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Anatomy of audience duplication networks: How individual characteristics differentially contribute to fragmentation in news consumption and trust

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Abstract

While partisan selective exposure could drive audience fragmentation, other individual factors might also differentiate news diets. This study applies a method that disentangles the differential contributions of the individual characteristics to audience duplication networks. By analyzing a nationally representative survey about US adults' media use in 2019 ($N=12{,}043$), we demonstrate that news fragmentation is driven by a myriad of individual factors, such as gender, race, and religiosity. Partisanship is still an important driver. We also distinguish between media exposure and media trust, showing that many cross-cutting ties in co-exposure networks disappear when media trust is considered. We conclude that audience fragmentation research should extend beyond ideological selectivity and additionally investigate how and why other individual-level preferences differentially contribute to fragmentation both in news exposure and in news trust.

Keywords

Audience duplication, cross-cutting exposure, fragmentation, network analysis, news consumption, news trust

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Whether news audiences are increasingly fragmented is a key debate in media research (Mitchelstein and Boczkowski, 2010). While some are concerned about "echo chambers"—that audience members are segregated into like-minded clusters—empirical studies offer mixed support. An accumulating amount of research suggests that audience fragmentation might be exaggerated. Individuals online are exposed to a diversity of news outlets that spread across the political spectrum (Bakshy et al., 2015; Dvir-Gvirsman et al., 2016), and media outlets often share substantial audience overlap (Fletcher and Nielsen, 2017). Yet, in experimental settings, audience members tend to select news from like-minded news outlets (Iyengar and Hahn, 2009; Mukerjee & Yang, 2020). On social media, media messages are more likely to diffuse within ideological in-groups (Barberá et al., 2015; Brady et al., 2017).

Yet, while scholars often argue that individuals' ideological selectivity in news diets leads to a fragmentation in the media landscape, relatively fewer studies have directly examined how much ideological selectivity could explain the overall audience fragmentation. Other individual characteristics, such as socioeconomic status, also shape news diets and lead to news consumption divides (Prior, 2005; Shehata and Strömbäck, 2011). Therefore, even if researchers observe fragmentation in the media landscape, it is difficult to attribute it solely to ideology-based selectivity or to contextualize the influence of partisan selectivity. How segregations along various individual characteristics together shape audience fragmentation remains a critical but underexplored question.

Prior research has frequently looked at the fragmentation of news exposure (e.g. Dvir-Gvirsman et al., 2016; Fletcher and Nielsen, 2017). Yet, even if news consumers share similar news diets, they do not necessarily hold similar interpretations of the same information, let alone find common ground and cultivate shared beliefs. Here we consider the role of trust and make a distinction between exposure-based audience fragmentation (whether audience members are exposed to a largely similar set of outlets) and trust-based fragmentation (whether audience members trust a similar collection of outlets). We propose that the level of fragmentation also depends on how individuals engage with media outlets, and individual characteristics should distinctly shape these two types of fragmentation.

To address these gaps, we conduct secondary data analysis of survey data from the American Trends Panel (ATP), a nationally representative panel of US adults, which includes people's use of and trust in a variety of outlets. We apply a method to identify the contributions of individual characteristics, measured at the individual level, to the extent of fragmentation in news consumption or news trust captured by audience duplication networks. We reveal the key differences between exposure-based and trust-based audience duplication networks and demonstrate that the level of fragmentation in these two types of networks is driven by a broad range of individual factors beyond political affiliations. We then discuss the implications of our conclusions in conversation with previous researchers in audience fragmentation, selective exposure, and media trust.

A generalized research framework of fragmentation in news consumption

This study aims to highlight a generalized research framework of news fragmentation, which goes beyond examining exposure and beyond investigating the role of political ideology in shaping fragmentation dynamics. Here, we adopt the broad definition of audience fragmentation as "dissolution over time of audience news exposure, public affairs knowledge, and political beliefs into smaller units in a society" (Tewksbury and Rittenberg, 2012: 120). We choose this definition because we believe that it especially relates to concerns raised by normative theories. Scholars worry that audience fragmentation could undermine democratic citizenship. For example, Sunstein (2017) argues that a healthy democracy requires citizens to be exposed to a diverse pool of information and unplanned experiences, which constitute the base of public forum and deliberation and also function as the social glue promoting social interaction and fellowship, which is crucial to social cohesion. Here, exposure is a means—a precondition to forge shared experiences and a common information pool among the public—rather than an end in itself. Moreover, any social division, not limited to the one along partisan lines, could prevent us from reaching this ideal democratic image. These ideas urge us to extend the previous research framework on news fragmentation in two ways.

First, prior research has mostly looked at fragmentation in news exposure. Some scholars have defined fragmentation as "a process by which the mass audience, which was once concentrated on three or four viewing options, becomes more widely distributed" (Webster, 2005: 367). However, news materials usually serve multiple needs and functions, and people do not necessarily refer to the news media they are exposed to for learning political information (Tsfati and Cappella, 2005). Moreover, due to biased processing and motivated reasoning, people do not necessarily develop similar interpretations of the same information. Cross-cutting exposure sometimes backfires and pulls people toward the more extreme ends (Bail et al., 2018; but see Guess and Coppock, 2018). Exposure to a counter-attitudinal media message might also elicit more negative evaluations of the message source and skepticism toward news media in general (Arceneaux et al., 2012). Therefore, co-exposure alone could not guarantee the formation of shared beliefs and common experiences among citizens. It is imperative to also examine news fragmentation regarding people's media engagement.

