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Networks and Selective Avoidance: How Social Media Networks Influence Unfriending and Other Avoidance Behaviors

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Abstract

From time to time, some social media users avoid content posted by specific people in their networks. Most research on such selective avoidance has focused on individual motivations and other psychological factors rather than on social network characteristics, and there is a need for a systematic analysis of the relationships between individuals' social media networks and selective avoidance. This study fills that gap in the literature, drawing on theory about egocentric or personal publics. We test our predictions using data from three surveys of adults in the United States, collected just before each of the last three major national elections. Results are discussed in light of theory about the role of media technology in shaping political communication and scholarly discourse about how selective avoidance affects information flows.

Keywords

unfriending, selective avoidance, social media, social networks, political discussion

From time to time, some social media users avoid content posted by specific people in their networks, and social media platforms provide a variety of ways in which people may do so. These options include relatively permanent actions such as unfriending or blocking social contacts (Bode, 2016; John & Dvir-Gvirsman, 2015; Yang et al., 2017), as well as less permanent strategies such as hiding individuals from their news feeds (Yang et al., 2017) or avoiding political discussion with those individuals (Peacock, 2019; Wells et al., 2017). Engaging in these kinds of

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selective avoidance behaviors may have the desired outcome of reducing the amount of content users see from specific people, which could have positive effects on their psychological well-being (John & Gal, 2018) and aid the creation of "safe spaces" for political expression (Zhu & Skoric, 2021). Avoidance may also reshape the broader flows of news and political content that comes across a user's feed, as social networks play a large role in determining what content people see on social media platforms (Thorson et al., 2021).

To this point, most scholarship has focused on predictors of selective avoidance including individuals' motivations, preferences, and other psychological factors (John & Dvir-Gvirsman, 2015; John & Gal, 2018; Neubaum et al., 2021), as well as outcomes such as political participation and expression (e.g., Kim et al., 2021; Zhu et al., 2017). While some research has examined individuals' social media networks as predictors (John & Dvir-Gvirsman, 2015; Yang et al., 2017; Zhu et al., 2017; Zhu & Skoric, 2021), and other work has examined the antecedent role of cross-cutting discussion or discussion with weak ties (Skoric et al., 2018, 2021; Yang et al., 2017), most prior studies do not place central focus on the role of social or discussion network structures, and the work that has been done has examined only one or two aspects of social media networks. Thus, there is a need in the literature to establish a systematic set of results from a broad-base of evidence about the relationships between network characteristics and selective avoidance. This study addresses that need by foregrounding the role of social media network structures in predicting selective avoidance.

The study also makes a theoretical contribution to the literature by developing a framework for understanding the relationships between network structures and selective avoidance. We draw from extant theory about egocentric or personal publics (John & Gal, 2018; Rojas, 2015) to develop hypotheses about how social networks shape not only content exposure, but also individuals' responses to it. We test our predictions using data from three surveys of adults in the United States, collected just before each of the last three major national elections in that country: the 2016 Presidential Election, the 2018 Midterm Elections, and the 2020 Presidential Election. Results are discussed in light of theory about the role of media technology in shaping political communication, as well as scholarly discourse about how selective avoidance affects information flows and improves mental well-being.

Egocentric Publics

Recognizing that the affordances of social media platforms have enabled individuals to restructure the ways in which they engage with public life in democratic societies, Rojas (2015) offered the term *egocentric publics* as a metaphor for reconceptualizing how individuals interact with the public sphere via social media platforms. The idea asserts that individuals perceive, rightly or wrongly, that they are at the center of a social network that is developed over the course of their lives, and this positionality shapes individuals' "perceptions of the worlds around [them]" (p. 93). The concept builds on older notions of personal community (Fischer, 1982; Wellman, 1979), which de-emphasize the importance of shared geographic space for community in favor of the resources embedded in a network of personal ties. The egocentric publics approach shares this emphasis on personal networks, but it places its primary focus on communication over other resources, and it problematizes the role of individual perspective within the network. Arguing that social networks are meso-level social structures that link individuals with the broader society around them, Rojas (2015) asserts that they act as information filters for "system-level" information, embedding information from broader communication infrastructures within a "robust interpretive framework provided by our social networks" that "enhance [s] the importance of the lifeworld as shared sense making" (p. 97).

One of the more obvious implications of this theoretical framework is that social networks shape the content to which we are exposed, an idea that fits with empirical evidence showing that friend networks play a role in determining the extent of cross-cutting exposure on social media platforms (Bakshy et al., 2015). It also fits with ideas about news curation. For example, Thorson et al. (2021) link the concept of egocentric publics with personal curation, arguing that "each actor in an individual's egocentric public is a curator, curating a selection ("flow") of content for the individual's consideration" (p. 313). Curation practices such as following a news organization on social media are considered *news-boosting*, while *news-limiting* practices include blocking or unfriending someone on social media (Merten, 2020).

Social media networks not only shape information exposure, they also shape how people respond to information when they encounter it. Recognizing the varied nature of avoidance behaviors and the influence of networks on those behaviors, John and Gal (2018) describe social media users as operating within a personal public sphere, which refers to "the communicative space in which political unfriending is carried out" (p. 2972). They conceptualize selective avoidance as a new form of boundary management, theorizing that individuals feel a sense of "sovereignty" over their personal public sphere: "[P]eople understand that their personal public sphere intersects with others—or in other words, that other people can see what is going on in their personal public sphere—and this creates a sense of obligation toward one's personal public sphere" (p. 2975). Thus, for many people, selective avoidance is an act of personal curation that helps individuals maintain normative boundaries for communication within social networks that are, for the average social media user, larger and more diverse than offline social networks. This expansion and diversification brings people into contact with more individuals who violate or threaten users' normative boundaries, and more active boundary maintenance is required in larger, more diffused, and more diverse networks. Therefore, variation in selective avoidance should be partially explained by variation in the structures of social networks.

This study considers two prevalent dimensions of social networks: general network characteristics and discussion network characteristics. The purpose of including both is to provide as many observable implications as possible within a coherent theoretical framework, while also recognizing that these dimensions differ in important ways. According to King et al. (1994), increasing the number of observable implications of a theory maximizes leverage over a research problem, and is therefore an important aim of social-scientific research. At the same time, it is clear from prior literature that generalized and discussion networks differ in important ways. Discussion networks are typically a subset of general networks and tend to be smaller (Song, 2015). Additionally, discussion networks are experienced through communication, whereas general networks are structures that exist in the background of people's lived experience. The political difference that is embedded in general networks is realized through communication (Barnidge, 2017), and therefore, discussion networks are more proximal to behavioral outcomes such as selective avoidance. Thus, while the logic undergirding hypotheses for general and discussion networks are largely the same, the implications for hypothesis testing are quite different in that failing to support hypotheses pertaining to distal factors (such as general network characteristics) is less injurious to theory than failing to support hypotheses related to proximal factors (such as discussion network characteristics). With these ideas in mind, we now outline our expectations for how three aspects of social networks—network size, tie strength, and network diversity—affect avoidance behaviors on social media platforms.

