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Exploring the effects of algorithm-driven news sources on political behavior and polarization

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ABSTRACT

Do algorithm-driven news sources have different effects on political behavior when compared to non-algorithmic news sources? Media companies compete for our scarce time and attention; one way they do this is by leveraging algorithms to select the most appealing content for each user. While algorithm-driven sites are increasingly popular sources of information, we know very little about the effects of algorithmically determined news at the individual level. The objective of this paper is to define and measure the effects of algorithmically generated news. We begin by developing a taxonomy of news delivery by distinguishing between two types of algorithmically generated news, socially driven and user-driven, and contrasting these with non-algorithmic news. We follow with an exploratory analysis of the effects of these news delivery modes on political behavior, specifically political participation and polarization. Using two nationally representative surveys, one of young adults and one of the general population, we find that getting news from sites that use socially driven or user-driven algorithms to generate content corresponds with higher levels of political participation, but that getting news from non-algorithmic sources does not. We also find that neither non-algorithmic nor algorithmically determined news contribute to higher levels of partisan polarization. This research helps identify important variation in the consequences of news consumption contingent on the mode of delivery.

1. Algorithms & news

According to a 2019 Pew Research Center survey, 57% of Americans report that they “often” get their news from a mobile device (Walker, 2019). This is true for all Americans but especially younger generations. Among 18 to 29-year-olds, 72% often go online via a mobile device for their news, suggesting this number will rise over time. Most Americans now clearly rely on online media for their news consumption. Yet, the political consequences of getting one’s news online and specifically the influence of algorithms in online news production remains underexplored. From YouTube to Google to Twitter, online news sources are often driven by complex algorithms, therefore more research is necessary to study their design and effects (Lazer, 2015). Furthermore, what these platforms present to users matters immensely to what information receives greater collective attention (Jürgens & Stark, 2017). While there may be notable differences between online platforms in terms of the information conveyed to users (Gillespie, 2010), ranking and recommendation algorithms represent the formulas by which these platforms determine what information to display to users. This paper

offers an exploratory analysis of the effects of various types of online algorithms on political behavior, specifically political participation and partisan polarization.

Online media algorithms often function on a broad set of variables including: time, content, age, location, knowledge of a user’s online history (and that of similar users), users’ cognitive attributes, users’ social attributes, users’ social networks, and the platform’s priorities (Cotter et al., 2017; DeVito, 2017; Hanani et al., 2001; Willson, 2014). A user’s social attributes and network are often a key factor for modern social media that drive these algorithms to filter information through a fundamentally social process (Willson, 2014). The broader interaction between algorithms and social forces may be so complex as to be near impossible to comprehensively understand (Bakshy et al., 2012) or reverse engineer in a meaningful way (Diakopoulos, 2015). While traditional, non-algorithmic media remain powerful in the news landscape, algorithms introduce a new layer of complexity to the effects of online news on everyday citizens and democratic values.

Algorithms have also fundamentally altered how journalists produce news. Where traditionally journalists and editors acted as gatekeepers

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between complex reality and the news conveyed to the public, algorithms and users themselves are now dominant forces in the gatekeeping process (Entman and Usher 2018; Pearson & Kosicki, 2017; Singer, 2014). The advent of algorithms and social media has shifted norms and routines of journalists, who now work to market their news to consumers (McGregor, 2019; Tandoc and Vos 2016).

Although previous studies have certainly analyzed the differential effects of news consumption via different platforms on users' political participation and polarization (e.g. Bakker & De Vreese, 2011; Hao et al., 2014), in this paper we seek to advance how we theoretically conceptualize and empirically approach the study of the effects of algorithmically-generated news, more precisely. We do so by offering a preliminary analysis of the consequences of algorithmically-generated news on political behavior. To begin, we distinguish between two types of algorithmically-generated news, *user-driven* and *socially driven*. User-driven algorithmic news is based on the past selections and assumed preferences of the individual user and has no known social network-related input. Socially driven algorithmic news, however, does consider the users' personal network when generating content for users resulting in information that is based on both the user as well as their network. These two types of algorithmically generated news stand in contrast to *non-algorithmic* news that is the same for every reader and viewer regardless of individual preferences or network influences.

We test the influence of user-driven, socially driven, and non-algorithmic news on political behavior using two secondary data sources, one a panel survey of young adults age 18–29, and the other a nationally representative cross-sectional survey of adults over 18. Taken together, the combined analysis offers an insightful, exploratory analysis of the influence of algorithmically generated news sources. We find that algorithm-based news sources predict higher rates of political engagement whereas non-algorithmic news sources do not. Specifically, people who report getting their news from user-driven or socially driven algorithmic sources have higher rates of *online* political participation. In the panel survey of younger adults, we find that user-driven algorithmic news leads to significant increase in *traditional* participation as well ($\beta = 0.24, p < 0.05$). Among the cross-sectional survey of adults, we see a positive and significant relationship between socially-driven algorithmic news and *traditional* political participation ($\beta = .10, p < 0.001$). Interestingly, we find that neither algorithm-driven news nor non-algorithmic news predict higher rates of reported political polarization. Overall, this study offers an initial look into the impact that algorithms have on the production and consumption of information as well as the political consequences of this innovation. This research is important in light of the opacity of many algorithms and the effects that these increasingly common online news platforms may have on political behavior. The results point to interesting variation in political engagement among news seekers depending on the platform by which they get their news.

2. Individual attention to news & algorithms

Most media outlets in the United States are privately held, profit seeking, and earn revenue from advertising or subscription (Bagdikian, 2004). Therefore, all private media need audience attention in order to survive and grow. However, the way in which media outlets seek attention and the level to which they cater are distinctive (Hamilton, 2004; Webster, 2016). To generate widespread attention, *non-algorithmic sources* such as magazines, TV, and radio generally tailor their content to appeal to a mass audience. In the case of the broadcast networks' nightly news, this is a large and diverse audience; while cable news audiences may be more ideologically directional, they still require mass appeal (Napoli, 2010). Algorithmic sources of information, however, use individual preferences in combination with social networks (*socially-driven algorithms*), or individual preferences alone (*user-driven algorithms*), to produce more finely tailored content to promote attention. We argue that the variety of content that is delivered to audience

members results from appealing to different audiences, and that this variation may yield important consequences for political behavior and polarization.