In this study, we pay particular attention to the role of trust, an important factor that shapes the effects of news exposure (Tsfati, 2003). We believe this factor is relevant to the political information one gains and collectively shared experiences the public could have. Trust in a message source shapes how people process and engage with content from that source. Research on persuasion shows that perceived source credibility and trustworthiness lead to a more favorable evaluation of the information and subsequent attitudinal change (Wallace et al., 2019). Individuals evaluate information from ideologically in-group sources as stronger than information from opposing sources (Druckman et al., 2013). In the current media landscape, media brands alone can function as ideological cues and lead individuals to evaluate content as politically slanted (Baum and Gussin, 2008; Turner, 2007). Thus, fragmentation among citizens regarding their trust in news might indicate a more dangerous signal of the lack of common ground gluing the society together.

Furthermore, news trust itself plays other essential roles in democracy, while trust-based fragmentation signals its dysfunction. Democracy requires informed citizens. It is usually the mainstream news outlets pursuing objective journalism that convey necessary and accurate political information to the public. Trust-based fragmentation, if driven by a group of citizens shifting trust from mainstream outlets to alternative sources that usually do not stick to editorial processes that ensure the credibility of information, might suggest that a significant portion of the public is vulnerable to misinformation (Ladd, 2012). A related point is that distrust of these mainstream outlets also makes people reluctant to learn policy outcomes, but they tend rather to pursue partisan positions to form beliefs, which hinders the media from functioning as a "watchdog" to hold politicians accountable for their policymaking (Ladd, 2012).

Besides calling for a generalized research agenda of fragmentation beyond exposure, we also expand the scope of factors that we consider to explain fragmentation beyond political ideologies. Assuming political position as an important driver of audience fragmentation, some scholars have defined fragmentation as "a situation where people increasingly use media they only share with small groups of like-minded individuals" (Fletcher and Nielsen, 2017: 476), and many empirical studies have examined selective exposure to partisan media outlets (Iyengar and Hahn, 2009; Stroud, 2008). However, society could be split along dimensions other than political ideologies. Other kinds of division could also undermine the formation of shared experience and hinder deliberative democracy, with inclusiveness as a key element (Young, 2002). This condition applies to people with various kinds of identities, backgrounds, and characteristics, not limited to partisanship. Therefore, the second extension of the research framework on news fragmentation asks us to examine how other characteristics, along with political affiliations, collectively shape news fragmentation.

From individuals' media preferences to audience fragmentation

We then moved on to the analytical tools employed for studying the questions related to these two extensions. One increasingly popular way to analyze fragmentation is to adopt an audience-centric approach to construct audience duplication (or overlap) networks (Dvir-Gvirsman et al., 2016; Fletcher and Nielsen, 2017; Lee and Zhang, 2019; Mukerjee et al., 2018; Taneja and Webster, 2016; Webster and Ksiazek, 2012; Yang et al., 2020). In an audience duplication network, two media outlets are connected if they share substantial overlap in their readerships—determined by various thresholding methods (Fletcher and Nielsen, 2017; Mukerjee et al., 2018). By analyzing the characteristics of the audience duplication network, researchers can investigate how fragmented the news audiences are. With this method, some conclude that there is substantial audience duplication with no clear evidence for fragmentation (Dvir-Gvirsman et al., 2016; Fletcher and Nielsen, 2017). Researchers can also compare the level of fragmentation across networks in different contexts, such as countries and channels (Fletcher and Nielsen, 2017).

One challenge in this line of research is to establish the link between selectivity based on individual characteristics and the fragmentation of news audiences in audience duplication networks. Previous research often assumes that fragmentation and the formation of echo chambers should be primarily driven by ideological selectivity. Yet, many other individual factors, such as gender and socioeconomic status—which we will elaborate on in the next section—also differentiate media outlets (Knobloch-Westerwick and Alter, 2007; Mitchelstein and Boczkowski, 2010; Prior, 2013). There lacks a way for us to identify how individual factors explain the fragmentation in audience duplication networks, making it difficult to attribute the source of fragmentation solely to ideological preferences or to contextualize the influence of ideological selectivity by comparing it with other forces.

Moreover, audience fragmentation is driven by a combination of individual and structural factors. Webster (2011) posits that the allocation of public attention is shaped by the duality between agents (i.e. media users) and structures that include "a wide array of macrolevel constructs such as language, routines of work and leisure, technologies, and institutions" (p. 47). In the context of partisan selectivity, with news consumers selectively attending to outlets that share their ideological positions, this ideology-driven fragmentation still cannot happen without a myriad of partisan media outlets that differentiate themselves on the political spectrum. Some scholars have investigated the sources of fragmentation by considering the characteristics of media outlets, showing that the political divide is not the only source of fragmentation (Lee and Zhang, 2019). In this approach, scholars determine the similarity between a pair of outlets regarding various characteristics—for example, if two outlets use the same language—and investigate how the similarities of media outlets regarding various outlet characteristics together predict audience overlap. Lee and Zhang (2019) analyzed survey data in Hong Kong and showed that audience overlap was likely to happen between two media outlets that were similar regarding audience size, political distance, market orientation, and language. Taneja and Webster (2016) analyzed global traffic to websites and showed that websites were more likely to share audiences if they shared proximity in language, geography, and genre.

