or between friends' posting behavior and exposure, but also the ways in which individual and peer behaviors connect to exposure *indirectly* by influencing algorithmic classification systems. Such an analysis helps to reveal the power of algorithms as independent actors in shaping news exposure.

Complicating the pathway from (political) interest to content exposure

Our expectation is that algorithmic interest classification mediates the relationship between Facebook users' self-reported interest in politics and exposure. People see political content on Facebook *not only* because of their actual interest in politics, *but also* because their behaviors and the behaviors of their friends lead to an algorithmic interpretation of their interests – and subsequent categorization — as politically interested. We propose two processes by which user behavior shapes categorization. First, through active customization of the platform, users intentionally tailor their information environments to their interests. Active customization entails the explicit expression of one's interests by choosing to receive (or remove) content within certain categories or from particular sources (e.g., 'liking' a Facebook page). In the case of algorithmic platforms like Facebook, customizations such as 'liking' or 'following' a news organization or politician may be interpreted as signals that a user is interested in receiving similar content in the future.

Second, we examine indirect pathways connecting political interest to exposure via homophily in friend groups. Previous research has shown that individuals tend to associate and maintain connections with those who share sociodemographic features, behaviors, and/or values (Lazarsfeld & Merton, 1954; McPherson, Smith-Lovin, & Cook, 2001). Following this pattern, those interested in politics tend to surround themselves with similarly interested others (Knoke, 1990). Accordingly, Facebook users who are more interested in news and politics should be more likely to have friends who share these interests. In several patents, Facebook has described classification systems that infer user interests not only from that user's behavior, but also from the expressed and inferred interests of their friends (DeVito, 2017). We expect that the degree of political interest represented in one's social graph will contribute to the extent to which users are algorithmically classified as interested in politics, even when controlling for users' own political interest.

Figure 1 illustrates our proposed theoretical model that connects political interest, user customization behavior, friends' behavior, and algorithmic user-interest classification to political content exposure on Facebook. We begin by treating political interest as a motivational variable that should encourage uses of Facebook that reflect this preference. The path between political interest and political content exposure *(a)* represents a direct exposure path. Next, we predict that political interest will be related to the proportion of friends who post about politics on Facebook (via processes of homophily, Lazarsfeld & Merton, 1954; McPherson et al., 2001, Path *h*). Path *c* in the diagram can therefore be interpreted as the homophily path – the role played by social others in shaping the amount of politics participants see.

Our main focus is on the role algorithmic classification plays in explaining political content exposure on Facebook. We expect that those higher in political interest will be