In the third quarter of 2019, Facebook generated \$17.4 billion in advertising revenue enabled by their algorithm's ability to harness the attention of their users (Facebook 2019b). Meanwhile, individuals themselves pay attention to media and news to meet their desired uses (Levy and Windahl 1984). However, it is important to recognize that what is attention grabbing for individuals may not be conducive to the maintenance of a healthy democracy (Bennett, 2012) especially when false or misleading information is promoted (see Tucker et al., 2018 for an overview), and may even have harmful social and political consequences (Tufekci, 2018).

Existing research into the types of news accessed online demonstrates that individuals tend to seek out and are attentive to news which meets certain social or emotional needs, is negative in nature, and which is most relevant to their interests (e.g. Bolsen & Leeper, 2013; Leung, 2013; Smith & Searles, 2014). Additionally, content which evokes strong positive or negative emotions like awe, anger, and anxiety are more likely to go viral (Bail, 2016; Berger & Milkman, 2012), and presumably be recommended by an algorithm. If we assume that algorithms are designed to maintain and increase attention, then the type of news that garners the most attention should be reflected in the type of news algorithms promote. For example, a mixed-method study of YouTube search results ranking concluded that the search function is highly reactive to attention cycles (Rieder et al., 2018).

Attention drives revenue at new media companies. Google employees state the goal of YouTube's efforts is to maximize users' "watch time" when describing the neural network-based recommender system running YouTube's algorithm (Covington et al., 2016). Moreover, the first slide of Facebook's first quarter 2019 earnings report does not report profit or revenue, but rather daily active users. For these companies that so heavily rely on attention for advertising revenue and data collection, capturing the attention of users is paramount to selling a product. Therefore, we believe it is reasonable to assume that online platforms create algorithms which aim to maximize user attention.

It is also well-documented that, when given a choice, individuals will pay more attention to negative news (Altheide, 1997; Soroka, 2014; Soroka et al., 2016; Soroka & Stephen McAdams, 2015; Trussler and Soroka 2014). Where traditional media is defined by the editorial decisions of what stories to run, online news allows users to act of their own volition. As a result, individuals seeking news online may be more likely to pay attention to negative news and those stories framed as horse races (Trussler and Soroka 2014). Similarly, Smith and Searles (2014) find that news coverage of candidates leads individuals to emphasize negative aspects of the opposition candidate rather than improving their assessments of their favored candidate. Humans tend to focus on the negative when consuming news. Therefore, we can expect algorithms to promote more negative news stories due to the increased attention they receive.

Individuals often choose to be an audience to news which ensures they are oriented to events most relevant to them (Weaver, 1980). Therefore, individuals have a tendency to pay the most attention to news that occurs in close proximity (Wise et al., 2009) and which relates to their various group and personal interests (Bolsen & Leeper, 2013; Rudat et al., 2014). Collectively these bits of human bias may encourage algorithms to display news to individuals which highlights their group affiliations, personal interests, proximal environment, and news that is emotional and negative in nature. As a result, because algorithms are proprietary information not shared with the public, we assume that media companies in general seek to maintain audience attention, and in the design of their algorithms, will prioritize the type of information outlined above in order to do so.

3. Algorithmically influenced news

In this study we examine three common and distinct sources of news information: *non-algorithmic news* that is the same for all consumers; *user-driven news* determined by an algorithm that takes into consideration a user's past clicks and preferences; and *socially driven news* determined by an algorithm that considers the user's network as well as their past behavior. In this section, we provide additional details on our conceptions of user-driven and socially driven algorithmic news.

3.1. User-driven algorithms

User-driven algorithms are unique compared to the more commonly researched social media algorithms as they emphasize the personal attributes and biases of citizens rather than their ties to other citizens, and how those other citizens mediate content. One example of a user-driven algorithm is YouTube, which explicitly only draws on user demographics, location, watch and search history to recommend videos (Covington, Adams and Sargin 2012). A lack of research into user-driven algorithms is especially surprising given the prevalence of online news services like MSN, Google and Yahoo News. Online news recommendation engines like automatically generated email lists, place greater focus on national and business news as well as opinion pieces (Thorson, 2008). When given a news recommendation based on what is "most-viewed," users choose to look at such stories significantly more often than those who are not exposed to the "most-viewed" news online (Yang, 2016).¹ News aggregation algorithms tend to deemphasize public affairs due to user preferences and encourage homogenization in headlines among media outlets (Boczkowski, 2010). Collectively, these pieces of research imply that individuals who use services based around user-driven algorithms will be more likely to see news that is seemingly popular, homogeneous across outlets, eschews public affairs, and emphasizes national and business news. Furthermore, these news stories may often not even be "news," but rather opinion pieces (Thorson, 2008).

Importantly, to maintain user attention, algorithms generate content based upon what the user clicked on in the past (Hanani et al., 2001; Willson, 2014), and this could lead user-based algorithms to display a much narrower set of topics and perspectives than users would otherwise be exposed to. User-driven algorithms allow for, explicitly or implicitly, the avoidance of political information for some while exposing other users to increasingly negative and attitudinally-reinforcing information (Prior, 2007; Stroud 2011).

3.2. Socially driven algorithms

Unlike user-driven algorithms, socially driven algorithms take into account users' personal online activity via social networking sites (SNS), as well as their ties to others in their network, to generate content for users. Facebook, for example, explicitly admits to using social connections in generating content recommendations – hence the "*Friend A and 30 other friends like this*" under so many posts (Kabiljo & Aleksandar Ilic, 2015). As a result, the content is a function of both the user as well as their network. The ideological diversity of viewed content, for example, largely depends upon the ideological characteristics of users' networks. If a user's network is more politically diverse, so too is the news the user will see (Park & Kaye, 2017). Twitter has a similar feature. Although there is the potential for political echo chambers to emerge on SNS (Bessi et al., 2016), growing evidence cautions against this alarm. For example, as people's online networks grow, their audience diversifies and is

¹ One could consider "most-viewed" to be a social effect, but in this case, we interpret "most viewed" as one tool algorithms have to approximate the quality and popularity of content. Mass viewership is not inherently tied to the social connectedness of a particular user.

increasingly composed of people from various relational contexts, such as friends, family, and co-workers (Bode, 2015; Child and Petronio, 2011, 2015). Additionally, more frequent users of SNS have more heterogeneous networks (Lee et al., 2014). Moreover, Beam (2014) finds that users elect to include counter-attitudinal content in their social media feeds, and studies show users engage with cross-attitudinal content, albeit perhaps uncivily (e.g. Conover et al., 2011). Given this audience diversification, users see and consume news and information shared by distant acquaintances they otherwise would not have seen (Bakshy et al., 2015; Messing & Westwood, 2014), a potential exposure that is less likely in a non-algorithmic news context, or when relying on search engines or news recommendation sites like Google or Apple News.