This study applies a method that measures the similarity between two media outlets regarding several individual characteristics, thus connecting individual-level characteristics and overall fragmentation in audience duplication networks. This approach is inspired by prior research that employed audience characteristics to quantify the attributes of media outlets. One prominent example is to use the aggregated political outlook of outlets' audiences to measure media bias and position media outlets on the ideological spectrum (e.g. Bakshy et al., 2015). Researchers can thus estimate the ideological difference between two media outlets and investigate whether the similarity in outlets' political affiliations explains the variance in audience duplication networks (Lee and Zhang, 2019). Similarly, we extend this approach to investigate whether media outlets are attracting audience members that share similar demographic and political dispositions (see section "Method"). Our approach does not capture solely individual characteristics or outlet characteristics but the correspondence between the two. Thus, we are able to investigate how media preferences, driven by various individual factors, together contribute to a fragmentation in audience duplication.

Fragmentation beyond ideological selectivity

We first examine a pool of individual factors that are potential candidates to explain audience fragmentation. In addition to political ideology and partisanship, we also consider the following variables: political engagement, education, income, gender, age, race/ethnicity, and religiosity. The selection of these variables was largely motivated by previous studies of news consumption, selective exposure, and media repertoires. These three lines of research are based on the notion that in a high-choice media environment, individuals often have to cope with the abundance of media options by creating subsets of media content to consume. Studies of news consumption provide descriptions on which factors predict the use of news media or consumption across different channels, outlets, and topics (e.g. Lee and Chyi, 2014; Shehata and Strömbäck, 2011; Tewksbury, 2005). The scholarship on selective exposure, largely based on psychological theories, examines how people with different backgrounds select certain kinds of media content to satisfy particular motivations (e.g. Dvir-Gvirsman et al., 2016; Knobloch-Westerwick and Alter, 2007). Research of media repertoires investigates the comprehensive patterns of media usage, or media repertoires (Hasebrink and Popp, 2006), and characterizes the dynamics that affect the choice among different repertoires (e.g. Hasebrink and Popp, 2006; Taneja et al., 2012; Van Rees and Van Eijck, 2003). These studies suggest that demographic factors (such as gender, age, religiosity, income, and education) and political dispositions could predict the use of different media diets.

First, individual dispositions to politics should influence news consumption. In previous research, political interest has frequently predicted higher news consumption (Shehata and Strömbäck, 2011). Variables related to political sophistication, such as political interest and knowledge, are often correlated to different patterns of news exposure across media channels such as the Internet, newspapers, and television (Lee and Yang, 2014).

News consumption is also linked to socioeconomic variables such as education and income. Socioeconomic status predicts not only a higher level of attentiveness to news but also the use of different channels to get news (Lee and Chyi, 2014; Viswanath and Finnegan Jr, 1996). For example, education is often positively associated with consuming news from newspapers but negatively related to television news consumption (Shehata and Strömbäck, 2011). An analysis of UK data showed that "social grade"—a measure of socioeconomic status based on occupation—is associated with a higher average number of media sources used, in both online and offline settings (Kalogeropoulos and Nielsen, 2018). Moreover, certain outlets (e.g. The Guardian) were more popular among higher social grade respondents, whereas other outlets (e.g. The Sun) attracted more low social grade viewers (Kalogeropoulos and Nielsen, 2018). There is also a research tradition that associates socioeconomic status with preferences for cultural products (Bourdieu, 1984). Lindell (2018) showed that in Sweden, individuals' cultural and economic capitals differentiate the news outlets and topics people read.

Other demographic variables such as gender, age, race, and religiosity also differentiate news diets. News outlets are often characterized by a distinct audience profile that differs in gender, age, education, income, and race/ethnicity (Reis et al., 2017; Tewksbury, 2005). Demographic variables have also been linked to attention to different news topics. Prior research suggests that men tend to follow news on politics, sports, business, and science/technology, while women report more interest in health and community-related news (Knobloch-Westerwick and Alter, 2007; Reis et al., 2017). An analysis of news articles shared on Twitter showed that Whites shared more news about health and technology, whereas Asians and African Americans shared more news about sports and arts (Reis et al., 2017). Religiosity might also play a role. While religiosity should be closely related to political conservatism, some research has also shown that religiosity additionally predicts ideological selective exposure beyond political leanings (Dvir-Gvirsman et al., 2016). Finally, several studies on media repertoires also support that demographic variables, including age, gender, and religiosity, could predict one's media repertoires (Hasebrink and Popp, 2006; Taneja et al., 2012; Van Rees and Van Eijck, 2003). As these factors explain how people select different media subsets, we believe they also have potential in shaping fragmentation.

Fragmentation beyond partisan media

As noted previously, fragmentation in news consumption should be driven by the correspondence between individual and outlet characteristics. Regarding ideological segregation, prior research has shown that partisan media outlets publish content that favors one particular political party or candidate over others, and they attract audience members of certain political affiliations (Bakshy et al., 2015; Peng, 2018). However, beyond their political leanings, media outlets might differ in other attributes that correspond to certain audience characteristics, thus contributing to fragmentation.

One example is the distinction between hard news and soft news. Previous research has used various criteria to define this division, such as timeliness, news production, and news style, with news topic being the most frequently mentioned criterion (Reinemann et al., 2011). Topics like domestic and international politics, economy, and science and technology are often regarded as hard news, whereas sports, entertainment, and celebrities are seen as soft news (Curran et al., 2010; Lehman-Wilzig and Seletzky, 2010; Reinemann et al., 2011). One should expect that hard news outlets should attract more political junkies who show higher political interest and political knowledge than audiences of soft news outlets. Some scholars have approached hard versus soft news from a news reception perspective and found that hard and soft news audiences differ in various characteristics, such as education, gender, and political knowledge (Baum, 2003; Prior, 2003; Reinemann et al., 2011).