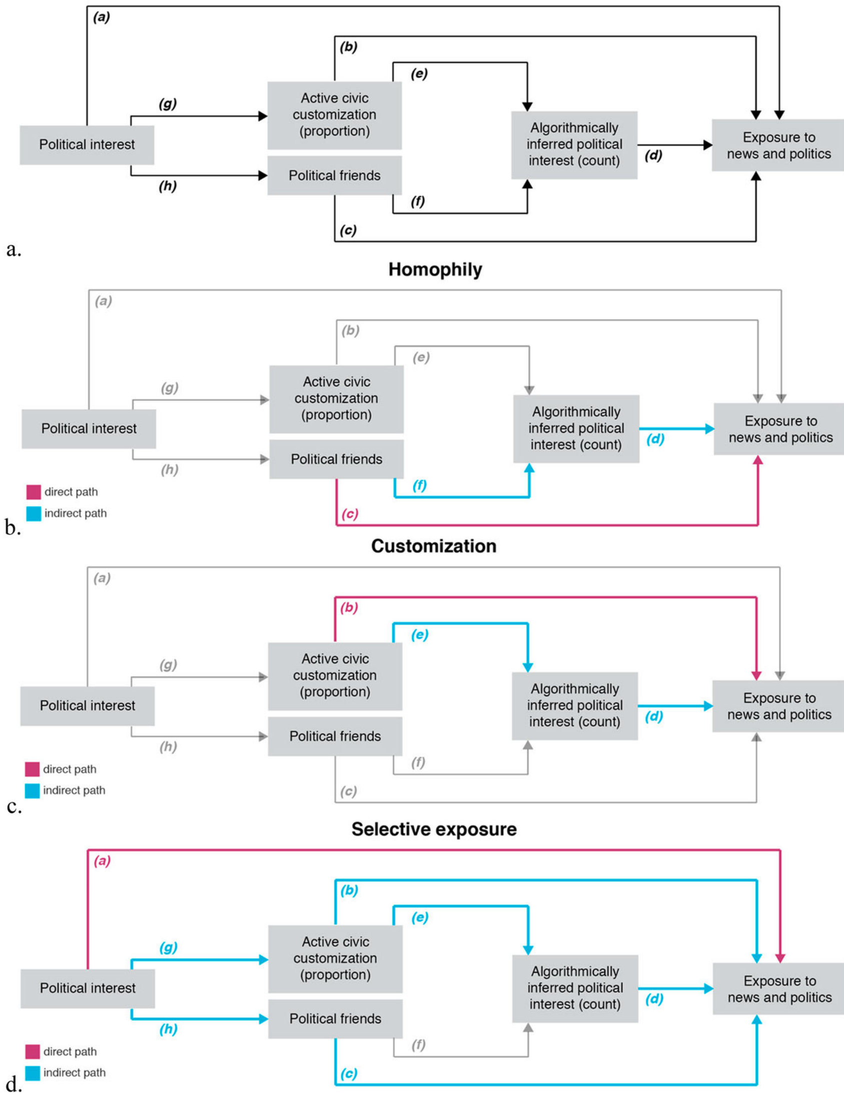

Figure 1. a-d. Path diagram illustrating the ways in which political interest directly and indirectly are expected to lead to exposure to news and politics. Figure 1a shows all potential paths. Figures 1b-d demonstrate the different processes predicting political content exposure: homophily (b), customization (c), and selective exposure (d).

more likely to use Facebook in ways that signal that interest to classification algorithms. In our model, we predict that those interested in politics will be more likely to 'like' or 'follow' news organizations and politicians on the site (path *g* in the model). We refer to this cluster of behaviors as active civic customization (Thorson, Xu, & Edgerly, 2018) and measure it with digital trace data from participants. In turn, we expect that both active civic customization and having friends who post about politics should predict the extent to which a user is algorithmically classified as interested in politics (paths *e* and *f*). Path *d* represents the direct path from algorithmic classification to political content exposure.

Method

There is no easy method to study how digital traces of user behavior result in classification into interest categories, or to analyze the impact of such classifications on content exposure (Kitchin, 2017). It is impossible to know how much each 'like' of a news post or a click on a politician's story might affect future exposure to civic content because such a signal is only one of hundreds of thousands of signals Facebook's algorithms consider in ranking content in users' feeds (Facebook Business, n.d.). However, we can engage in a practice Kitchin calls 'examining how algorithms do work in the world' (p. 25). In this study, we do so by examining the algorithmically determined list of interests that Facebook associates with each individual – the end result of the algorithmic interest inference process – as well as digital traces of active customization, defined by the pages that users have liked. These data provide us with a window into how and why user interests are classified on Facebook, a way to see how users are 'sorted,' and how such sorting processes shape content visibility (Bowker & Star, 2000).

Our method combines a survey of participants with a collection of digital trace data from Facebook. Because Facebook does not commonly make individual or advertiser data publicly available, we rely on participants' own Facebook data archives. Facebook has provided users with the option to download their information since 2010 (Palis, 2012). Following complaints filed with the Irish Data Protection Commissioner over Facebook's storing of user information, Facebook greatly expanded the range of data users could download about their use of the platform (Palis, 2012). The use of the Facebook data archive is rare in scholarly research. We were able to find only two published examples, in social psychology and information science (Eslami, Kumaran, Sandvig, & Karahalios, 2018; Marino, Finos, Vieno, Lenzi, & Spada, 2017).

The Facebook data archive includes multiple files that provide information about users' Facebook activity, their timeline, messages, and – most important for our purposes— information about pages they have liked and how they have been categorized for sale to advertisers (for a complete list of data included: https://www.facebook.com/help/131112897028467). This last component of the data archive provides a material trace of algorithmic classification of user interests. Though these classifications are presented to users as part of their *advertising* settings, as previously noted, readings of Facebook patents and the existing scholarly literature suggest they are drawn on for both advertising targeting and ranking stories in the newsfeed, among other purposes (e.g., DeVito, 2017; Hegeman et al., 2014; Juan & Hua, 2012; Kendall & Zhou, 2010; Zhou & Moreels, 2012).