General Network Characteristics and Selective Avoidance

Network size is the first characteristic of social media networks to consider, and social media platforms have generally facilitated the expansion of social networks (Rojas, 2015). Some unfriending/avoidance studies have included network size as a control variable or secondary predictor, but these studies have yielded mixed findings. For example, John and Dvir-Gvirsman (2015) found a positive, log-linear effect of network size on politically motivated unfriending, but Yang et al. (2017) find no relationship between network size and unfriending. Therefore, a deeper discussion of network size is needed that outlines theoretical expectations based on anthropological research on the limits of human social connections.

For the past three decades, anthropologists have investigated whether there is a limit to the number of relationships that humans can maintain (Dunbar, 1992). These limits are thought to be biological or cognitive, stemming from the physiology of the human brain, and researchers have observed a correlation between "neocortical volume" and group size in both primates and humans. Based on these observations, Dunbar (1992) famously concluded that 150 (which is really the midpoint of a range of numbers between 100 and 200) is the number of stable relationships humans can maintain, and these relationships are organized into layers of relational types based on closeness/distance. There are of course other factors that limit human's capacity for social relationships, such as scarcity of time and attention (Gonçalves et al., 2011), and Dunbar's number has also been critiqued for reducing human information processing to brain physiology (De Ruiter et al., 2011). However, despite these criticisms there is some evidence in support of the idea that human social groups tend to have a limit of about 200 people.

Social media have called this theory into question, as they have afforded people the ability to radically expand their social networks. Some have theorized that social media have "broken" Dunbar's number by expanding each circle of social contacts, such that people are able to develop larger inner circles as well as more expansive outer circles of social ties (Rainie & Wellman, 2012). This claim has received some empirical support. For example, Striga and Podobnik (2018) find that Facebook users maintain more social connections at all layers of their social circle. In particular, social media users have, on average, between 400–600 connections (Bohn et al., 2014; De Ruiter et al., 2011). But it remains an open question as to whether these additional social connections are truly meaningful, or whether they are the types of connections that are easily discarded or severed if disagreement or conflict arises. For instance, studies that focus on traditional notions of interaction or reciprocity tend to find support for Dunbar's assertions—social media users only meaningfully interact with approximately 100–300 people (e.g., Arnaboldi et al., 2013; Gonçalves et al., 2011).

In part, the discrepancy between these numbers stems from the fact that larger networks are more likely to bring users into contact with different views about social and political issues—differences that could create negative feelings toward specific others (Barnidge, 2018), act as extreme exemplars of the other side (Rojas, 2015), and motivate avoidance out of a sense of responsibility to maintain the boundaries of egocentric publics (John & Gal, 2018). Therefore, we can extend from theory about the cognitive limits of human connection to the study of avoidance via the egocentric publics framework. That is, larger networks produce more instances of communicative norm violation, which requires individuals' to take a more active role in maintaining normative boundaries through selective avoidance. Therefore, we hypothesize (**H1**) a positive relationship between network size and selective avoidance.

Tie strength is another important network characteristic to consider, and it is associated with network size—that is, larger networks tend to contain more weak ties. Granovetter's work on tie strength (1977) established that weak ties are better than strong ties at spreading information, and this insight has been supported by research in social media environments. Whereas stronger ties may be more influential in terms of behavior (Centola, 2010), information spreads more easily via weak ties, which serve as informational bridges between otherwise unconnected portions of social networks (Granovetter, 1973). Research has shown that the radical expansion of networks on social media platforms means individuals are connected to relatively more weak ties than they were in the past (Rainie & Wellman, 2012), and these weak ties are more likely to spread cross-cutting political information, because they carry information from different communication ecologies (Granovetter, 1973).

The importance of tie strength is related to anthropological conversations about the stability of social relationships. While these concepts are not necessarily the same—it is possible to have a stable (and meaningful) relationship with a weak tie—they are related. Weak ties are not characterized by dense connections to an inner circle of social contacts, and therefore, they are not maintained by the same affective and communicative bonds that promote stability and interaction. Thus, limiting connection with weak ties may be less costly than doing so with strong ties, particularly if those ties serve as extreme exemplars of the other side or violate communicative norms (John & Gal, 2018; Rojas, 2015). Previous work bears out this idea, showing that politically motivated unfriending on Facebook is most likely to occur in larger networks and among weak ties (John & Dvir-Gvirsman, 2015). Therefore, we expect a positive relationship between the prevalence of weak ties in a network and selective avoidance (**H2**).

The third characteristic of social networks that should affect avoidance behavior is diversity, which is closely related to both network size and tie strength. Network diversity refers to the extent that one's social network is composed of differing elements. In this study, we use indicators of network diversity drawn from previous work, including structural diversity and informational diversity. Structural network diversity is based on occupation, which is a relatively good indicator of individual's position with socio-economic and class structures (Hampton et al., 2011). A broader range of occupations within a social network therefore reflects greater diversity in terms of social position and the perspectives about public affairs that may accompany them (Hampton et al., 2011). Informational diversity, on the other hand, is based on encountering differing types of political information within a network, which is a good indicator of an individuals' political leanings (Kim et al., 2021). This approach has less to do with discussion (see below for our approach to conceptualizing discussion diversity), and more to do with information, including news and public affairs content. Thus, informational diversity indicates the "degree of [political] heterogeneity among an individual's contacts" (Su et al., 2020).

Larger networks with greater numbers of weak ties also tend to diversify communication, because they spread ideas between otherwise disconnected networks. In these networks, people are more likely to encounter cross-cutting political information (Peacock, 2021), which may be accompanied by an increased frequency in communicative norm violation. Perhaps for this reason, people are more likely to avoid others who are socially or politically different (Wells et al., 2017). Theoretically, individuals will take a more active role in managing the boundaries of their social networks when norm violation is more common (John & Gal, 2018). Therefore, we expect a positive relationship between network diversity and selective avoidance (**H3**).