Media outlets also differ in other dimensions that might attract different segments of the news audience. A concept relevant to hard/soft news is the division between the elite press and the popular press (Lee and Zhang, 2019; Lehman-Wilzig and Seletzky, 2010). Similarly, the elite and popular press differ not only regarding news production but also regarding audience characteristics. The elite press tends to attract a relatively limited set of the audience—elites and opinion leaders who have high socioeconomic status, whereas the popular press addresses a much broader audience (Lehman-Wilzig and Seletzky, 2010). In addition, legacy media brands, which rely on both online and offline readerships, and born-digital media, which primarily publish through online channels, might also attract audiences of different demographic characteristics. One study of five European countries showed that consumers who used legacy brands more than born-digital media tended to be male and have higher education and income (Vara-Miguel, 2020).

To summarize, various individual characteristics differentiate news diets and potentially contribute to news fragmentation. This differentiation happens in terms of not only the overall news consumption but also the types of news topics, information channels, media outlets, and media repertoire people attend to (Knobloch-Westerwick and Alter, 2007; Reis et al., 2017; Tewksbury, 2005). Furthermore, media outlets also differentiate themselves beyond political affiliations and aim to appeal to audience groups that vary among other dimensions (Lee and Zhang, 2019; Reinemann et al., 2011). The potential correspondence between individual and structural factors again supports our claim that it is crucial to study the source of fragmentation beyond ideological selectivity. We propose the first research question as follows:

> *RQ1*. Fragmentation in audience overlap networks might be driven by political affiliation, political engagement, age, gender, race/ethnicity, education, income, and religiosity. Among these factors, which characteristics contribute to fragmentation when controlling for each other?

Fragmentation beyond news exposure: the role of trust

As noted earlier, this study also extends the analysis of audience fragmentation to incorporate news trust. Here we make a distinction between exposure-based audience fragmentation and trust-based fragmentation. We should expect differences between co-exposure and co-trust networks. First, previous studies often reveal that exposure-based audience duplication is not substantially fragmented (Dvir-Gvirsman et al., 2016; Fletcher and Nielsen, 2017; Mukerjee et al., 2018; Webster and Ksiazek, 2012). This is likely due to the fact that individuals still encounter a few extremely popular media outlets in their information environments. Prior research has also shown that partisans on opposite ends of the political spectrum often share substantial overlap in their media diets that include sources from multiple sides (Dvir-Gvirsman et al., 2016; Eady et al., 2019). Yet, many individuals expose themselves to media sources they do not trust (Tsfati and Cappella, 2005). Even if individuals happen to be exposed to news from the other side, it is unlikely that they will trust the information to the extent that they trust their like-minded sources. Therefore, we expect that many cross-cutting ties in co-exposure networks should disappear in co-trust networks. On the contrary, ties in co-trust networks may not show up in co-exposure networks. News consumers may resort to various media attributes, such as readership size, journalistic ethics, and content focus, to evaluate the credibility of news sources (Knudsen and Johannesson, 2019). Research also shows that people across the political spectrum rated mainstream outlets as more trustworthy than hyper-partisan ones (Pennycook and Rand, 2019). Therefore, we propose the following research question:

> *RQ2*. What are the differences between trust-based audience duplication networks and exposure-based audience duplication networks?

This study also investigates the drivers of fragmentation in co-trust networks. First, political affiliations should be a primary driver of media trust. In the United States, conservatives/Republicans often express more distrust of the mainstream media and report trust in fewer media sources than liberals/Democrats (Jones, 2004; Lee, 2005; Mitchell et al., 2014; Verma et al., 2018). Also, trust signals a positive, affiliative relationship with a source, which should be relevant to attitudinal consistency. Liberals and conservatives often trust a different set of media outlets (Mitchell et al., 2014). It is less clear whether other individual characteristics should also contribute to the fragmentation of trust-based audience duplication. A few demographic variables, such as age, gender, and education, might be related to trust in online information sources (Verma et al., 2018). We propose the following research question:

> *RQ3*. Among the individual characteristics proposed in RQ1, which factors contribute to a fragmentation in news trust when controlling for each other?

Method

Data

We used one wave of survey data from the ATP, a nationally representative panel maintained by the Pew Research Center, conducted between 29 October and 11 November 2019 (N = 12,043). We referred to this dataset as ATP2019. A detailed description of ATP's sampling and recruitment procedures can be found on its website.[1]

Measures

In ATP2019, respondents were first shown a list of outlets and asked to "click on all of the sources that you have HEARD OF, regardless of whether you use them or not." Then respondents were presented with the list of outlets they had heard of and were instructed to choose sources they had gotten political and election news from in the past week (media use) as well as sources they generally trust for news about government and politics (media trust). We excluded news aggregators from our analysis. Thirty outlets were included in ATP2019 (see Supplemental Appendix B). These outlets were then used to construct co-exposure and co-trust networks.

In ATP2019, survey respondents provided their political ideology, partisanship, political engagement, education, income, gender, age, race/ethnicity, and religiosity. The specific measurements for political engagement and religiosity can be found in Supplemental Appendix B.

Network construction

Co-exposure and co-trust networks. We built a co-exposure audience duplication network and a co-trust network. Each node represented an outlet. Each edge denoted the number of duplicated audiences who used (co-exposure) or trusted (co-trust) both outlets. We dichotomized the networks after removing edges resulting from random noise using a dyadic thresholding technique (Mukerjee et al., 2018).[2] Only the unweighted version of networks was used in the following analyses.