Data collection took place during Fall 2017 among a sample of college students (n = 327). After providing informed consent, participants completed a survey on Qualtrics and were asked to download and provide data from their Facebook archive. Participants received step-by-step instructions for the download process (for more information see https://www.facebook.com/help/131112897028467). Participants were asked to upload two of the multiple files produced from the Facebook download: an 'index' file, which lists pages liked by the participant, and an 'ads' file, which provides 'A list of topics on which you may be targeted based on your stated likes, interests and other data you put in your Timeline' (Facebook Help Center, n.d.).[1] Participants' data files were downloaded from Qualtrics and saved to a secure drive. To preserve confidentiality, the raw data archive files were not reviewed by any member of the research team. Instead, data contained in the files were extracted and coded via an automated process described below. Thus, participants were assured of the confidentiality of both their survey responses and Facebook data. The university institutional review board formally approved the project.

Survey measures

Demographics

Because we relied on a student sample, we used parents' education and income as controls in our analyses. The education variable was the average of participants' mother's and father's levels of education (1 = some high school, 2 = graduated high school, 3 = graduated trade school, 4 = graduate college, 5 = MA/MS/PhD/MD/JD; $M = 3.62$, $SD = 1.04$). Parental household income was measured across seven income brackets (1 = less than \$25,000, 2 = \$25,000–\$49,999, 3 = \$50,000–\$74,999, 4 = \$75,000–\$99,999, 5 = \$100,000–\$124,999, 6 = \$125,000–\$149,999, 7 = \$150,000 and more; $M = 5.58$, $SD = 2.08$).

Political interest

To measure political interest, participants were asked to indicate their levels of interest in politics and national government on a 5-point scale (1 = Not at all interested, 5 = Extremely interested; $M = 3.70$, $SD = 1.16$).

Friends' political posts

To get a sense of the scale of political content participants saw that originated from interpersonal contacts on Facebook, we asked participants to estimate what percentage of their Facebook 'friends' post about politics, indicated via a slider bar ranging from 0 to 100 ($M = 36.68$, $SD = 19.95$).

Exposure to political content on Facebook

We measured the degree of exposure to political content on Facebook via self-report, by asking participants how often they saw 'content about politics or political issues' on Facebook in the past week (1 = Never, 5 = Very often; $M = 3.66$, $SD = 1.25$).

Digital trace data measures

Matching the Facebook archive data

Relevant information was extracted from the two Facebook data archive files automatically via software we developed. This software works in two steps: First, it extracts the list of pages a user has 'liked' and the list of interest categories assigned to the user. Next, the code matches these two lists with a dictionary of politicians, media, advocacy and activist organizations, and political keywords. The politician list included all governors (The Council of State Governments, 2016), all 538 members of Congress (GitHub, 2017), the mayors of the 100 biggest cities (BallotPedia, 2017), all state legislators (Open: States, 2017), as well as the president and the cabinet members. The news media dictionary was compiled using the social listening tool Meltwater's media search. We included all news organizations and reporters who reported about politics and/or government. The dictionary included more than 8,000 politicians, as well as 13,026 reporters, 5,868 media organizations, 692 advocacy and activist organizations, and 382 political keywords.

To ensure an efficient matching between the Facebook data and the news media/politician dictionary, we implemented following matching rules: decapitalize both entries from the Facebook data and our list of names and keywords, remove any abbreviated middle names from items when applicable, and sequentially match the item from the Facebook data with each item from our list. To decide a match, the algorithm first breaks an item from our list into words when applicable (e.g., 'Donald Trump' → 'donald trump' → 'donald, trump'). If all the words included in at least one item from our list (e.g., 'donald' *and* 'trump' in our example) are also included in the item from the Facebook data (e.g., 'president donald trump'), we concluded that the Facebook item was a match. The matched entries, extracted from the original data, were then manually reviewed to ensure validity. The coding program and dictionaries are available on GitHub.