The social nature of SNS also facilitates social pressure and connectivity that are otherwise not experienced in news consumption and information seeking. Indeed, a motivating force behind social media use is the need to belong (Nadkarni & Hofmann, 2012) and social connection (Conroy et al., 2012; Ellison, Steinfeld, & Lampe, 2007). Another by-product of socially driven algorithms is that they expose SNS users to news they do not actively seek out (Feezell, 2017; Gil de Zúñiga, Weeks, & Ardevol-Abreu, 2017), including information with which they disagree also known as "cross cutting" information (Brundidge, 2010; Fletcher & Nielsen, 2017; Liang, 2018). Taken together, there is good reason to expect that socially driven algorithms will expose users to politically diverse content, which may lead to additional information seeking, mitigate polarization, and encourage further political engagement, online and offline.

4. Non-algorithmic news, algorithmic news, and political behavior

In this section, we theorize about the relationship between each of the three forms of news consumption and their effect on political behavior.

4.1. Non-algorithmic news

This study examines the influence of non-algorithmic and algorithmic news on political behavior, specifically political engagement and political polarization. We define "non-algorithmic news" as information that is accessed in a manner void of algorithmic influence and is therefore not tailored to individual-level characteristics. Therefore, physical or online copies of newspapers and news magazines, talk radio, broadcast news, and cable news would fit this criterion. Although non-algorithmic news consumption is declining, more people still indicate they get most of their news from television programs compared to any other news source, however it will be surpassed soon by online sources (Gottfried & Shearer, 2017). Despite concerns that developments in non-algorithmic news production, like economic pressure faced by media organizations, a growth in adversarial press (Norris, 2000), increased choice (e.g. Prior, 2005), and emphasis on conflict and ideological groups (McCluskey and Kim 2012) would lead to a decline in the quality of news and therefore contribute to less knowledgeable and participatory citizens, most research on the subject finds consuming news through these mediums has positive effects on knowledge and participation (Baumgartner and Morris 2010). In fact, regular consumers of news via newspapers, television, and radio are often the most informed (Druckman, 2005; Norris, 2000) and participatory (Bakker & De Vreese, 2011).

With respect to polarization, given that there is no evidence that evening newscasts on broadcast networks have grown more partisan (see Prior (2013) for review), even as they increasingly focus on conflict (e.g. McCluskey and Kim 2012) we do not expect non-algorithmic news consumption taken as a whole to contribute to individual level polarization. Although polarization has increased among the more politically engaged (Hetherington, 2009; Layman & Carsey, 2002), there is little

evidence that this is related to consumption of non-algorithmic news, as we define it. There is some evidence, however, that cable news consumption contributes to polarized audiences (Levendusky, 2013), but as Prior (2013) cautions, the impact of partisan cable news is largely mediated by preexisting attitudes and political sophistication. *Therefore, we anticipate that traditional non-algorithmic news use will be positively related to participation (H1) but should have no effect on political polarization.*²

4.2. User-driven algorithmic news

We define “user-driven algorithmic news” as news generated by an algorithm that takes into consideration a user’s past clicks and preferences. A broad meta-analysis of the effects of online news by Boulianne (2009) found that those who use the Internet for news participate more than they would otherwise. Given that user-driven algorithms should provide politically interested individuals with political news, individuals who make use of user-driven algorithms for their news should be more likely to participate politically as the steady flow of news maintains their interest. However, as this is likely to be attitude-consistent news and traditional media sources remain prevalent in online news (Maier, 2010), user-driven algorithms should encourage individuals to participate through traditional channels such as voting or letter writing. This is supported by early research into the relationship between Internet use and participation (prior to the rise of socially driven algorithms like Facebook), which find increases in participation because of Internet use (e.g. Boulianne, 2009; Kenski & Natalie Jomini Stroud, 2006).

User-driven algorithms respond to individual preferences but are likely to result in more negative news than if no choice were involved. In an experimental analysis of the demand side of news, Trussler and Soroka (2014) find that politically interested people prefer negative stories. Additionally, existing work shows that fear and anxiety are crucial motivators of turnout (Valentino et al., 2011). Because user-driven algorithms are likely to introduce and reinforce negative emotions toward the political environment, consumers of user-driven algorithms should be more likely to participate.

Given that user-driven algorithms have no direct incentive to provide users with counter-attitudinal information unless the user selects it, such algorithms should drive users to further extremes as they are more likely to share information that is consistent with the user’s predispositions. This is consistent with previous work, which demonstrates that increased selective exposure leads toward greater partisan polarization (Levendusky, 2013; Prior, 2007; Stroud 2010). However, in the absence of counter-attitudinal information provided through social connections, user-driven algorithms should lead individuals to be more polarized than their non-algorithmic or socially driven algorithmic brethren. *As a result, we expect that people who get their news from sources that employ user-driven algorithms will lead to higher levels of political participation and political polarization (H2).*

4.3. Socially driven algorithmic news

We define “socially driven algorithmic news” as news generated by an algorithm that takes into account users’ personal online activity via social networking sites (SNS), as well as their ties to others in their

network, to generate content for users. The news generated, and therefore consumed, via socially driven algorithms engages affordances of social media such as social pressure and increased connectivity and, similar to research on social media expressly, should be positively correlated with political participation (Bakker & De Vreese, 2011; Bennett & Segerberg, 2012; Bond et al., 2017; Valenzuela et al., 2018). For example, Bond et al. (2017) demonstrate how information that is packaged with a social message has distinct effects from information that is not packaged as social. They found reports of voting to be higher for individuals in this “social message” treatment, compared to the control, and the “information message” treatment, which did not disclose any voting information about users’ friends. This study is evidence that information consumed in social settings or perceived to have social implications will have unique effects on participation. Additionally, the exchange of information and facilitation of coordination should correlate with more collective action styles of participation and higher rates of civic engagement (Bakker & De Vreese, 2011; Bimber & Copeland, 2013; Kim et al., 2017; Jost et al., 2018; Valenzuela, 2013; Valenzuela et al., 2018). Moreover, Feezell and Jones (2019) find that youth who engage in political disagreement online report higher levels of online political participation. Therefore, the social aspect of social networking is found to largely spur political participation, both online and offline.