Audience similarity networks. If one individual characteristic explains audience fragmentation, then each pair of outlets with similar audiences regarding this characteristic should have a significant amount of duplicated audience. We generated a series of characteristic-based audience similarity networks, in which each node represented an outlet and each edge corresponded to the similarity between two outlets regarding one individual characteristic. In particular, we first divided each characteristic into several groups or levels. For each outlet, we calculated the number of audience members falling into each group of this characteristic. Next, using chi-square tests,[3] we determined whether the audience compositions between each pair of outlets were similar regarding this characteristic and connected the two outlets if they indeed shared a similar audience breakdown (Figure 1). Using this procedure, we generated a series of *exposure similarity networks* and *trust similarity networks* for co-exposure and co-trust relationships, respectively. As our method relies on chi-square tests, we represented individual characteristics as categorical variables with a limited number of groups.[4]

Analytical strategy

To explain how different individual preferences accounted for audience fragmentation, we regressed the edges in the audience duplication (co-exposure or co-trust) networks on the edges from various audience similarity networks (exposure-based or trust-based). As the edges of one network could not be deemed independent observations, we adopted quadratic assignment procedures (QAPs), which have been frequently used in prior research (Guo, 2012; Lee and Zhang, 2019; Riles et al., 2018). We used logistic regression QAP (LRQAP) since our dependent variables are binary. As the network size in our study was relatively small, we might encounter the issue of complete separation.[5] Therefore, we used a penalized likelihood estimation method, Firth bias-correction (Firth, 1995). All the variance inflation factors (VIFs) in our specifications were smaller than five (Gareth et al., 2013; Vittinghoff et al., 2011). The coefficient was theoretically meaningful only when it had a positive value,[6] as our research assumes that the more similar the audiences of two media outlets are regarding one individual characteristic, the more likely these two outlets will share an edge in the audience duplication network. Therefore, the regression analysis used one-tailed p-values.

Results

Network descriptive analysis

To answer RQ2, Table 1 presents the descriptive statistics for co-exposure and co-trust networks (Luke, 2015). At first glance, we did not detect a clear pattern of fragmentation-level difference between the two networks. Specifically, the co-exposure network was slightly denser than the co-trust network, while the latter had a higher value of transitivity, which revealed that the co-trust network was more likely to contain tightly connected communities.

Figure 2 presents the co-exposure and co-trust networks. We examined the discrepancies between co-exposure and co-trust networks. The co-exposure and co-trust networks shared 288 edges. The vast majority of edges that appeared in the co-exposure network but not in the co-trust network ($N=33$) were links between conservative sites and liberal or relatively neutral sites, such as The Daily Caller–The New York Times, Fox

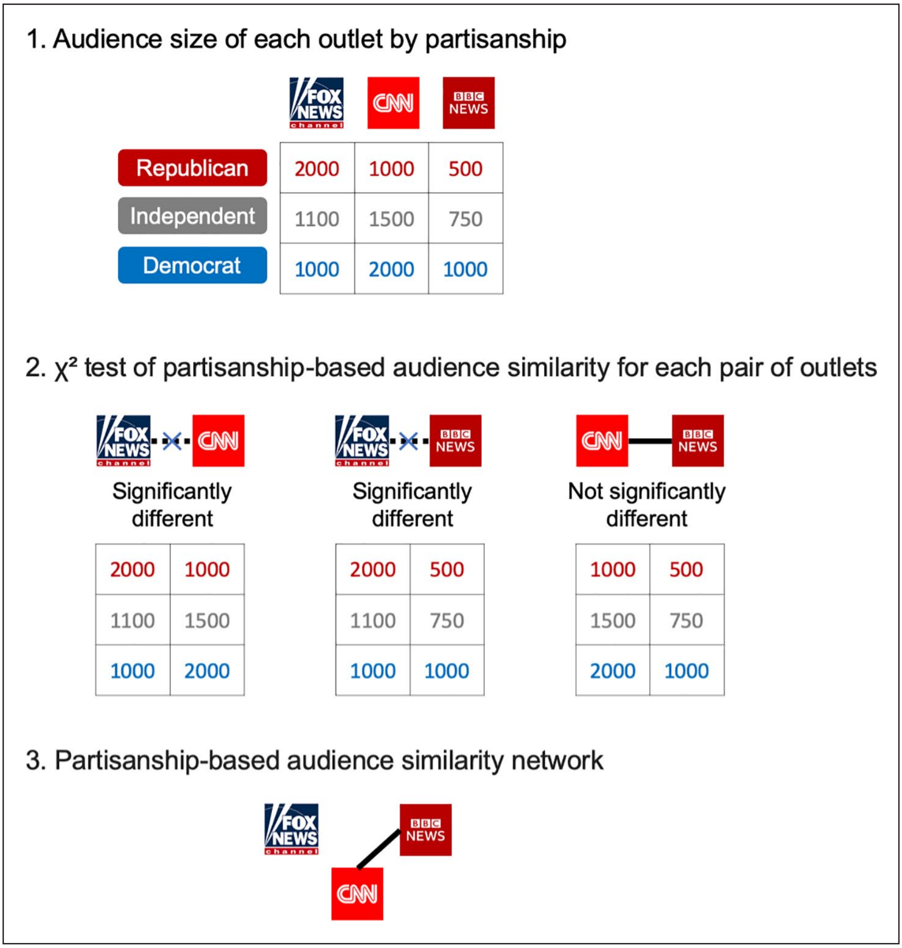


Figure 1. The construction of audience similarity networks, using partisanship as an example. Numbers are for illustration purposes and do not represent percentages in our dataset.