Active civic customization. To approximate the degree to which participants engage in active civic customization, we used data from the 'index' file of participants' Facebook data. This file lists the pages participants had 'liked.' We were unable to enter the total counts for digital trace measures of 'liked' pages and advertising categories in the same model due to problems of multi-collinearity ($r = .89$, $p < .001$).[2] Thus, our measure of active civic customization is the proportion of 'liked' political or media-related pages to total 'liked' pages ($r = .50$, $p < .001$) in participants' index files ($M = .03$, $SD = .03$) – that is, the proportion of all liked pages that are related to news and politics.

Algorithmically inferred political interest. This variable reports the degree to which Facebook has categorized participants as interested in news media and politics. It was measured by computing the number of political or media-related topics listed in the 'ads topics' file of participants' Facebook data, captured as described above. Descriptives for this variable are reported below.

Participants

Participants consisted of 327 undergraduate students at a large Midwestern university. Participants were recruited from communication and political science courses, with 53% of students coming from political science. Among them, 63% were female. The age of participants ranged from 18 to 56 ($M = 20.12$, $SD = 2.78$).

Results

To our knowledge, no previous study has reported the rate at which any population is packaged by Facebook to advertisers as interested in news or politics. Among this student sample, nearly a quarter of the participants (23%) had *no* news media or politics categories listed as available for targeting by advertisers (Mdn news/politics categories = 4). Another 26% had one to three relevant categories associated with their account. The remaining 51% had four or more media or politics keywords listed as available for advertiser targeting. The majority of listed keywords were the names of specific media organizations or politicians (e.g., CNN, NPR, Bernie Sanders, Barack Obama, Donald Trump).

Modeling the paths of exposure

In order to distinguish the indirect impact of algorithmic inference of political interest from the direct consequences of users' 'intended' behaviors, we appled path analysis to users' self-reported and digital-trace data. The main rationale behind this methodological choice is that users' preferences and behaviors not only directly shape what they see, but also have an indirect influence by affecting how the algorithm regulates content visibility for individual users. Algorithmic categorization is proposed to mediate the relationship between users' political interest and content exposure.

For estimation, we used the R package 'lavaan' (Rosseel, 2012) and all variables were standardized. Note that all paths are recursive so the regression results are the same as separately run linear regressions. While the results are the same, the true value of the path model is the estimations of direct and indirect effects within our proposed model (Figures 1b-1d), and evaluations of their statistical significance. The standard errors for this evaluation were calculated by bootstrapping.

Our first expectation was that political interest would be positively related to behaviors that could be 'read' as indicators of political interest. We expected that political interest would predict active civic customization (path g) and the proportion of friends who post about politics (path h) and we find that political interest predicts both (the regression results are in the first two columns of Table 1). We included gender, parents' education, and parents' income as control variables, as these have been shown to be the demographic variables most closely related to political involvement (Schlozman, Verba, & Brady, 2012). For friends who post political content to Facebook, the model explains a small but significant amount of variance ($R^2 = 0.05$). As predicted, political interest was a significant predictor of homophily ($\beta = 0.16$, $SE = 0.06$, $p = .005$). As political interest increases, so too does the percentage of friends who post political content. For active civic customization, a significant proportion of the total variation was predicted by the model ($R^2 = 0.08$). Political interest was a significant and positive predictor of active civic customization ($\beta = 0.27$, $SE = 0.06$, $p < .001$).

We expected that active civic customization and having a political social graph would predict the extent to which a user's 'algorithmic identity' (Cheney-Lippold, 2011) would be classified as interested in news and politics. The third column of Table 1 shows the results

Table 1. Regression results predicting exposure to political content on Facebook.

	Percentage of Facebook friends who post political content	Active civic customization	Digital trace-based measure of political interest	Exposure to political content on Facebook
Demographics				
Gender (Male)	0.12 (0.05)*	−0.07 (0.06)	−0.11 (0.04) **	0.16 (0.05) **
Parental Education	0.01 (0.06)	0.02 (0.07)	−0.07 (0.05)	−0.00 (0.06)
Parental Income	−0.12 (0.06)	−0.09 (0.06).	−0.04 (0.05)	0.01 (0.06)
Political interest	0.16 (0.06) **	0.27 (0.06) ***	0.03 (0.05)	0.11 (0.06)
Political friends			0.13 (0.05) **	0.23 (0.06) ***
Active customization			0.65 (0.05) ***	0.03 (0.07)
Algorithmically inferred Political Interest				0.20 (0.07) **
R^2	0.05	0.08	0.47	0.16
N	304	304	304	304