Discussion Network Characteristics and Selective Avoidance

Much of the political communication literature has focused on discussion network characteristics rather than general network characteristics as factors that shape key political outcomes (Kim et al., 2013), and some prior studies have investigated the connections between structural features of social media discussion networks—particularly network size and weak tie discussion—and selective avoidance (Skoric et al., 2018; Zhu et al., 2017; Zhu & Skoric, 2021). Discussion is, of course, the key element that differentiates discussion networks from general networks, and though this point may seem obvious, it is not trivial because discussion has important effects on individuals' cognitive activity and, potentially, on the (de)construction of their social environment. Political discussion not only affords individuals opportunities to encounter and engage with new ideas (Peacock, 2021), the act of expressing one's own beliefs facilitates information processing, because it requires people to connect new information to previously held beliefs (Shah et al., 2005). It also gives people the chance to reflect on their thoughts and generate new ideas and beliefs, making it possible to reorient their political identities and behaviors over the course of a discussion (Shah et al., 2007). Thus, political discussion is critical to processes of political self-development (Lane et al., 2019), as it helps clarify and establish commitment to particular issue-based attitudes, ideological stances, and group identities. Prior literature has found that structural features of discussion networks—including network size, density, and diversity—have substantial impacts on individuals' politically motivated behavior (e.g., Eveland & Hively, 2009; Scheufele et al., 2006; Song, 2015).

Political discussion networks may also have an impact on individuals' politically motivated *social* behavior, including selective avoidance. At least two prior studies have found evidence of a connection between discussion network size and politically motivated unfriending (Skoric et al., 2018; Zhu & Skoric, 2021; but see Zhu et al., 2017). One potential explanation for this connection is the prevalence of political disagreement in diverse networks (Peacock, 2021; Skoric et al., 2021). Although diversity and disagreement are distinct phenomena, they are closely related and share some operational overlap (Barnidge, 2017). For example, encountering a position with which one disagrees does not necessarily indicate diversity, although to encounter diversity there must be some amount of difference which commonly manifests as disagreement (Peacock, 2021). Thus, disagreement is a common manifestation of diversity, and it may facilitate the effects of diversity on selective avoidance.

Other studies have found no relationship between the frequency of encountering disagreement in social media spaces and unfriending (Yang et al., 2017), which suggests there could be an alternative explanation based not on the content of discussions but rather on the structures of discussion networks. Song (2015) argues that discussion networks have "endemic" effects—that is, the makeup of discussion networks are best understood as auto-reflexive in that aspects of the networks themselves affect whether people engage in discussions in the first place. Song (2015) documents a process of "triadic closure" in discussion networks, in which discussants who discuss politics with the same third party tend to enter into discussions with each other, as well. In that sense, discussion networks tend to be relatively tight-knit as compared to general social networks (see also Morey et al., 2012).

From this perspective, selective avoidance on social media platforms can be seen as a form of discussion-network maintenance in an online environment that generally facilitates the expansion of general social networks. Where networks grow larger, less tightly connected, and more diverse, it becomes necessary for individuals to more actively maintain the boundaries of their relatively tight-knit discussion networks by avoiding discussion with particular others or by culling them from their networks completely. By this reasoning, as discussion networks become larger and more diverse, individuals should engage in selective avoidance more often. Therefore, we predict positive relationships between selective avoidance and discussion network size (**H4**), discussion with weak ties (**H5**), and discussion network diversity (**H6**).

Methods

Data

This study relies on three online survey datasets fielded by either Qualtrics or Survey Sampling International (SSI, now Dynata) in 2016, 2018, and 2020, respectively. Details about the datasets are included in Supplementary Material. Each survey was conducted prior to a major national election in the United States (presidential elections in 2016 and 2020 and midterm elections in 2018). All three datasets are based on samples of the U.S. adult population, and each employed quotas based on population parameters from 2016 American Community Survey (ACS) conducted by the U.S. Census Bureau. The demographic profiles of each dataset are reflective of the target population quotas. Each dataset was also weighted by education and annual household income, demographics that were not included as quota criteria. Demographic profiles and weights for each dataset can be found in Supplementary Material online. Missing values were imputed using the R package "mice" (Groothuis-Oudshoorn & Van Buuren, 2011), resulting in sample sizes of $N = 1624$ for the 2016 dataset, $N = 1493$ for the 2018 dataset, and $N = 1244$ for the 2020 dataset.

Measures

Table 1 provides a summary of important measurement information, including the number of questionnaire items for each variable, along with reliability metrics (where appropriate), brief descriptions of computational processes, and descriptive statistics. The general network variables are available only in the 2016 and 2020 datasets, but not in 2018. Meanwhile, the discussion network variables are available only in the 2018 and 2020 datasets, but not in 2016. Finally, the 2018 dataset is the only one of the three that contains separate measures for specific avoidance behaviors. Some variables are measured differently across the three datasets. Thus, the study trades specificity for breadth in observation. But there is value in maximizing breadth in this way, as doing so increases the observable implications of the theory (King et al., 1994) and therefore the amount of evidence available to test the hypotheses. We have noted important discrepancies in measurement, and we have assessed their predictive validity when possible (see Supplementary Material online).

Selective Avoidance

The *selective avoidance* variables were constructed based on recent research (John & Dvir-Gvirsman, 2015; Skoric et al., 2018; Yang et al., 2017). The question wording differs across the three datasets, and these are differences in operationalization and rather than conceptualization.[1] In the 2016 survey, avoidance was measured with a single item that asked respondents how often they "block or unfriend" people who post news or opinions they "disagree with" on social media. Respondents who indicated that they engage in these behaviors more often than "never" received a score of 1, and everyone else received a score of 0. In the 2018 survey, the variable was measured with eight items, which asked respondents whether they had, in the last 12 months, (1) stopped talking, (2) unfriended, (3) hid, or (4) blocked somebody on social media because of (a) political disagreement or (b) hate speech. Respondents who engaged in any of these behaviors received a score of 1, and those who did not engage in any behaviors received a score of 0. Finally, the variable was measured with three items in the 2020 survey, which asked respondents whether, in the past month, they had "blocked, unfriended, or otherwise changed the settings" on their social media accounts in order to "reduce the amount of posts" they see from people who post too much political content, post political content that they disagree with, and post political or social content that they find offensive, abusive, or harassing. As with the other variables, respondents who engaged in any of these behaviors received a score of 1, while those who did not received a score of 0.[2]

General Network Characteristics

We measured three dimensions of general network characteristics (Burt, 1984; Marsden, 1993): *network size*, *weak ties*, and *network diversity*. These variables are available in the 2016 and 2020

Table 1. Reliability Metrics and Descriptive Statistics for Variables in the Current Study.

