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Business as Usual? A Social Capital Approach to Understanding Interactions with Journalists on Twitter

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ABSTRACT

On the surface, it seems that journalists are more publicly accessible than ever before, largely thanks to the popular microblogging website/app, Twitter. But determining who is interacting with journalists on Twitter is important in order to understand who benefits from these interactions. We argue that social capital provides a useful framework for understanding this phenomenon because it sheds light on the ways in which journalists are embedded in structures of formal and informal social connection, and it highlights social inclusion and exclusion in these processes. Relying on a two-wave, online survey collected before and after the 2018 Midterm Elections, we examine the relationship between social capital and interactions with journalists on Twitter. Results show that people with higher levels of social capital are more likely to interact with journalists, which can be interpreted as a form of social exclusion. Results are discussed in light of the role of journalism in fostering social connectivity and civic engagement.

KEYWORDS

Journalist interactions; social capital; social media; digital democracy; journalism studies; political communication

On the surface, it seems that journalists are more publicly accessible than ever before, largely thanks to the popular microblogging website/app, Twitter. Because journalists co-occupy this digital space alongside members of their audience, it is arguably more possible for the public to interact with journalists in a meaningful way (Bossio and Holton 2018; Gil de Zúñiga, Diehl, and Ardèvol-Abreu 2018; Molyneux and Mourão 2019; Neilson 2018). Indeed, research shows that doing so can have some benefits for audiences and journalists alike (Gil de Zúñiga, Diehl, and Ardèvol-Abreu 2018; Molyneux, Holton, and Lewis 2018; Molyneux and Mourão 2019).

But determining who is interacting with journalists on Twitter is important in order to understand who benefits from these interactions (Molyneux and Mourão 2019; Usher, Holcomb, and Littman 2018). Does Twitter open up new avenues for people outside of the traditional circles of power to access journalists? Or is it simply a new tool for the “usual suspects” to have even more access to journalists than they already did? These questions are not a new, even if the context for asking them is. We argue that social capital provides a useful framework answering these questions—and one that has not previously been used for the study of user—journalists interactions—because (a) it sheds light
on the ways in which journalists in the social media age are technologically embedded in structures of formal and informal social connection, and (b) it highlights social inclusion and exclusion in these processes.

Journalism is, of course, integral to maintaining and, at times, changing structures of social power. In local communities, for example, journalists are more likely to interact with (at least on a professional basis) officials, elites, and other influential community members. Indeed, journalists are tasked with communicating to the public about the activities and perspectives of powerful figures, and thus their interaction with these individuals is, in many cases, part of their job description (e.g., Gans 2004). Therefore, outside of the digital media realm, individuals with higher levels of social capital—people who are more connected and have more influence in their communities—are the people with the easiest access to journalists. Twitter has the potential to counteract these tendencies because it presents opportunities for people with less social capital to engage with journalists where they may not otherwise have them.

Relying on a two-wave, online panel sample of adult Internet users in the United States (Wave 1 N = 1493), this study contributes to literature in two ways. First, the study advances social capital theory by examining the ways in which journalists are embedded in the broader communication ecology that includes both formal and informal communication within institutions and social networks. Second, it fills an important gap in the literature by applying the social capital framework to answer the question of who is more likely to engage with journalists on Twitter.

Interactions with Journalists on Twitter

Twitter has become a widely used tool for journalists to engage with their audiences. Journalists use it as a venue for breaking news, a way to build their follower base, and a space in which they can interact with the public (Molyneux, Holton, and Lewis 2018). Although Twitter is not exactly new—it has existed since 2005—it has generally reshaped professional journalistic norms, encouraging, in particular, higher levels of social interaction and reciprocal collaboration with audience members (Lewis, Holton, and Coddington 2014). Twitter users can share news, ask questions to journalists directly, follow a conversation around the news, and see personal details about journalists (Hermida 2010; Hermida et al. 2012; Lasorsa, Lewis, and Holton 2012).

Research shows that these user—journalist interactions can have some beneficial effects on both audience members and on journalists themselves. These include but are not limited to the reduction of perceived media bias (Gil de Zúñiga, Diehl, and Ardèvol-Abreu 2018), public engagement with important public issues (Molyneux and Mourão 2019), and the building of journalists’ personal brands (Molyneux, Holton, and Lewis 2018). However, studies also show that many journalists express fatigue with public engagement on Twitter (Bossio and Holton 2018; Neilson 2018). Moreover, some research has shown that Twitter tends to exacerbate existing gender biases in journalism (Usher, Holcomb, and Littman 2018), and it seems possible, if not likely, that user—journalist interactions tend to reproduce deep-seeded social inequalities along other dimensions, as well, for example race-based or economic-based social cleavages. These considerations raise several important questions, including the question of whether or not public engagement
is “worth it” for journalists. Indeed, scholars and journalists alike have started to argue that it is not (Manjoo 2019; Molyneux 2019).