Notes: Cell entries are standardized final regression coefficients. $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

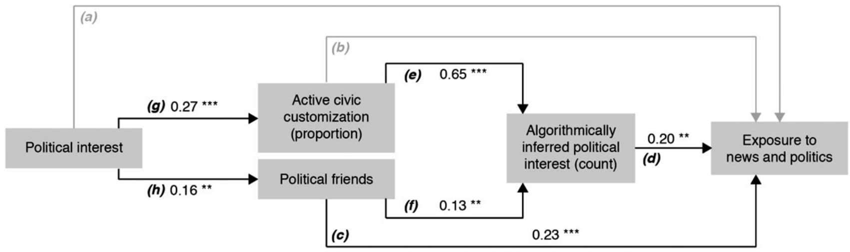

Figure 2. Statistically significant paths that predict exposure.

of our test ($R^2 = 0.47$). As expected, active civic customization (the proportion of 'liked' pages related to news and politics) and having politically interested friends were both positively related to the number of political keywords available for targeting by advertisers ($\beta = 0.65$, $SE = 0.05$, $p < .001$; $\beta = 0.13$, $SE = 0.05$, $p = .003$, respectively). Male participants had slightly fewer political and news categories in their ad topics than female participants on average ($\beta = -0.11$, $SE = 0.04$, $p = .008$).

Our final expectation was that algorithmically inferred political interest categories would predict political content exposure on Facebook above and beyond other likely suspects. The last column of Table 1 demonstrates support for this hypothesis. Gender, parental income, and parents' education were again included as controls. The model suggests that a significant and substantial proportion of the variance in exposure to political content is explained by algorithmic inference of preferences ($R^2 = 0.16$). The impact of self-reported political interest on political exposure ($\beta = 0.11$, $SE = 0.06$, $p = .062$) was not significant, whereas the impact of political friend networks was ($\beta = 0.23$, $SE = 0.06$, $p < .001$). Further, our measure of algorithmically inferred political interest, a proxy for Facebook's assignment of an individual's algorithmic identity, is a strong and positive predictor of political content exposure ($\beta = 0.20$, $SE = 0.07$, $p = .005$). Active civic customization, operationalized as the proportion of political or media-related 'liked' pages to total 'liked' pages, did not directly predict exposure ($\beta = 0.03$, $SE = 0.07$, $p = .673$).

Figure 2 summarizes the findings by visualizing significant paths. Table 2 shows the aggregated direct and indirect effects of Facebook users' traits on political exposure. As discussed above, there was no evidence of a direct relationship between active civic customization and political exposure ($\beta = 0.03$, $SE = 0.07$, $p = 0.673$). However, active civic customization did have an *indirect* impact on exposure through participants' algorithmic identities ($\beta = 0.13$, $SE = 0.47$, $p = 0.005$). Having politically interested friends on Facebook had significant direct and indirect effects, though the direct effect had a larger effect size than the indirect ($\beta = 0.23$, $SE = 0.06$, $p < 0.001$).

Table 2. Aggregated direct/indirect effects of users' traits on political exposure.

	Estimates	Standard Errors	*P*-values
Customization Direct (path *b*)	0.030	0.071	0.673
Customization Indirect (paths *e, d*)	0.130	0.047	0.005
Homophily Direct (path *c*)	0.232	0.056	0.000
Homophily Indirect (paths *f, d*)	0.027	0.013	0.041
Selective Exposure Direct (path *a*)	0.111	0.059	0.062
Selective Exposure Indirect (paths *b, c, d, e, g, h*)	0.081	0.024	0.001

Discussion

The results of this study suggest that the extent to which a Facebook user sees news and political content on the site depends not only on their own preferences or on the posting habits of their friends, but also on how digital traces of their behavior on the site are used to infer information about their interests and content preferences. Facebook uses digital trace data about each user to infer their interests in order to (a) aid the newsfeed ranking algorithm in deciding which stories will be most 'meaningful' and 'relevant' to that user, and (b) package that user to be targeted by advertisers. The newsfeed ranking algorithm is not available for study, so we cannot know for certain how important these signals about user interest are for determining story ranking. However, the advertiser categories *are* available, and we have provided evidence that their composition is related in important ways to self-reported political content exposure – and perhaps even that these categories are a fair proxy for what Facebook 'knows' about each user's topical interests.