With respect to polarization effects, we consider whether news generated in this manner is attitude consistent or inconsistent. News and information generated by socially driven algorithms is likely to convey both attitude consistent and inconsistent (cross-cutting) information given the nature of users’ online networks (Bakshy et al., 2015; Lee et al., 2014; Liang, 2018; Messing & Westwood, 2014). Exposure to cross-cutting information can have consequences for polarization. Social endorsements present in socially shared news have the potential to overcome partisan selective exposure, which would perhaps minimize political polarization (Messing & Westwood, 2014). Exposure to cross-attitudinal information, however, has also been shown to encourage additional information gathering (Weeks et al., 2017), which yields information that is likely to be attitude reinforcing, as a response to identity threat and confirmation bias (Bessi et al., 2016; Mason, 2015). Indeed, when users stumble upon political information with which they disagree on SNS, Weeks et al. (2017) find that partisans will then seek out like-minded content to share, and therefore possibly contribute to individual level polarization. Additionally, Lee et al. (2014) find that people with diverse networks who engage in discussion have higher levels of polarization, with discussion being the key moderator. Moreover, Yardi and Boyd (2010) discover that discussion on Twitter around a divisive event led to discussion with both like-minded people, but also cross discussion (see also Conover et al., 2011). Deriving news from sources that use socially driven algorithms therefore leads to more diverse informational exposure, however it is not clear that this exposure without further discussion or additional information seeking should have a significant effect on polarization.

Taken together, we expect that news encountered through sources that use socially driven algorithms will lead to higher rates of political participation (H3), however because the information encountered through social media sites is often diverse, we do not expect it to have a positive effect on political polarization.

The three primary hypotheses and overarching theoretical model are illustrated in Fig. 1.

5. Data and methods

We conduct two separate analyses of our hypotheses using two secondary data sources. The first analysis is of a nationally representative sample of young adults (18–29) that allows for excellent measures and a panel design to assess change over time resulting from different news sources. The second analysis is a replication using a nationally representative sample and a pooled cross-sectional design; the replication

² Recognizing that cable news fits our definition of non-algorithmic news, but that it appeals to a niche audience that exists somewhere between a mass audience and a social network, we account for cable news specifically in our modeling using the data from Pew (see Appendix C). Model 3 shows that cable news is the only form of non-algorithmic media that is positively correlated with polarization. It is important to note, that these data are cross-sectional and therefore only show a correlation between cable news and polarization, one that is largely a function of preexisting preferences and beliefs (Prior, 2013).

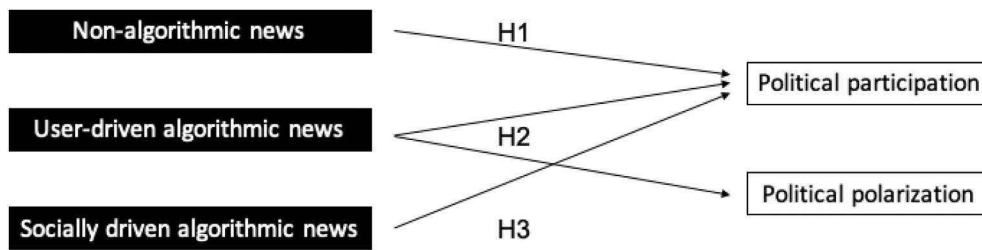


Fig. 1. Primary hypotheses.

lacks a true panel design but lends external validity to our previous findings by surveying a more representative adult sample.

We begin by testing these relationships and the extent to which non-algorithmic news differs from algorithm influenced news sources in predicting political behavior and polarization using the Youth Participatory Politics Survey (YPP) administered by GfK. The YPP survey is a nationally representative three-wave panel survey of young adults in the United States conducted between 2011 and 2015. The surveys were administered in both English and Spanish languages and include an over-sample of African Americans and Latinxs. This study uses waves 2 and 3 of the full panel. Wave 2 was surveyed from July–November 2013 (N = 2,343). Wave 3 was surveyed from June–November 2015 and retained 44% of the Wave 2 respondents (N = 1,033). The Wave 2–3 panel consists of 1,033 respondents age 18–29 years of age.³

Our theoretical assumptions and hypotheses are not specific to young adults, however young adults are an interesting sample in their own right because, while often overlooked in research on media effects, young adults might be more susceptible to the impact and enduring effects of media exposure. Much younger youth age 15–25 are in their “formative” political years where the opinions and behaviors developed during this period can mature into long-lasting patterns of political engagement (Jennings & Niemi, 1981; Niemi & Hepburn, 1995). Recent work has identified distinct news repertoires among youth that are correlated with higher levels of participatory behavior (Edgerly, Thorson, & Wells, 2018). Additionally, exposure to political information through social media, for example, can increase vote certainty among first-time voters (Ohme et al., 2018). While it is well established that it is important to cultivate healthy civic behaviors during one’s formative years, the role that media play in predicting the political behavior of youth in particular - and therefore their political trajectory - remains understudied.