	Variable(s)	2016 dataset	2018 dataset	2020 dataset
Dependent variable	Selective avoidance	43% (1 item, dichotomized)	49% (8 items, dichotomized)	54% (3 items, dichotomized)
Predictors	Network size	*M* = 4.7, *SD* = 1.5 *Min*. = 0.0, *Max*. = 8.5 1 item, logged	*M* = 1.2, *SD* = 1.6 *Min*. = 0.0, *Max*. = 6.9 1 item, logged	*M* = 2.3, *SD* = 1.7 *Min*. = 0.0, *Max*. = 6.0 1 item
	General Discussion			*M* = 1.7, *SD* = 1.2 *Min*. = 0.0, *Max*. = 4.0 1 item
	Weak ties	*M* = 1.3, *SD* = 0.5 *Min*. = 0.0, *Max*. = 2.2 2 items, logged product	*M* = 2.3, *SD* = 1.8 *Min*. = 1.0, *Max* = 7.0 α = .88, 2 items averaged	*M* = 1.6, *SD* = 0.9 *Min*. = 0.0, *Max*. = 4.0 α = .89, 7 items
	General Discussion			*M* = 3.2, *SD* = 3.5 *Min*. = 0.0, *Max*. = 16.0 2 items, product
	Network diversity	*M* = 3.1, *SD* = 1.0 *Min*. = 1.0, *Max*. = 5.0 α = .87, 4 items	*M* = 2.5, *SD* = 1.8 *Min*. = 1.0, *Max*. = 7.0 α = .96, 7 items averaged	*M* = 8.5, *SD* = 6.5 *Min*. = 0.0, *Max*. = 22.0 22 items, index
	General Discussion			*M* = 2.5, *SD* = 1.3 *Min*. = 0.0, *Max*. = 5.0 *r* = .59, 2 items, averaged
Controls	News use	*M* = 3.0, *SD* = 1.1 *Min*. = 1.0, *Max*. = 5.0 α = .90, 3 items	*M* = 3.0, *SD* = 1.6 *Min*. = 1.0, *Max*. = 7.0 α = .89, 5 items averaged	*M* = 2.2, *SD* = 1.7 *Min*. = 0.0, *Max*. = 5.0 1 item
	Political interest	*M* = 3.8, *SD* = 1.2 *Min*. = 1.0, *Max*. = 5.0 1 item	*M* = 4.3, *SD* = 1.8 *Min*. = 1.0, *Max*. = 7.0 α = .89, 3 items averaged	*M* = 2.3, *SD* = 1.3 *Min*. = 0.0, *Max*. = 4.0 1 item
	Ideological extremity	*M* = 1.4, *SD* = 1.1 *Min*. = 0.0, *Max*. = 3.0 1 item	*M* = 2.1, *SD* = 1.8 *Min*. = 0.0, *Max* = 5.0 α = .95, 3 items averaged	*M* = 2.6, *SD* = 2.0 *Min*. = 0.0, *Max*. = 5.0 1 item

datasets, and they are operationally different.[3] In the 2016 dataset, network size is measured by asking respondents how many friends they have on their "favorite" social media platform, and the raw number was unobtrusively logged in order to normalize the distribution. In the 2020 survey, the variable relies on a single item that asked respondents how many people they are friends with or follow on Facebook (0 = None to 5 = More than 2000).

There are key operational differences in the measures of weak ties, as well. In the 2016 survey, respondents were asked about the percentage of their social media network to whom they "feel very close" or "frequently discuss personal issues and feelings." This percentage was subtracted from one (to obtain the percentage of people to whom they do *not* feel close) and then multiplied by the raw network size item to create a measure of weak ties, which was then unobtrusively logged to normalize the distribution. In the 2020 survey, the weak ties variable was measured with seven items (averaged for each respondent) asking respondents how many people are in their Facebook networks who (1) they know from current work or school, (2) they know from past work or school, (3) they know socially, (4) they have never met in person, (5) live in their city/town, (6) live in other cities/towns, and (7) live in other countries.

The network diversity measures are not only operationally different, but also represent different conceptual dimensions of diversity. While this divergence is not ideal, the strategy does take advantage of available data. The 2016 measure reflects an "informational diversity" dimension, whereas the 2020 represents a "structural diversity" dimension. Both are theoretically important, and theory also suggests similar predicted relationships with key outcomes (Brundidge, 2010; Wells et al., 2017). In the 2016 survey, the variable relies on four items (averaged for each respondent) asking respondents how often they encounter information (a) critical of and (b) favorable toward political candidates they (1) support and (2) oppose. In the 2020 survey, the variable relies on a validated measure of structural diversity that asks respondents whether they know people in their social media networks who work in 22 different occupations (responses summed; see Lu & Hampton, 2017 for list of occupations).

Discussion Network Characteristics

We measure the same three dimensions in terms of discussion network characteristics, and these variables are also based on prior literature (Eveland & Hively, 2009). These discussion network variables are available in the 2018 and 2020 datasets, and they are operationally different. In the 2018 survey, *network size* was measured by asking respondents how many people they have talked to about "government, elections, politics, or the news" on social media. The raw number was unobtrusively logged to normalize the distribution. In the 2020 survey, the variable was measured with a single Likert scale asking respondents how many people they talk to about "government, elections, politics, or the news" on Facebook (0 = "None," 4 = "Many").

The weak-tie discussion measures are also operationalized differently in the two datasets. The variable was measured in 2018 by taking the average of two items asking how often respondents talk on social media with (1) coworkers or classmates and (2) other acquaintances. There is no direct measure of weak-tie discussion in the 2020 dataset, and therefore, a proxy was created by multiplying the discussion network size variable and the general weak ties variable (both described above). Thus, the measure weights the prevalence of weak ties in a respondent's general network by the number of people with whom that respondent discusses politics.

The discussion network diversity measures account for both the heterogeneity and frequency of discussion. While some scholars have used a "frequency-free" measure of discussion diversity (e.g., Mutz, 2006), others have argued that discussion frequency is a critical aspect of diversity because measures should capture the frequency with which respondents engage in discussions with a heterogeneous set of others (McLeod et al., 1999; Scheufele et al., 2006). The 2016 measure uses four questionnaire items (averaged for each respondent) asking respondents how often they talk about those same subjects on social media with (1) people on the left, (2) people on the right, (3) people with very similar political views, (4) people with very different political views, (5) people of a different nationality, (6) people living in a different city, and (7) people living in a different country. While discussion diversity was measured directly in 2016, a measure of *political disagreement*—a closely related outcome (Barnidge, 2017)—was used as a proxy in 2020 because a direct measure is not available in the data. The variable was measured with two items (averaged for each respondent) asking respondents how often they talk with people who (1) agree with their political views and (2) disagree with their political views.

Control Variables

Prior research suggests that informational uses of social media, political interest, and political predispositions are related to both characteristics of social media networks and avoidance behaviors (John & Dvir-Gvirsman, 2015; Skoric et al., 2018; Yang et al., 2017). Therefore, this study controls for *social media news use*, *political interest*, and *ideological extremity*, in addition to a standard set of demographic controls.