Our results complicate our understanding of the role of individual choice in shaping content exposure. Existing research has suggested that individual choice is *more* important for determining political content exposure than the role of algorithms (e.g., Bakshy, Messing, & Adamic, 2015). We suggest that the two cannot be separated: individual behavior, motivated by personal interest, *shapes* how the algorithm categorizes the interests of each user over time. In turn, a user's 'algorithmic identity,' as categorized by Facebook, has an independent relationship to content exposure above and beyond user-reported levels of topical interest.

In the political communication literature, exposure to political content is often theorized in terms of selective or incidental exposure. We propose that neither of these approaches alone provides sufficient scaffolding to make sense of exposure under conditions of algorithmic classification and curation of content. Selective exposure approaches suggest that individual preferences, realized through active media *choices*, are the most important predictors of political content exposure. Selective exposure studies often implicitly assume that users have complete control over exposure in their media environments (Cinelli et al., 2019; Dylko et al., 2017; Flaxman, Goel, & Rao, 2016; Garrett, 2009; Messing & Westwood, 2014; Nelson & Webster, 2017).[3] This assumption holds for more traditional media (e.g., television: viewers can simply change the channel), but only imperfectly applies to social media. On platforms like Facebook, user agency over content exposure is limited by the complex assemblage of actors influencing information flows (Thorson & Wells, 2016). Our findings suggest that in the current version of Facebook's algorithmic systems, individual preferences (as read into trace data) do have an important role to play in shaping content exposure, but that role is perhaps less direct than often theorized. Our findings also suggest that the influence of individual preferences on content exposure is *dependent* on the contours of the algorithmic system. Changes to the algorithmic sorting process or changes to newsfeed ranking algorithms could amplify or reduce the connection between preferences and exposure. Such changes are exclusively under the control of the platforms themselves.

Incidental exposure approaches emphasize the role of friends and serendipitous encounters with news and political content – a user can be exposed to news even when she is not seeking it out (Tewksbury, Weaver, & Maddex, 2001). Our findings suggest that incidental exposure approaches should also be nuanced when applied to algorithmically curated social media platforms. Empirical studies have shown that those who are already interested in news and politics are more likely to have incidental encounters with news and are more likely to engage with such content when they see it (Karnowski, Kümpel, Leonhard, & Leiner, 2017). A long line of research on homophily shows that people who are interested in politics are more likely to have friends who are also politically engaged, a finding that is borne out in our data (Knoke, 1990; McPherson et al., 2001). Further, on social media, users determine which information channels they open, such as adding a friend or following a politician's page, but algorithms regulate what content shows up in an individual's feed based on the predicted relevance and/or importance of content to the user. Algorithms curate content based on past user expressions of interest (e.g., clicking on or reading stories). Incidental exposure approaches to social media therefore perhaps under-emphasize the role of the individual in shaping content exposure.

Facebook's business model is to create attention that can be sold to advertisers (as CEO Mark Zuckerberg quipped in his 2018 congressional testimony, 'We sell ads, Senator.'). The classification systems we analyzed are 'interested readings' of user data, designed in service of categorizing users for sale (Rieder, 2017). Like any categorization system, the classification process itself is largely invisible to users, while at the same time having substantial consequences for the visibility of content (Ananny, 2016; Bowker & Star, 2000; Gillespie, 2014). This means users are exposed to content according to a commercial logic that they cannot fully control or critique. Classification and ranking algorithms diminish individuals' abilities to control their experiences on social media, even when they make use of customization features (Bode, 2016).

Facebook's newsfeed and categorization algorithms, like other algorithms, make probabilistic predictions and rely on correlation (Andrejevic, 2013; Cheney-Lippold, 2017; Eubanks, 2017). In practice, this means classification algorithms necessarily make mistakes at the individual level. Though algorithms 'assume that the world is made of things or events that fit in stable and distinct categories' (Mackenzie, 2015, p. 433), interests are fluid. As such, the way an algorithm understands a user may not fully reflect the user's own self-definition, wants, and needs – or their capacity for change. More concretely, algorithmic inference of interests may produce a discrepancy between users' desire for news and political content and their actual exposure, which is shaped by datafied readings of their behavior and its similarity to the behavior of others on the platform (Ananny, 2016).