5.1. Measures

We operationalize news sources according to three categories (See Appendix A for question wording). The first is *non-algorithmic news*, which is the same for every consumer and does not differ according to individual-level decisions or one’s network composition. Non-algorithmic news is measured by taking the average of four questions measuring the frequency of online or offline newspapers and magazines, TV, and radio use (Cronbach’s Alpha = .82). The second is *user-driven algorithmic news*, which presents different content to the consumer based on their past behavior on the site or current selections. User-driven algorithmic news is measured by taking the average of two questions that measure the frequency of getting news from a news portal like Google news or a Yahoo homepage or from blogs or YouTube (Cronbach’s Alpha = .62). The third category is *socially driven algorithmic news*, which offers idiosyncratic newsfeeds based on individual decisions constrained within a personal network. Socially driven algorithmic news is measured using one question about the frequency of getting news from

social networking sites like Facebook and Twitter. Table 1 presents the descriptive statistics for the independent, dependent, and control variables used in this analysis and Table 2 describes which media make up each of our primary independent variables.

Hypotheses 1-3 address both political participation and political polarization as outcome variables. In this study, we run an exploratory analysis on three distinct forms of political participation. The first is *traditional political participation*, which is a count variable of five different forms of participation to which the respondents indicated they did (1) or did not (0) participate in during the last 12 months summed together (Cronbach’s Alpha = .81). This variable includes forms of participation that are tied to a party or campaign such as donating money, working for a campaign, and attending a meeting. The second measure is *online political participation*, which describes political activity that takes place in an online setting. This variable is composed of six forms of online participation where frequency of participation is measured using a five-point scale of participation over the past 12 months (Cronbach’s Alpha = .93). These individual measures, which were averaged, include following politicians on Facebook or Twitter, commenting or Tweeting about a candidate or issue, and signing up to receive information from candidates or a campaign online. The third measure of political participation is *civic engagement*. This a count variable that includes seven dichotomous measures of political engagement that are less tethered to political campaigns, including boycotting, boycotting, participating in protests, and being active in a group that addresses political issues that are summed together (Cronbach’s Alpha = .78). (See Appendix A for question wording.)

We measure *political polarization* using an indicator of partisan bias that ranges from 0 to 100. This variable is calculated by taking the absolute value of the difference between two feeling thermometers (0–100) about the Democrat and Republican parties. A score of 100 indicates the highest level of partisan polarization, where a respondent favors one party (100) and dislikes the other (0); a low score indicates low levels of partisan polarization, where the difference between the two thermometer scores is smaller.

We include several control variables in order to better isolate the influence of the independent variables we are interested in. Because people tend to become more participatory as they grow older, we restrict

Table 1
Descriptive statistics for YPP data.

Variable	Min.	Max.	Mean	SD	N
Age	18	29	23.66	3.51	909
White	0	1	0.34	0.47	909
Female	0	1	0.55	0.5	909
Household Income	1	19	10.78	4.88	885
Education	1	4	2.93	0.86	908
Traditional Political Participation	0	5	0.27	0.83	893
Online Political Participation	1	5	1.44	0.82	890
Civic Engagement	0	7	0.78	1.4	885
Political Polarization (absolute value)	0	100	35.62	31.02	1019
Political Interest	1	4	2.26	0.88	889
Non-algorithmic News	1	8	2.38	1.62	888
User Algorithm News	1	8	2.14	1.62	889
Social Algorithm News	1	8	2.74	2.18	890

³ Additional details on the YPP survey can be found in Kahne and Bowyer (2018).

Table 2
News sources YPP data.

Non-algorithmic News	TV or radio news; print newspaper or magazines (accessed in hard copy and digitally via internet or cell phone)
User-Driven Algorithmic News	Portal news website (Google News) or news aggregator (Yahoo), blogs or YouTube
Socially Driven Algorithmic News	Twitter or Facebook posts

our analysis to all subjects 18 years of age or older at the time of Wave 3 and control for age in the models. We also include control variables for race and gender to measure the influence of these factors on political engagement and polarization. Studies show that those with higher socioeconomic status are also more participatory (Thorson et al., 2018; Verba, Schlozman, and Brady 1995), as a result we include control variables for household income and the respondent's level of education. We control for political interest using a 4-point measure of agreement with the statement "I am interested in political issues."

Last, given that these data are collected from a panel, which surveys the same people over time, we can observe within-subject change over time by controlling for prior levels of the dependent variable (Bartels, 2006). Therefore, all models presented in this paper include lagged dependent variables from T1 (Wave 2) when predicting the outcome variable at T2 (Wave 3).

6. Results

Table 3 presents the findings from four models predicting three forms of political participation and political polarization. The results are also plotted in Fig. 2. The models predicting traditional political participation and civic engagement use Poisson analysis to account for the count nature of the dependent variables. The models predicting online political participation and partisan polarization use OLS regression analysis. H1 proposed that non-algorithmic news would lead to higher levels of political participation among consumers but would not have an effect on political polarization. The findings in Table 3 indicate that non-algorithmic news does not have a significant impact on any of the forms of political participation measured here or political polarization. This finding is somewhat surprising given the established literature that links news consumption to political engagement, however these results indicate that non-algorithmic news does not have a positive effect among young adults today who may be more accustomed to digital and interactive news sources (e.g. Hao et al., 2014; c. f.; Bakker & De Vreese, 2011). In summary, H1 is not supported as non-algorithmic media fail to predict both political participation and polarization in this study.

H2 proposes that people who encounter news through sites that employ user-driven algorithms will have higher rates of political participation and political polarization. This is expected because user-driven algorithms, though proprietary and opaque, use previous user decisions to determine future media provision in an effort to reinforce and maintain the attention of the user. Our findings here are somewhat mixed. User-driven algorithm sources positively predict traditional and online political participation, but we fail to reject the null hypothesis for civic engagement and political polarization. We conclude that news generated by user-driven algorithms successfully predicts political participation, in both the traditional and online forms, but does not impact the partisan polarization of the consumers. While we expected that the consumption of like-minded content produced by user-driven algorithms would reinforce partisanship, and therefore increase polarization, we did not find this to be the case. One limitation of our study exposed here is that while we assume user-driven algorithms generate politically consistent information, we cannot measure this with our survey. Alternatively, this finding may lend support for the thesis that exposure to diverse political views (which are less likely to be generated

by user-driven algorithms) is a mechanism for retreat into individuals' existing political beliefs, and therefore leads to more extreme viewpoints (e.g. Lee et al., 2014). But this is potentially inconsistent with our argument that exposure to different points of view on SNS might mitigate partisan polarization. These two hypotheses can coexist, as SNS allow for discussion, and "when coupled with more frequent discussions, the exposure to heterogeneous networks enhance awareness of rationales for both oppositional and congenial positions," and therefore discussion plays an important conditioning role in this relationship (Lee et al., 2014, p. 708).