In the 2016 survey, social media news use was measured with three items (averaged for each respondent) asking respondents how often they use social media to get news or public affairs information, to read information about campaigns or politics, or to click on links to other news sources. In the 2018 survey, respondents were asked how often they get news from five types of social media sites (items averaged for each respondent), including social networking sites (e.g., Facebook), microblogging sites (e.g., Twitter), video-sharing sites (e.g., YouTube), photo-sharing sites (e.g., Instagram), and mobile-messaging apps (e.g., Snapchat). In the 2020 survey, the variable was measured with a single item that asked respondents how often they get news or public affairs information from Facebook.

Political interest was measured with a single item in the 2016 and 2020 surveys, which asked respondents how interested they are in politics. In the 2018 survey, the variable was measured with three items (averaged for each respondent), asking respondents how interested they are in local, national, and international politics.

Likewise, political ideology was measured with a single item (11-point L-R scale) in the 2016 and 2020 surveys. In the 2018 survey, three such items were used (averaged for each respondent), asking about respondents' ideologies on economic issues and social issues in addition to their general political ideologies. In each dataset, the political ideology variable was folded to create a measure of ideological extremity, where low values indicate moderate ideologies and high values indicate extreme ideologies.

Finally, we controlled for demographics, including age, gender (binary where 1 = female), education, annual household income, and race (binary where 1 = person of color).

Analysis

All statistical analyses reported in the main manuscript are conducted using quasibinomial logistic regression (i.e., weighted logit),[4] which is appropriate for data in which the unweighted outcome variable is binary, but the inclusion of weights renders the outcome non-binary (i.e., quasibinomial). The tests are structured around the hypotheses and the availability of variables. Some of the network predictors are strongly correlated, and coefficients are greater than r = .80, which could create multicollinearity issues. Research has established that Variance Inflation Factors (VIFs) greater than 2.5 indicate potentially substantial multicollinearity issues (Johnston et al., 2018), and when fitting models including all three network predictors together, several VIFs exceed that threshold (see Supplementary Material online). Therefore, we separated these variables into difference models, and, for the sake of consistency, we estimated the other two sets of variables in separate models, as well.

Results

Tables 2 and 3 report coefficients and standard errors from the regression models, but odds ratios (ORs) are reported in the text for ease of interpretation. These ratios can be interpreted as the increase in the odds that the outcome variable equals 1 (i.e., a "success") for each one-unit change in the explanatory variable. Positive coefficients translate to ORs greater than 1, and negative coefficients translate to ORs less than 1.

The first three hypotheses predict positive relationships between the three general network predictors and selective avoidance. Results from the relevant regression models are reported in Table 2 and visualized in Figure 1. For network size, a statistically significant and positive relationship is observed in 2016 (OR = 1.10). For 2020, the relationship is also positive (OR = 1.06), but it is not statistically significant. Taken together, these results indicate that avoidance is more likely in bigger social media networks, but the increase in odds is relatively small. These results therefore provide mixed support for H1. For weak ties, positive relationships are observed in both survey years, but the relationship is only statistically significant in 2020 and not in 2016, perhaps because of the relatively large standard error associated with the multiplicative variable in that year ($b = .20$, $SE = .11$). Larger odds ratios are observed for weak ties (OR = 1.22 in 2016 and 1.72 in 2020) than for network size. Thus, these results suggest a relatively stronger relationship with avoidance for weak ties than for network size, but confidence in the 2016 finding is low, indicating mixed support for H2. Results for network diversity are more consistent in terms of confidence, but mixed in terms of magnitude. Results in both survey years are positive and statistically significant, but the odds ratio is substantially higher in 2016 (OR = 1.43) than it is in 2020 (OR = 1.07). Together, the results provide support for H3, with some differences between the datasets in terms of the strength of the relationships.

Hypotheses 4–6 predict positive relationships between the discussion network characteristics and selective avoidance, and the relevant regression models are reported in Table 3 and visualized in Figure 2. Generally results are more consistent than results for the general network characteristics, as all estimates for the three predictors across both survey years (2018 and 2020) are positive and statistically significant. Additionally, the relationships are relatively stronger in 2018 than they are in 2020. For example, odds ratio for network size is 1.85 as compared to 1.16 in 2020. Similarly, the odds ratio for weak ties is 1.47 in 2018 as compared to 1.17 in 2020. Finally, the odds ratio for network diversity is 1.74 in 2018 versus 1.32 in 2020. These results provide relatively strong support for H4 (discussion network size), H5 (weak tie discussion), and H6 (discussion network diversity), although they do point toward some inconsistencies in terms of the magnitude of those relationships in 2018 versus 2020.

Discussion

This study contributes to an already substantial literature on unfriending and other selective avoidance behaviors by providing a foundational set of results based on a systematic and broad-based analyses of the ways in which social networks shape responses to the disagreeable or cross-cutting political information people encounter on social media platforms. While some literature has included network variables as controls or secondary predictors (Yang et al., 2017; Zhu & Skoric, 2021), and other studies have examined specific features of discussion networks (Skoric et al., 2018), research has not to this point systematically assessed the ways in which networks

Table 2. The Relationships Between General Network Characteristics and Selective Avoidance in the 2016 and 2020 Datasets.

	2016 survey			2020 survey		
Variable	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)
Intercept	−1.89 (0.36)***	−1.71 (0.34)***	−1.80 (0.32)***	0.49 (0.28)	−0.15 (0.31)	0.26 (0.28)
Age	−0.01 (0.00)***	−0.02 (0.00)***	−0.02 (0.00)***	−0.03 (0.00)***	−0.02 (0.00)***	−0.02 (0.00)***
Gender (female = 1)	−0.17 (0.12)	−0.14 (0.11)	−0.14 (0.12)	−0.22 (0.14)	−0.18 (0.14)	−0.20 (0.14)
Education	0.15 (0.04)***	0.15 (0.04)***	0.15 (0.04)***	−0.01 (0.04)	−0.05 (0.04)	−0.03 (0.04)
Income	−0.02 (0.02)	−0.01 (0.02)	−0.02 (0.02)	0.05 (0.03)	0.05 (0.03)	0.03 (0.03)
Race (non-white = 1)	−0.01 (0.14)	0.00 (0.14)	−0.02 (0.14)	−0.20 (0.14)	−0.24 (0.14)	−0.17 (0.14)
Ideological extremity	0.18 (0.05)***	0.17 (0.05)***	0.15 (0.05)**	0.13 (0.03)***	0.10 (0.03)***	0.12 (0.04)***
Political interest	−0.05 (0.05)	−0.05 (0.05)	−0.12 (0.05)*	−0.02 (0.06)	−0.05 (0.06)	−0.02 (0.06)
News use	0.41 (0.06)***	0.44 (0.06)***	0.31 (0.06)***	0.24 (0.04)***	0.19 (0.04)***	0.17 (0.04)***
Network size	**0.10 (0.04)***			**0.06 (0.04)**		
Weak ties		**0.20 (0.11)**			**0.54 (0.10)*****	
Network diversity			**0.35 (0.07)*****			**0.06 (0.01)*****
Pseudo R^2	.12	.12	.13	.14	.16	.16

Note: Cell entries are coefficients and standard errors from quasibinomial logistic regression models.
***$p < .001$, **$p < .01$, *$p < .05$. $N_{2016} = 1623$, $N_{2020} = 1244$.