News–ABC, and Breitbait–Politico. In comparison, the majority of edges that only appeared in the co-trust network (N=21) were links between Univision, a Spanish-language television network, and other outlets, which could be due to the fact that people might trust Univision but not consume it due to a language barrier. These differences suggested that the two networks might be shaped by distinct sets of factors, which were formally tested in the following section.

Table 3 visualizes several audience similarity networks based on co-exposure/co-trust relationships (for network descriptive statistics, see Supplemental Appendix C), which reveal different relationships among media outlets based on different individual characteristics. In the partisanship-based exposure similarity network, media outlets are segregated into three political tribes. Conservative sites such as Breitbart, The

Table 1. Network descriptive statistics.

Network	Node	Edge	Components	Density	Diameter	Transitivity
Co-exposure	30	321	1	0.738	3	0.903
Co-trust	30	309	1	0.710	3	0.931

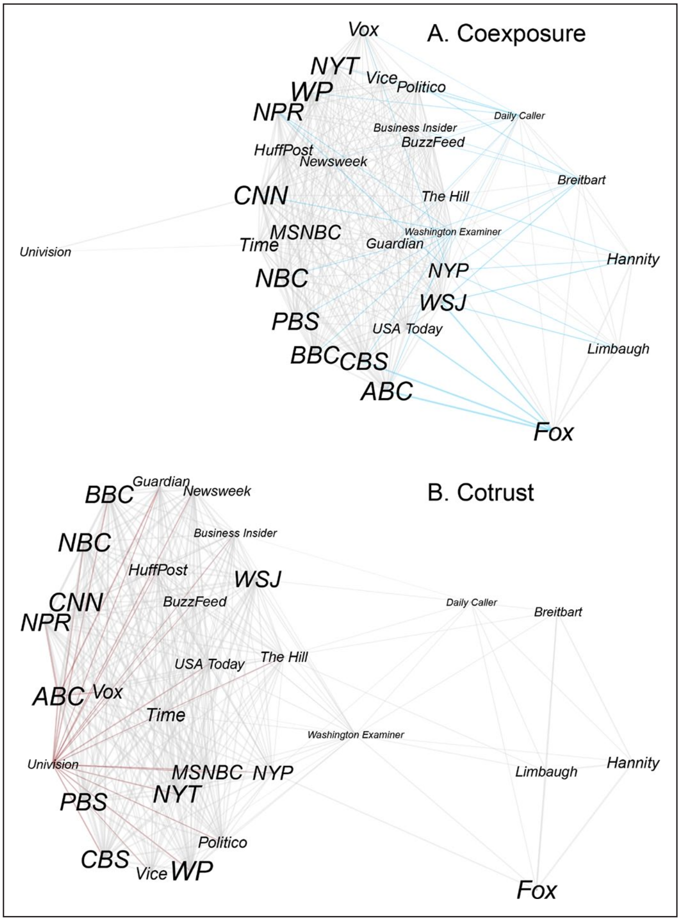


Figure 2. Co-exposure and co-trust networks: (a) co-exposure and (b) co-trust.
The size of the labels and the width of the edges are proportional to the sizes of the audience. The blue edges in (a) and the red edges in (b) only appear in the co-exposure and co-trust network, respectively. The gray edges appear in both networks.

Daily Caller, and Fox News formed two small components, whereas liberal sites and relatively neutral sites formed one large component. Within this large component, liberal sites like The New York Times and Huffington Post and relatively neutral sites like USA Today were on the opposite ends. In the exposure similarity network based on

Table 2. Predicting co-exposure and co-trust networks using audience similarity networks.

	Co-exposure	Co-trust
Intercept	−1.323	−0.870
Political engagement	0.040	0.581*
Political ideology	−0.175	0.734†
Partisanship	4.266***	3.176***
Education	0.295	0.222
Income	−0.435	−0.416
Gender	1.174***	0.425†
Age	0.140	1.737**
Race	1.710***	0.419
Hispanic	1.108*	0.644†
Religiosity	1.850**	2.038**

All p-values were one-sided and calculated based on 1000 permutations using LRQAP.
†$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

political engagement, mainstream television networks such as NBC and Fox are on one side, whereas niche media outlets that extensively publish political content, such as Politico and The Hill, are on the other side. In the age-based exposure similarity network, born-digital sites such as BuzzFeed and Vox are located on one component, whereas television platforms such as PBS and CBS are on another. Two conservative talk radio shows, The Rush Limbaugh Show and The Sean Hannity Show, form a separate component. These patterns provide initial evidence that individual characteristics differentially segment media outlets and together contribute to a fragmentation in news consumption.