A key line of inquiry for future research will be to explore how levels of political interest and content exposure on Facebook are related over time. The answer to this question has important consequences. If existing political interest predicts higher levels of political content exposure on Facebook, and engagement with that content predicts more exposure, we can expect a spiral effect in which the already-interested gain increasing exposure to political content, and the uninterested are left out of politics and given few opportunities to change (Thorson et al., 2018). Moreover, the algorithmic classifications of political interest we analyzed represent a shift in agency regarding content exposure: a (partial) delegation of control over one's information environment to algorithms. As a result of this shift and the fact that categorization systems themselves shape users' possibilities for action, those 'left behind' cannot necessarily reassess and redress their previously expressed lack of political interest via new encounters with political content on Facebook.

Thousands of interest categories are available to advertisers via Facebook's Ad Manager platform (Figure 3). Politicians and news organizations use these categories to target audiences (for an example, see Figure 4) (see also Kim, 2016). The series of scandals unfolding in the aftermath of the 2016 US presidential election demonstrated the use of Facebook's advertising platform to target specific American audiences with advertisements meant to amplify discord and sway voter behavior (Kim, 2016; Kim et al., 2018; Kreiss & McGregor, 2017; Shane & Goel, 2017). During and after the election, partisan media sites achieved extraordinary rates of user engagement on Facebook, in part, by using the site's advertising platform to run ads and by paying for targeted 'boosts' in visibility for posts that seemed to perform well organically among audiences (Silverman, 2017). Mainstream news organizations make frequent use of Facebook's advertising platform to grow their subscriber bases (Moses, 2015; Roberts, 2017), as do non-profits, advocacy organizations, and politicians at all levels of office. These advertiser strategies are also entangled with the interest classification processes we analyze here.

The findings reported here are limited by the contours of our sample. We are using a student sample and cross-sectional data to describe the links between self-reported user interests and the algorithmically generated categorization by Facebook. Based on our own observations of how we have been categorized by Facebook, we expect that these advertising categories are not static: changes in behavior seem to correspond to changes in categorization. Our cross-sectional data do not allow us to assess how often or at what speed these changes happen. These factors will influence the degree to which early

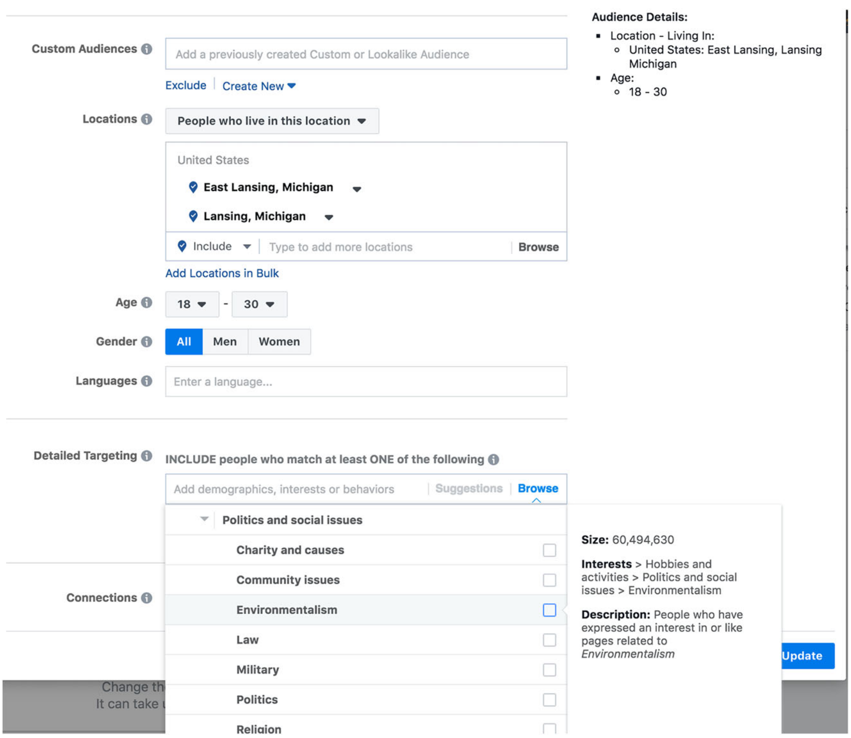

Figure 3. The Facebook Ads Manager platform, and an example of how interests or behaviors can be used to target for ads.