Table 3. The Relationships Between Discussion Network Characteristics and Selective Avoidance in the 2018 and 2020 Datasets.

	2018 survey			2020 survey		
Variable	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)	*b* (*SE*)
Intercept	−1.81 (0.39)***	−2.22 (0.38)***	−2.26 (0.39)***	0.45 (0.28)	0.41 (0.27)	0.25 (0.28)
Age	−0.01 (0.01)*	−0.01 (0.01)	0.00 (0.01)	−0.03 (0.00)***	−0.02 (0.01)***	−0.03 (0.00)***
Gender (female = 1)	0.22 (0.17)	0.29 (0.16)	0.37 (0.17)*	−0.19 (0.14)	−0.15 (0.14)	−0.17 (0.14)
Education	0.05 (0.05)	0.03 (0.05)	0.03 (0.05)	−0.02 (0.04)	−0.04 (0.04)	−0.03 (0.04)
Income	0.03 (0.04)	0.04 (0.04)	0.04 (0.04)	0.06 (0.03)	0.05 (0.03)	0.06 (0.03)
Race (non-white = 1)	−0.24 (0.16)	−0.30 (0.16)	−0.28 (0.16)	−0.18 (0.14)	−0.17 (0.14)	−0.18 (0.14)
Ideological extremity	0.04 (0.04)	0.07 (0.04)	0.03 (0.04)	0.12 (0.03)***	0.10 (0.03)**	0.11 (0.03)**
Political interest	0.12 (0.04)**	0.11 (0.04)*	0.06 (0.04)	−0.04 (0.06)	−0.08 (0.06)	−0.06 (0.06)
News use	0.22 (0.05)***	0.22 (0.05)***	0.14 (0.06)**	0.23 (0.04)***	0.18 (0.04)***	0.20 (0.04)***
Network size	**0.62 (0.06)*** **			**0.14 (0.07)***		
Weak ties		**0.38 (.05)*** **			**0.16 (.03)*** **	
Network diversity			**0.55 (.05)*** **			**0.28 (.06)*** **
Pseudo R^2	.25	.19	.24	.14	.15	.15

Note: Cell entries are coefficients and standard errors from quasibinomial logistic regression models.
***$p < .001$, **$p < .01$, *$p < .05$. $N_{2018} = 1493$, $N_{2020} = 1244$.

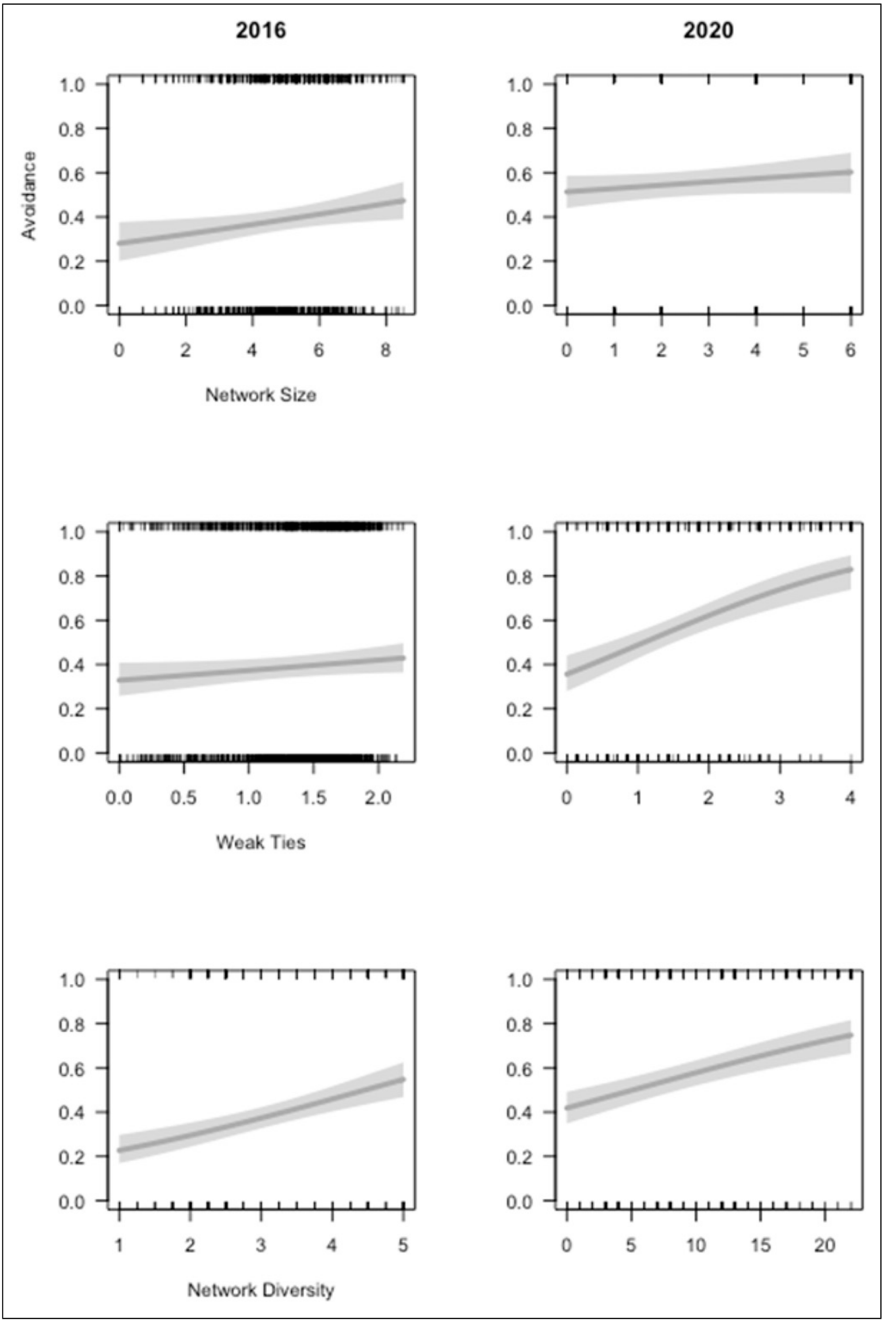

Figure 1. The Relationships Between General Network Characteristics and Selective Avoidance in the 2016 and 2020 Datasets.