Finally, H3 states that people who consume news from socially driven algorithms will have higher levels of political participation but not polarization. H3 is supported in the findings reported in Table 3 for online political participation and civic engagement only. However, getting news from socially driven algorithmic sources does not predict higher levels of traditional political participation. As expected, assumed to be due largely to the diversity of information shared socially, socially driven algorithmic news does not predict increased political polarization. As noted above, discussion may moderate this relationship (e.g. Lee et al., 2014).

Overall, these findings suggest that getting news from sources that use algorithms, user-driven or socially driven, leads to an increase in some forms of political participation among those 18–29, but does not contribute to increased political polarization. Getting news from non-algorithmic sources that do not consider user characteristics or social factors when determining their content, however, do not predict higher rates of political participation. Additionally, none of our independent variables predicts political polarization, or liking one political party over the other.

7. Replication of results

Are the reviewed results simply a consequence of a young sample? Additionally, the questionable inclusion of blogs with YouTube in our measure for user-driven algorithms may be influencing the measure's effect on our outcome variables. To ascertain whether the findings hold with a nationally representative sample and without a measure of blog usage alongside YouTube access, we make use of the Pew Research Center's *American Trends Panel*. Drawing on waves 14, 16, 19 and 23 of the panel, we create a pooled cross-sectional dataset ($N = 1734$) capable of replicating most of the analysis performed on the YPP panel. Taking place between January 2016 and August 2017, these waves ask relevant questions concerning news consumption habits, political participation, and polarization.

To recreate our independent variables, we make use of two questions asked in wave 14 of the *American Trends Panel*. To operationalize *non-algorithmic news*, we create a variable which is the summation of the frequency of use of cable news, national TV news, local TV news, print newspapers, and radio news. To operationalize *user-driven news*, we use a question asking respondents if they use YouTube to get news – algorithm driven news compilation sites such as Google or Yahoo News were unfortunately not addressed in the survey. Finally, to operationalize *socially driven news* we create a variable which is the summation of using Facebook, Twitter, LinkedIn, Instagram, Vine, Tumblr and Snapchat for news (descriptive statistics can be found in Appendix B).

Turning to our dependent variables, to operationalize *traditional participation* we create an index variable using a question which offered respondents dichotomous options for whether they had attended a rally, volunteered for a campaign, displayed a button, sign or worn clothing related to a political campaign, contacted an elected official, contributed money to a candidate, or are a member of an organization which attempts to influence public policy or government (Cronbach's Alpha = 0.72). To measure *online political participation*, we make an index from two relevant questions (Cronbach's Alpha = 0.75). The first asked respondents if posted links to political articles, posted their own thoughts or comments on politics, or reposted content from someone else. In

Table 3
Multivariate analysis at T2 of respondents 18 and older (YPP data).

	Traditional Political Participation	Online Political Participation	Civic Engagement	Partisan Polarization
Non-Algorithmic News	0.12 (0.09)	0.03 (0.03)	0.03 (0.08)	0.63 (1.08)
User-Driven News	0.24** (0.10)	0.07** (0.03)	0.09 (0.07)	0.49 (1.08)
Social-Driven News	0.01 (0.05)	0.07*** (0.02)	0.11*** (0.04)	0.12 (0.64)
Age	-0.07** (0.03)	-0.00 (0.01)	-0.05*** (0.02)	0.07 (0.39)
White	-0.01 (0.27)	-0.01 (0.08)	0.17 (0.16)	1.4 (2.17)
Female	0.31 (0.23)	-0.07 (0.06)	0.11 (0.14)	3.22 (2.64)
Household Income	-0.05** (0.02)	-0.01 (0.01)	-0.02 (0.01)	-0.15 (0.35)
Education	0.42** (0.11)	-0.02 (-0.04)	0.19** (0.08)	-3.18 (2.35)
Political Interest	0.46*** (0.21)	0.09** (0.04)	0.27*** (0.10)	1.19 (9.50)
Traditional Pol. Participation (T1)	0.52*** (0.06)			
Online Pol. Participation (T1)		0.24*** (0.06)		
Civic Engagement (T1)			0.27*** (0.03)	
Partisan Bias (T1)				0.54*** (0.04)
Constant	-3.28*** (0.82)	0.69*** (0.22)	-1.30** (0.55)	17.7 (9.50)
Observations	813	808	793	810
R-squared		0.324		0.30
Wald Chi-squared	372.68		366.47	

Notes: Robust standard errors in parentheses; ***p < 0.01, **p < 0.05, *p < 0.1.

addition, we use a question which asked respondents whether they follow any candidates or political figures on social media. These two questions, with all responses summed, result in our online participation index. Due to a lack of relevant survey questions, civic engagement is not replicated in this analysis. Finally, *political polarization* is again measured by taking the absolute value of the difference between a feeling thermometer concerning the Republican party and one concerning the Democratic party.

As with the previous analysis, controls are included for age, race, sex, income, formal education and political interest. Unlike the previous analysis using YPP data, we cannot include a lagged dependent variables in the analysis. While Pew continues to complete additional survey waves for their American Trends Panel, they substantively altered their media use questions too much in 2018—the most recently available year of data—for us to include them in this analysis. As such, our analysis of the ATP data is a pooled cross-sectional analysis and does not include lagged dependent variables.