Predicting co-exposure and co-trust networks

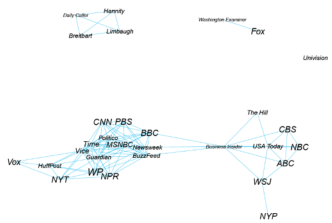
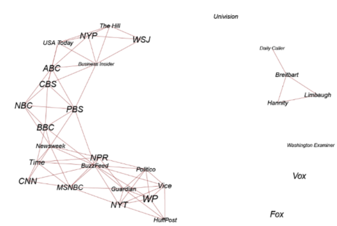
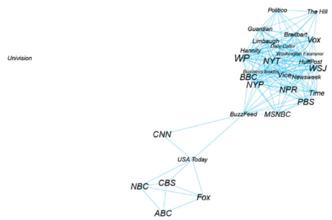
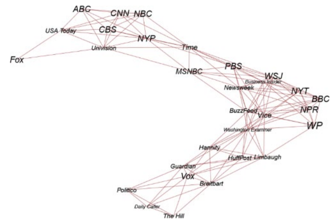
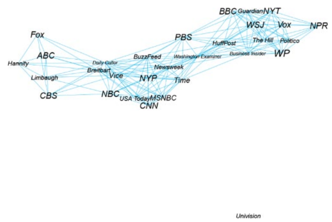
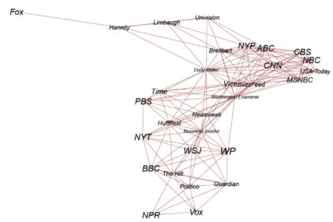
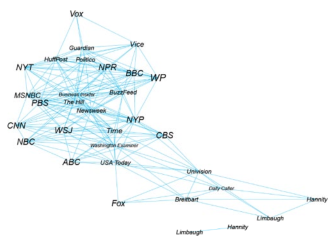
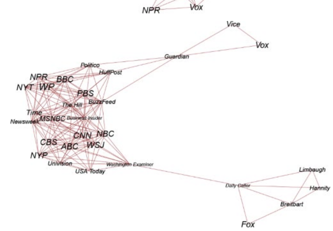
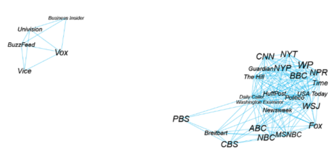
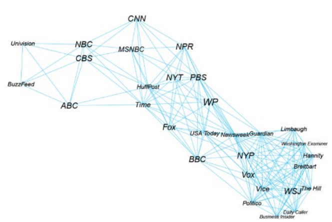
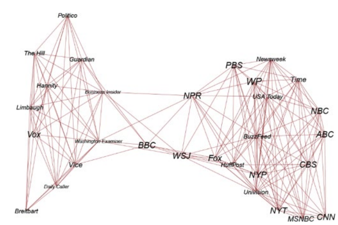
Regarding RQ1, we ran an LRQAP to predict the co-exposure network using exposure-based audience similarity networks (Table 2). First, partisanship contributed to fragmentation in the co-exposure network ($p < .001$). Unexpectedly, we did not find significant evidence for the roles of political engagement, education, age, and income. Nevertheless, a myriad of factors, including gender ($p < .001$), race ($p < .001$), ethnicity ($p = .017$), and religiosity ($p = .001$), significantly predicted the co-exposure network.

We ran another LRQAP to examine how various trust-based audience similarity networks predicted co-trust networks (RQ3, Table 6). First, partisanship ($p < .001$), again, predicted the co-trust network. Race/ethnicity, education, income, and gender did not show significant effects. Still, there were an array of factors that predicted the co-trust network, including political engagement ($p = .026$), age ($p = .001$), and religiosity ($p = .001$).

Robustness

We conducted two robustness tests. First, we tested whether our results remained the same with another wave of survey data in the ATP ($N = 2901$) in 2014. Our analysis

Table 3. Examples of characteristic-based audience similarity networks.

	Co-exposure	Co-trust
Partisanship		
Political engagement		
Education		
Religiosity		
Age		
Gender		

revealed qualitatively similar results.[7] Moreover, we repeated all our analyses but changed the *p*-value threshold to .01 when we constructed the networks (see Supplemental Table D1). While most findings remained the same, there were some changes: for the co-exposure network, political ideology became a significant predictor. For the co-trust network, the effects of race and gender became significant, while the effect of political engagement became just marginally significant.

Discussion

To summarize, this study makes three contributions. Theoretically, we highlight a generalized research framework of fragmentation in news consumption. In particular, inspired by normative theories, we argue that trust-based fragmentation is another important type of fragmentation, and factors other than political ideologies, including demographic variables and political dispositions, could also shape both types of news fragmentation. Empirically, we show that multiple factors collectively contribute to fragmentation, such as gender and religiosity, with partisanship still being a key factor. We also distinguish between co-exposure and co-trust networks, showing that these two types of networks reveal different relationships among media outlets and are predicted by somewhat different sets of individual factors. Finally, this study makes a methodological contribution by detailing a technique that tracks the unique contributions of individual-level segregation to fragmentation in audience duplication networks, which could be applied in future research.

Drivers of audience fragmentation in news consumption

Our results show that audience fragmentation is driven by a myriad of factors, including partisanship. Prior research on audience fragmentation has demonstrated that most audiences still gravitate toward a few major outlets that dominate the media landscape, and audience duplication networks do not show clear signs of ideological segregation (Dvir-Gvirsman et al., 2016; Fletcher and Nielsen, 2017). Such patterns are sometimes interpreted as a lack of support for partisan selective exposure or ideological echo chambers. Our conclusions do not necessarily contradict this narrative but highlight that it is necessary to adopt a comparative lens when we evaluate the contribution of partisan selective exposure. Compared with a wide range of potential drivers, partisan selectivity is consistently an important predictor that could account for audience fragmentation, which suggests its prominent role in shaping news consumption.