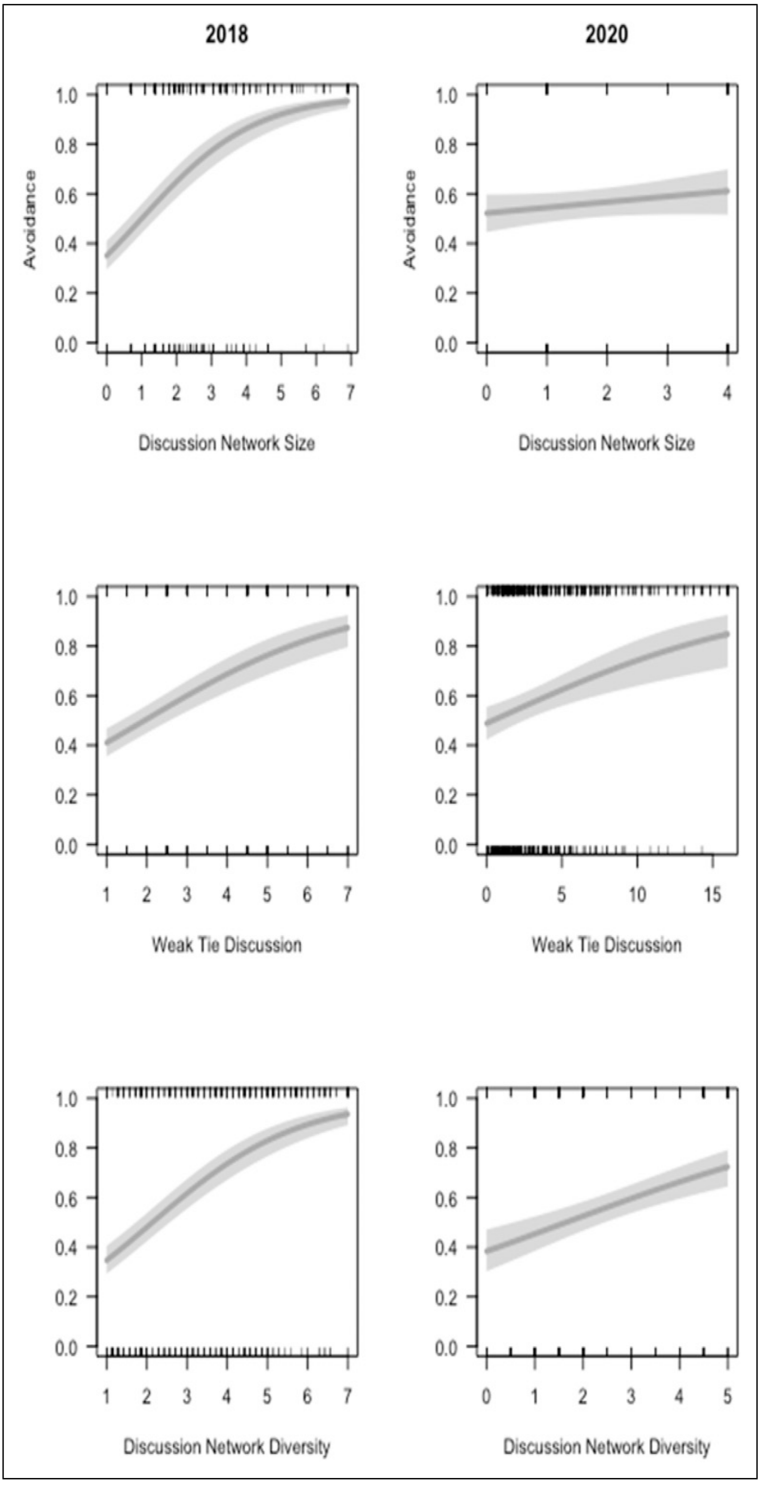

Figure 2. The Relationships Between Discussion Network Characteristics and Selective Avoidance in the 2018 and 2020 Datasets.

affect the likelihood of selective avoidance behaviors. Building on Rojas' notion of ego-centric publics (2015) and John and Gal's (2018) corollary about "sovereignty" in boundary maintenance of those publics, we reasoned that social networks not only shape the information to which people are exposed, but also the actions people take in response to that information, including selective avoidance.

The findings largely support this reasoning, and with the caveat that conclusions must be tempered by the possibility of omitted variable bias introduced in the effort to avoid multicollinearity, the results generally show that selective avoidance is more likely among individuals who are situated within larger networks, more diverse networks, and networks that contain more weak ties. Of course, some avoidance behaviors are relatively more common than others. Supplemental analyses (see Supplementary Material) show that the proportion of the sample reporting unfriending and stopping talk (~37% for each) is significantly greater than the proportions reporting hiding (31%) and blocking (26%). Because relationships with network characteristics are similar across these behaviors (bearing in mind that we did not directly compare models and the differences between behaviors are small), we can safely conclude that network characteristics are more commonly connected to unfriending and stopping talk than to hiding and blocking.

Although the analysis does not afford us the ability to compare the coefficients directly, there is also some variation in terms of the magnitude of the relationships between network characteristics and selective avoidance across the specific dimensions of network characteristics, as well as the datasets under examination. That said, we must emphasize that the results are remarkably consistent given the rather important differences in the operationalization, measurement, and temporality of these characteristics. We tested 12 separate regression models, and positive relationships are observed in 10 of these tests, including in models of both general network characteristics and discussion network characteristics, in models with different measures of the same variables, and in models that rely on three different datasets collected at different points in time. The two exceptions are results for the general weak ties variable in 2016 and for the general network size variable in 2020. We cannot be certain whether these null findings arise from differences in measurement, sampling, or the timeframe. That said, we did find statistically significant results for the equivalent variables in the "other" dataset in Table 2 (i.e., for weak ties in 2020 and network size in 2016). Thus, we found at least one significant result for each variable in the analysis. Future research should continue testing these variables in additional datasets to assess the robustness of these findings.