The results of the second analysis are available in Table 4. As traditional and online political participation are count variables, the first two models represent Poisson regression models. Political polarization is specified using a standard linear regression model, with all models using robust standard errors. The results of this analysis are largely reflective of the previous YPP results. Non-algorithmic news use is not a significant predictor of traditional political participation or political polarization, an identical result to our YPP analysis. Non-algorithmic news is, however, a significant predictor of *less* online political participation among this sample. This change may be due to the introduction of older generations to the analysis. User driven news remains a significant predictor of online political participation, but no is longer a significant predictor of traditional political participation. Curiously, user-driven news still fails to predict political polarization. Socially driven news continues to be a significant and positive predictor of online participation, but also predicts increased traditional participation among the more

representative sample.⁴

8. Discussion

In this paper we seek to define and understand the role that algorithms play in influencing political behavior and attitudes, specifically participation and polarization. However, news generated by algorithms has arguably lacked some conceptual clarity. Therefore, we begin by defining three primary ways in which people consume news today: through non-algorithmic news sources, through user-driven algorithmically generated sources, and through socially driven algorithmically generated sources. We describe each source and how the various inputs for each source should be expected to impact political behavior at the individual level, by relying on insights from previous scholarship. To assess the behavioral consequences of these three news sources, we conduct an exploratory analysis and find that getting news from sites that use socially driven or user-driven algorithms to generate content corresponds with higher levels of political participation - especially online - but that getting news from non-algorithmic sources does not. We also find that neither non-algorithmic nor algorithmically generated news contribute to higher levels of partisan polarization. Given that algorithmically generated news is trained in part by individual-level media selectivity, we suggest there is something unique to this mode that influences political participation. However, we also find that the type of algorithm employed yields important variation in the expression of political behaviors.

Unlike previous work that differentiates between news seekers and

⁴ Because partisan polarization and cable news consumption are highly correlated, we disaggregated the non-algorithmic news variable to examine each source of news specifically. The table in Appendix C reports these results and shows that cable news is a positive and significant predictor of polarization.

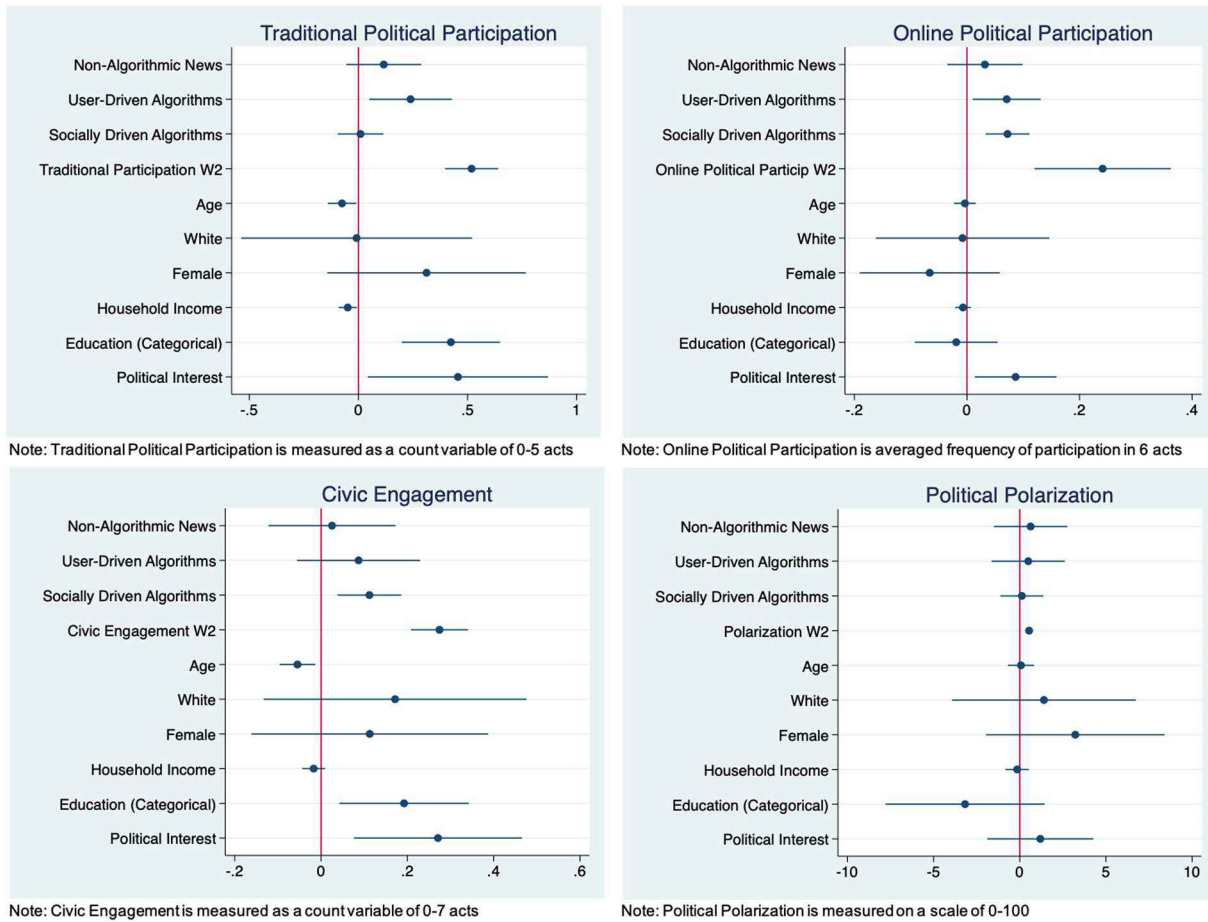


Fig. 2. Coefficient plots of multivariate analysis of respondents 18 and older (YPP data).

Table 4
Multivariate analysis of Pew American trends panel.

	Traditional Political Participation	Online Political Participation	Political Polarization
Non-algorithmic News	0.0367 (0.0487)	-0.0972* (0.0387)	0.0375 (1.204)
User Driven News	-0.00907 (0.0576)	0.186*** (0.0402)	-1.048 (1.457)
Socially Driven News	0.101*** (0.0272)	0.491*** (0.0243)	0.0792 (0.705)
Age	0.135*** (0.0354)	-0.00526 (0.0275)	3.440*** (0.872)
White	0.0324 (0.0838)	-0.0718 (0.0588)	-0.779 (1.952)
Female	0.0588 (0.0588)	0.0543 (0.0482)	1.361 (1.509)
Family Income	0.0196 (0.0144)	-0.0214* (0.0107)	0.378 (0.342)
College Graduate	0.295*** (0.0661)	-0.0222 (0.0506)	2.298 (1.592)
Political Interest	0.626*** (0.0498)	0.432*** (0.0359)	9.195*** (1.009)
Constant	-3.043*** (0.225)	-2.187*** (0.173)	-4.186 (4.542)
Observations	1734	1734	1734
R2	0.096	0.15	0.089