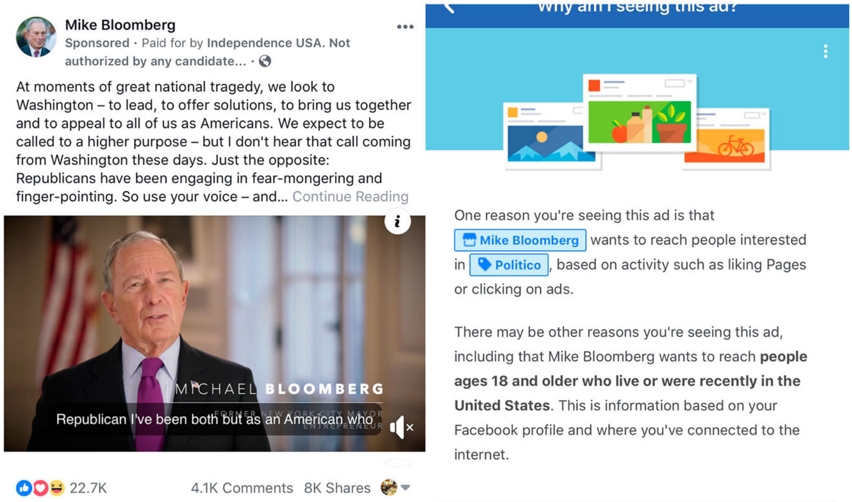

Figure 4. An example of how advertisers use political keywords when targeting for ads.

behavior on Facebook shapes users' political content exposure months or years in the future. While our study cannot speak to the process across time and we are unable to test causality, it represents a significant first step in better understanding how user behavior translates into algorithmic categorization and subsequently affects exposure.

We are also limited by our self-report measure of news and political content exposure. Individual exposure data are not available from Facebook: the API that enabled previous studies (e.g., Wells & Thorson, 2017) to obtain exposure data from the platform has been shut down, and content exposure information is not available in individuals' Facebook data archives. However, and as a result, self-report measures of exposure have been used consistently throughout social media research (e.g., Boyle, LaBrie, Froidevaux, & Witkovic, 2016; Ohme, Albaek, & de Vreese, 2016; Zhu, Skoric, & Shen, 2017). In spite of the limitations of self-report measures of exposure, we followed best practices by providing respondents with a definition of 'news' and 'politics' to anchor their reports of exposure (Guess, Munger, Nagler, & Tucker, 2018), and we separated exposure questions by medium and mode of consumption (e.g., television vs. watching) (Ohme et al., 2016).

This study adds to research on media exposure by combining digital traces of user interest classification with self-report data. Our findings provide a window into how user interests are classified by Facebook, and offer an opportunity to consider the ways that such classification processes may shape what content becomes visible to each user. We also add complexity to our understanding of the relationship between individual choices and eventual content exposure, making salient the partial control nature of social media. Choices made by individual users to customize their newsfeeds do not alone determine the content they will see in the future, although they have a role to play. Likewise, the content delivered via a user's newsfeed from peers and content-producing organizations depends upon multiple factors. There is a dynamic, intersecting relationship between an individual's online behaviors, algorithmic inferences based on behavioral data, and the responses of other actors – advertisers, politicians, and news media organizations alike – who shape the stream of content available to be made visible.

Notes

1. These topics do not represent ads individuals have seen, but rather topics they may be interested in. Facebook does not provide any information about ad or newsfeed content exposure, but does provide information about ads users have interacted with previously in "Ads History" and in a list of "Advertisers you've interacted with."
2. The number of liked pages related to news and politics is highly correlated with the number of ad topics related to news and politics assigned to each user. However, the name of the actual pages liked and what is listed in the ad categories are often not the same — algorithmic translations occur frequently.
3. This assumption of control is implicit, suggested through the ways researchers measure selective exposure: the studies cited above and many others rely on measures of clicks, time spent reading, selecting articles they wish to read, listing sources commonly used, and engagement on articles. These measures are based on the premise that selection and exposure occur simultaneously, indicating that through their selection choices, individuals directly control their media exposure.

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No potential conflict of interest was reported by the authors.

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