Another important question—and one that has not been systematically addressed by prior research—is the question of who is interacting with journalists and with whom journalists are interacting. Xenos and Foot (2005) posed a similar question about candidates and their websites, asking whether these new (at the time) venues for candidates to engage potential voters represented “politics as usual” or a more open, inclusive space in which folks who traditionally lack access to politicians might engage with them. The study found mixed evidence—there were clear instances of new and different types of political dialogue that occurred on candidate websites. However, much of the discourse was decidedly within the bounds of “normal” politics, which is to say that candidate websites provided new spaces for the same types of people to make the same kinds of arguments that they did in the past. Drawing from this idea, we examine a similar question with regards to interacting with journalists on Twitter. Do these interactions represent “business as usual” for journalists? Or do they interact with different types of people? In the following section, we outline how social capital provides a useful framework for asking and answering these questions.

Social Capital

Bourdieu (1985) defined social capital as individual-level “resources which are linked to the possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition.” This approach to social capital as resources available to individuals resulting from membership in social networks and other social structures is reflected in much of the subsequent scholarship on the subject, most notably that of Coleman (1990) and Burt (1992). These scholars emphasized the benefits individuals can reap from “investing” in groups and relationships (Portes 1998), articulating the myriad benefits individuals can potentially derive from their social investments, including but not limited to job opportunities (MacGillivray and Walker 2000), access to social support (Lin, Cook, and Burt 2001), involvement in civic and community projects and programs (Brehm and Rahn 1997; Shah 1998), and social connectedness (Putnam 2000).

Importantly, social capital is not inherently good or bad, but rather results in outcomes that could be interpreted in a positive or negative light depending on normative assumptions about sociopolitical structures and processes. In that sense, social capital has a “dark side” in addition to benefits (Van Deth and Zmerli 2010). For example, while most would agree that exposure to people with different perspectives or backgrounds is normatively desirable (Putnam 2000; Sirianni and Friedland 2001), the same voluntary associations that promote these cross-cutting interactions can also promote values and norms that result in group conformity, “uncivic” culture, and intolerance of outsiders (Li, Savage, and Pickles 2003; Paxton 2002). Likewise, while it is normatively desirable, in the Tocquevillian sense, that voluntary associations pursue policies and actions that further their own interests, they may also pursue social goods that benefit only a few, rendering such pursuits more an exercise in oligarchic power than democratic action (Warren 2001; Zmerli 2008; Zucker 1986). The normative assumptions of this study reflect the tensions inherent in this duality: While it is normatively desirable that social capital enables people to interact with journalists, it is also important that these interactions reflect a diverse plurality of viewpoints and lived experiences.
Social Capital and User—Journalist Interactions

Two forms of social connection are important for understanding journalist—audience interactions: association membership and political talk network size. Voluntary associations are organized, often institutional forms of social connection that are rich in mobilizing information that gets people involved in community and civic life (Rojas, Shah, and Friedland 2011). This kind of civic engagement makes it more likely that people interact with journalists and that journalists interact with them. Individuals who belong to voluntary associations may be more responsive to mobilization efforts, and these efforts may lead them to communicate directly with journalists. Additionally, the social connections afforded by these associations may make individuals feel more efficacious when reaching out to journalists—they are involved with their communities and believe they can have an impact on its members. Journalists, for their part, are also more likely to respond to members of voluntary associations. Part of their job, of course, is to cover powerful individuals, including politicians, officials, leaders of informal associations, and community organizers (Becker and Vlad 2009; Gans 2004; Shoemaker and Reese 1996). Therefore, journalists are more likely to interact with these “rich-in-social-capital” individuals than they are with people who do not belong to voluntary associations. Thus, journalists are embedded in local, community-based power structures, and their day-to-day routines tend to reinforce these structures (Tichenor, Donohue, and Olien 1973; Tuchman 1973).