The results speak directly to two ongoing conversations related to selective avoidance on social media: the question of echo chambers and the emerging cultural logic of self-care. Initially, scholars in this area have been concerned with the former question—that in addition to algorithmic filtration on social media sites (Pariser, 2011), people themselves will filter out the remaining disagreeable content they encounter, creating online echo chambers that preclude or exclude cross-cutting content and limit the ability of online media to act as deliberative or quasi-deliberative spaces. But empirical evidence suggests these fears are unfounded, as social media tend to expose people to more cross-cutting information, not less (Bakshy et al., 2015; Barnidge, 2017), particularly among people situated in larger and more diverse networks. Therefore, selective avoidance can be viewed as a form of boundary maintenance where the goal is to maintain a sustainable level of political diversity rather than to exclude it completely (John & Gal, 2018). Our findings align with this latter view, as the evidence suggests selective avoidance is more likely in larger networks, more diverse networks, and networks with more weak ties, as well as in discussion networks with the same features (size, diversity, and weak ties). Situated in these kinds of networks, which are, on average, substantially larger than humans could previously manage (Dunbar, 1992) and/or threaten the relatively tight-knit nature of discussion networks

(Song, 2015), people may find it necessary to establish some boundaries on disagreeable content and cut ties with particular individuals.

Thus, while the data are merely cross-sectional, our results speak to the dynamics of how selective avoidance shapes the composition of social networks. It is tempting to extrapolate from the positive association between selective avoidance and weak ties to infer that selective avoidance of weak ties could, over time, contribute to the homogenization of communication within social networks. But in fact our evidence contradicts this narrative, as a homogenizing process should manifest, at any given time point, in the form of a negative relationship between weak ties and selective avoidance, because those who frequently engage in avoidance should have fewer weak ties in their networks. This counterintuitive conclusion is elucidated when one considers the steady growth of social media networks over time. The partial avoidance of weak ties does not counteract the addition of new weak ties to individuals' networks, and therefore, the selective avoidance is best understood not as a homogenizing force, but rather as a tool for sustaining a manageable level of diversity as networks grow (John & Gal, 2018).

The emerging cultural logic of self-care also highlights this boundary-maintenance phenomenon. Seemingly at odds with earlier concerns about the *lack* of diverse views in online social networks, recent public sentiment in the United States seems more concerned with encountering *too much* political disagreement, which could negatively affect psychological well-being over time. Therefore, the thinking goes, removing some or all of the cross-cutting views from one's network is an act of self-care (John & Gal, 2018), and creating likeminded safe spaces for political expression is a social good (Zhu & Skoric, 2021), as it provides people the opportunity to derive the benefits of political expression (Lane et al., 2019) without fear of conflict or harassment from individuals on the other side. This shift in discourse manifests from a broad cultural change in the way political disagreement is conceptualized and discussed in institutions and industries of knowledge production. During the "deliberative turn" of the 1990s, writers, intellectuals, and scholars emphasized the need for exposure to cross-cutting conversations as a critical aspect of deliberative processes (Fishkin, 1991; Mansbridge, 1999; Mutz, 2006). More recent research recognizes the individual and interpersonal costs of engaging in political disagreement (Peacock, 2019)—something many people choose to avoid when possible. Our findings suggest that people tend to strike a balance between the need for political diversity and the need to maintain the boundaries of their ego-centric public sphere.

The study is limited in several important ways. First, the design relies on cross-sectional surveys, and therefore is unable to establish the time order necessary to make causal inferences. Neither is the design able to resolve the endogeneity issues inherent in the study of network diversity and avoidance (Noel & Nyhan, 2011). Future research should design studies specifically to address these issues. Second, measurement relies on self-reports, and while this is common practice in survey research, it is possible that respondents have systematically over- or under-estimated the independent or dependent variables. For example, Naab et al. (2019) found that respondents are likely to report higher estimates of media use characteristics (e.g., use duration and gratifications) through retrospective self-report than via in-situ reports. Comparing survey responses to digital trace data, Haenschen (2020) found that participants underestimated how often they post statuses and overestimate the amount of news they share. The use of digital trace data does come with its own set of limitations, which include recruitment, selectivity and sampling bias, theoretically driven measures, and changes to the Facebook application programming interface (API), which have limited researchers' ability to access data (see Stier et al., 2020). Self-reported data, although imperfect, offers an opportunity to compare key relationships across multiple datasets. However, it is important to recognize that respondents may have systematically over- or under-reported phenomena of interest.

Additionally, the measures are limited by a lack of standardization across the three datasets. Future research could also work toward creating a standardized set of measures. This issue is particularly acute for the general weak ties measures, especially the multiplicative measure used in 2016. This is the only one out of 12 network measures that "failed" the tests of predictive validity (see Supplementary Material). Therefore, results for this particular measure should be interpreted with caution. Furthermore, while this study is limited by available data, future research should provide additional tests of the relationship between weak ties and selective avoidance. Another measurement limitation arises from the use of proxy variables for weak-tie discussion and discussion diversity in the 2020 dataset. These results should also be interpreted with caution, and future research should test these relationships with a standard measure across different datasets. Finally, the analysis is also limited in important ways. The network predictors were not included in the same model in order to avoid multicollinearity bias, opening the possibility of omitted variable bias. Additionally, the sample distributions of the dependent variables also limit the analysis. Given the "zero-hurdle" distribution of these variables, we have opted to dichotomize them and perform logit analysis.

Social media have encouraged broad-based social connection and facilitated the expansion and diversified of social networks. At the same time, selective avoidance has developed as is the key mechanism through which people manage the implications of this expansion and set limits on the amount of cross-cutting information they are willing to sustain. Thus, selective avoidance is not fundamentally anti-deliberative, but rather a critical aspect of quasi-deliberative systems, as it is the primary way in which social media users optimize social connection to create a manageable and beneficial sphere of informal political engagement.

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Data Availability

The data supporting this manuscript wil be made available at the following pre-reserved DOI upon publication: DOI: 10.17632/sy8mbvnkbh.1.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. We assessed the predictive validity of the selective avoidance measures. Prior literature suggests that (1) political expression on social media and (2) political participation are key outcomes (Kim et al., 2021; Zhu et al., 2017), and both are available in all three datasets. Results indicate that there are similar, positive relationships between selective avoidance and these two outcomes. Therefore, the selective avoidance

measures behave similarly despite their differences in question wording. See the online supplemental materials (Supplementary Material) for additional details.

2. The dependent variables were dichotomized because the continuous distributions take a "zero-hurdle" shape, with a high number of "no" or "never" responses (i.e., zeros) and normally distributed responses thereafter.
3. We evaluated the predictive validity of all network variables by testing their relationships with news use on social media. Prior literature suggests that social media users with larger and more diverse networks are more likely to encounter news content on those platforms (Thorson et al., 2021). With one exception (general weak ties in 2016), we find that all network variables are positively related to news use on social media, with relatively similar standardized effect sizes across comparable pairs of predictors. See Supplementary Material for details.
4. There are two options for analyzing dependent variables with "zero-hurdle" distributions. The simpler approach is to dichotomize the variables and then analyze with logistic regression. The second approach is to run an additional, second-stage analysis using linear regression to assess effects on a continuous variable containing only responses greater than zero. We have run both sets of analyses, and the second-stage analyses are available in Supplementary Material.

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