Notes: Robust standard errors in parentheses; *p < 0.05, **p < 0.01, ***p < 0.001.

news avoiders (Delli Carpini & Keeter, 1996; Prior, 2013), or new versus old media (Bakker & De Vreese, 2011; Hao et al., 2014) this study focuses on the variation within news seekers according to their news delivery mode, by drawing conceptual distinctions between algorithmically generated news, (e.g. Edgerly, Vraga, et al., 2018; Saldaña et al., 2015; Smith & Searles, 2013). Using two nationally representative datasets we find that using news sources that employ user-driven algorithms to determine their content leads to higher levels of traditional and online political participation. We suspect that this is because users are presented with a greater proportion of stories that appeal to their interests based on their preferences indicated via previous selectivity. User-based algorithms tend to produce more homogenous collections of stories than non-algorithmic media (Boczkowski, 2010), which may make it cognitively easier for a user to approach and interact with this platform, but could limit the breadth of their story exposure and potentially restrict the knowledge base they bring with them into higher rates of political participation.

We also find that attending to news sources that use socially driven algorithms leads to higher levels of online political participation and civic engagement, but not traditional political participation. For the most part, this finding is as expected as information encountered on social media sites is often shared by people we know and trust making us more likely to read it and act on it within the online environment (Anspach, 2017). Socially shared news also encourages the exchange of information, discussion (Lee et al., 2014), and facilitates coordination, making collective action and civic engagement easier and more common (e.g. Bimber & Copeland, 2013; de Zuniga et al., 2016; Jost et al., 2018; Valenzuela, 2013). We are surprised, however, to find that news from socially driven algorithmic sites does not lead to higher levels of traditional political participation. Previous research finds that there are

certain messages conveyed through social media sites that can increase voting (Bond et al., 2017), but general exposure to news generated by socially driven algorithms does not have the same effect.

Surprisingly, we find that people who use non-algorithmic sources of news, which present the same content to all consumers, does not lead to higher levels of traditional or online participation or civic engagement. This finding suggests to us that it is important to exercise caution when making general statements about the strong tie between traditional news consumption and political engagement because it does not always convey.

Finally, we do not find that any of our media sources predict increased political polarization. The impetus of this paper came from an opinion piece written by Zeynep Tufekci titled “You Tube: The Great Radicalizer” (Tufekci 2018) in which she describes her slow descent on YouTube from videos about Donald Trump to auto-play suggestions for videos that contain white supremacist content. It struck us that algorithms may be behind some of the political discord and partisan affect that we see today. This resonated with our scholarly guts and we expected to find a strong relationship between user-driven algorithmic news and partisan polarization. But we do not. Neither non-algorithmic news nor either conception of algorithmic news we assess predict higher levels of partisan polarization in this study. This finding suggests to us that partisan polarization is likely driven by other established phenomenon such as general dislike of the parties (Klar & Krupnikov, 2016; Klar et al., 2018), increasing affective polarization (Iyengar et al., 2012), or general partisan extremity (Abramowitz, 2010) – phenomenon that media may play an indirect, but perhaps not a direct, role in. Media platforms, especially social media platforms, can certainly facilitate these phenomena such as dislike or negative partisanship, but may not, on their own, be the source of polarizing beliefs.

Of note, consistent across the first and second analysis, we find that algorithmically generated news (user-driven and socially driven) is a strong predictor of higher rates of online political participation. While there is slight variation among the other results, this relationship is persistent; those who consume algorithmically generated news are more likely to be politically participatory online. As algorithmically generated news sources are likely to continue to grow in popularity given the sheer abundance of information, this could also continue to grow rates of online engagement; While that is significant on its own, this may also have positive downstream effects on other more traditional forms of political engagement (Bode, 2017; Boulianne and Theocharis 2020; Lane et al., 2017; de Zuniga, Barnidge and Scherman 2016).

In sum, algorithms – the engines of our online lives – remain largely black boxes. This paper explores one potential dimension along which we might expect algorithms to differ – in their inputs – and explores whether these different types of algorithms relate to different political behaviors and beliefs. While we make informed assumptions regarding the intention of these algorithms, reverse engineering to determine exactly what the creators aim to promote is nearly impossible to do because it involves so many individual, social, and random variables (Diakopoulos, 2015; Rieder et al., 2018). An alternative approach is to analyze the output of algorithms across platforms, or content analysis, to study general trends to see how they compare (see Munger & Phillips, 2020, for example). Future research is needed to understand whether the stated goals of their creators match the content provided to users. We operate on the basis that algorithms above all are designed to maintain user attention, however perhaps media have other intentions in mind. While algorithms are proprietary and highly protected, interviews and qualitative research might be informative here. Additional exploration is also needed to understand whether algorithms emphasize human biases as we expect, and whether certain differences in individual personalities and tendencies lead algorithms to have differential effects. Panel surveys designed with both comprehensive media usage and psychological batteries would allow for initial exploration of these interactions.

Finally, this study relies on the combination of two slightly imperfect survey datasets to test our hypotheses. The YPP dataset is a panel design

with excellent measures of our variables of interest allowing us to observe individual level change over time. However, the YPP sample is of young adults age 18–29 and this limits generalizability to older age groups. Therefore, as a robustness test and to increase generalizability of our findings, we replicate the analysis using the Pew American Trends Panel, which is a nationally representative survey of adults. This dataset allows for a broader sample but lacks a true panel for the measures we are interested in, resulting in a pooled cross-section lacking a longitudinal analysis. The findings from our initial analysis of the YPP dataset were replicated using the Pew ATP data, however, the analysis would have ideally been run on one nationally representative sample of adults. Alternatively, an experimental design would be beneficial allowing for better isolation of the independent variables.

Credit author statement

Jessica T. Feezell: Conceptualization, Methodology, Formal analysis, Writing, Visualization, Project administration. John K. Wagner: Conceptualization, Methodology, Formal analysis, Writing. Meredith Conroy: Conceptualization, Methodology, Writing.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chb.2020.106626>.

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