This study reveals several factors that have been less examined in prior research on fragmentation but should deserve scholars' attention. Religiosity, for instance, predicted fragmentation both in co-exposure and in co-trust networks, additively beyond the influence of political affiliations. Prior research often views political ideology as a two-dimensional structure that includes economic and social dimensions (Jost et al., 2009). One possible explanation is that religiosity is often related to the social dimension of ideology, and certain media outlets might primarily target audiences emphasizing cultural issues. Future research can examine whether different components of ideology differentially drive partisan selectivity and audience fragmentation. Unexpectedly, we did not see the influence of socioeconomic status measured by education and income, which contrasts with previous studies (e.g. Lindell, 2018). Instead, demographic variables such as gender and race play a more important role in shaping audience fragmentation. It is possible that the effects of socioeconomic status are eclipsed by other factors when we consider them together. Finally, we show that exposure- and trust-based fragmentation could be explained by somewhat different sets of factors: for example, age significantly predicts co-trust networks, while its effect is insignificant in models predicting co-exposure networks. This suggests that we should differentiate news exposure and news trust, which will be discussed in the next section.

Differentiating news exposure and news trust

This study distinguishes co-exposure and co-trust networks and argues for the importance of considering how audience members engage with news media in fragmentation research. Previous research has documented a lack of fragmentation in the media landscape, which might imply that the echo chamber in news exposure is less of a worrisome issue. However, the analysis of news trust reveals a somewhat different picture. In our results, many cross-cutting exposure ties that connect audiences from ideologically opposite sides disappear in co-trust networks, suggesting that people are not trusting the same set of information sources. For example, Fox News was connected to a few popular outlets such as ABC and USA Today in co-exposure networks, but almost exclusively linked to other conservative sites in co-trust networks (Figure 2). Echoing this observation, the regression analysis reveals that partisanship is still a key driver of fragmentation in news trust. The potential partisan divide in news trust should warrant scholars' future attention. Certainly, exposure is an important precondition for creating shared experiences and finding common ground. Yet, our conclusions pose additional questions about whether cross-cutting exposure alone is enough to facilitate these processes, as audience members do not necessarily trust information from the other side.

There could be some other social implications of trust-based fragmentation. Importantly, there seemed to be a divide between mainstream media and alternative, hyper-partisan (usually conservative) outlets such as The Daily Caller, BreitBart, The Sean Hannity Show, and The Rush Limbaugh Show. This echoes previous research showing a declining trust in mainstream media, particularly among the conservative segment of the public (Jones, 2004; Lee, 2005; Mitchell et al., 2014). While mainstream news outlets are often bounded by journalistic ethics and aim to provide fact-based political information to the public, previous research has found that these alternative outlets, such as The Daily Caller and BreitBart, frequently disseminate misinformation and conspiracy theories (e.g. Grinberg et al., 2019; Guo and Vargo, 2020). Such a fragmentation in news trust could suggest that a segment of the public is more vulnerable to misinformation, which could undermine our democracy that requires citizens to be factually informed about political affairs. Besides, in addition to providing accurate and objective coverage of public affairs, mainstream or quality media outlets also need to fulfill other democratic roles, such as preventing the abuse of power in politics and other parts of society (Strömbäck, 2005). Such a function could also be hampered if a segment of the public perceives the mainstream media as untrustworthy and is hostile to their coverage.

Limitations and future research

Due to the nature of secondary data analysis, we had to rely on existing items, which might not capture well the concepts in this study. Future research might use better measures of variables such as political engagement and religiosity.

This study focuses on the United States, an outlier in terms of the level of cross-platform news audience polarization (Fletcher et al., 2020) and partisan divide on news trust (Newman et al., 2019: 21), which might prevent us from generalizing our findings to other contexts. This limitation leaves space for future studies applying our approach in different countries. Nevertheless, besides political positions, multiple factors still pose additional effects explaining audience fragmentation in this hyper-partisan context. This fact should lead us to expect that in other countries with a lower level of political polarization, factors other than political ideologies, which were understudied in previous studies on audience fragmentation, might play greater roles in shaping co-exposure and co-trust dynamics.

The use of self-reported survey data provides both advantages and limitations for our study. In surveys, individuals may not accurately recall their news consumption (Prior, 2013). Respondents also had to select answers from a limited pool of media outlets, leaving out small media outlets that might collectively play an essential role in people's media diets. Nevertheless, the use of survey data allowed us to examine the roles of a wide range of individual characteristics, which are typically not available in digital trace data. The data also allowed us to compare exposure-based and trust-based audience duplication networks. Furthermore, digital trace data often involve website or mobile logs but do not typically track people's use of traditional media. Using survey data, this study can analyze news consumption across different platforms and channels. Acknowledging both the limitations and advantages of our datasets, we call for future research to combine survey and digital trace data to replicate, challenge, and improve our conclusions.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. See https://www.pewresearch.org/methods/u-s-survey-research/american-trends-panel/
2. As each network has about 30 nodes, we conducted about 500 statistical tests to determine the significance of audience overlap for each edge. We thus applied Bonferroni's correction with a threshold of 0.0001 (0.05/500). We additionally presented results using the conventional threshold of 0.01 in the Supplemental Material.
3. We used the same *p*-value threshold as that for generating co-exposure and co-trust networks.
4. For more details, see section 2 in Supplemental Appendix B.
5. Complete separation means that in logistic regression, for certain combinations of predictors, if we could perfectly predict the outcome, the model could not provide sensible estimates on coefficients and standard errors for these predictors. In our case, when one value of an independent variable associated with only one outcome of the dependent variable, logistic regression provided a large standard error as well as a large coefficient. The direct interpretation (a nonsignificant effect) based on this result was meaningless.
6. If a coefficient is negative, the model suggests that the more two outlets' audiences differ regarding a particular characteristic, the more audience overlap these two outlets have. This interpretation could not fit into this article's theoretical framework because we focus on how segregations based on different factors account for audience duplication. Therefore, we decide to only focus on positive values for this study.
7. Except for political engagement and race, all significant results persisted.

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