Formal group membership is not the only important form of social connection to consider. Informal connections with political discussants are also important. Drawing from a network conceptualization of community (Fischer 1982), informal social connections form a micro–macro bridge between individual-level orientations and community action (Rojas, Shah, and Friedland 2011). Specifically, talk network size has consistently been found to be associated with civic engagement (e.g., Kim and Ball-Rokeach 2006) because having more interpersonal contacts exposes people to more mobilizing information and builds self-belief in one’s ability to influence the community (Rojas, Shah, and Friedland 2011). Twitter provides a space in which individuals can discuss politics and interact with other users on an informal basis (Park 2013). Talking politics with more people enlarges personal networks and builds efficacy (Rojas 2008). From the standpoint of journalists, the number of contacts a user has is an indicator of their relative influence on the site. Once again, it is part of journalists’ job to interact with and cover influential individuals, and therefore they are more likely to interact with Twitter users they with more followers. Thus, as with formal associations, journalists’ norms and routines likely reinforce the redistribution of influence within social networks by interacting with those who have higher levels of social capital. Therefore, this study expects to find positive relationships between both indicators of social capital—formal association membership and informal talk networks—and user—journalists interactions on Twitter.

H1: User—journalist interactions on Twitter will be a positively predicted by (a) association membership and (b) network size.

Research suggests that communication is the theoretical mechanism through which latent outcomes of social capital are realized. This idea posits that social capital is derived through “communication and the sharing of knowledge and understanding” between individuals embedded in networks and/or communities (Rojas, Shah, and Friedland
Drawing from prior research on cognitive and community-based resources generated via communication (e.g., Ball-Rokeach, Kim, and Matei 2001; Delli Carpini, Cook, and Jacobs 2004; Fishkin 1995; McLeod et al. 1999; Shah et al. 2005), as well as the idea that communication helps integrate communities by engaging individuals and institutions within a communicative ecosystem of “rich, cross-cutting networks of association” (Fischer 1982; Friedland 2001), the theory asserts that the benefits of social capital are not derived merely from the existence of social relationships, but rather from the communication that occurs between two or more people who are socially connected.

Specifically, this activation of latent resources occurs through two forms of communication: news use and political talk (Rojas, Shah, and Friedland 2011). Informational uses of media have been shown to be associated with higher levels of civic participation (Brehm and Rahn 1997; Romer, Jamieson, and Pasek 2009; Shah 1998). Meanwhile, discussion within social networks is also associated with civic and community engagement (McLeod et al. 1999; Sirianni and Friedland 2001). Based on this theory and prior literature, we hypothesize that the relationship between social connection and journalist—audience interactions will be moderated by both news use and political talk.

H2: The relationship between association membership and user—journalist interactions on Twitter will be stronger among (a) those who use the news more often (b) those who talk politics more often.

H3: The relationship between network size and user—journalist interactions will be stronger among (a) those who use the more often and (b) those who talk politics more often.

Methods

Sample and Data

This study underwent expedited review by the Institutional Review Board at The University of Alabama and was approved on 16 May 2018 (Protocol # 18-OR-188). It relies on a two-wave, online panel survey of adult internet users who are residents of the United States. The first wave was collected between 19 and 29 September 2018, six weeks before the 2018 US Midterm Elections, and the second wave was collected during the month after the Elections, from 7 November to 5 December 2018. The survey was administered by a private survey firm, Survey Sampling International (SSI, now called Dynata), which uses a three-stage sampling process. First, SSI randomly selected respondents from their online panel using a “sample matching” procedure (Callegero et al. 2014). SSI invited specific individuals to join the panel based on geographic and demographic quotas, such as age, gender, race, and census region, in order to reflect the US population as estimated by the 2016 American Community Survey (ACS) conducted by the US Census Bureau. Second, subjects were filtered out of the study who were ineligible to participate because they were (a) under the age of 18, (b) not US residents, or (c) had no internet access. This step is a failsafe to prevent ineligible respondents from participating in case some made it through the first stage of the process. Third, subjects were invited to take the study based on their likelihood to complete it. This final step was taken in order to maximize the completion rate and avoid non-response bias, which is critical to obtaining unbiased estimates (e.g., Groves and Peytcheva 2008).
The first survey wave has a sample size of $N = 1,493$ and a cooperation rate (an appropriate metric when traditional response rates cannot be reported because parameters of sample invitations are unknown) of approximately 70% (AAPOR 2016; CR3). The second survey wave has a sample size of $N = 576$ and a 39% retention rate. The first-wave sample is broadly reflective of the population of interest (see Appendix A), with an average age of 48.39 ($SD = 16.18$), 51% women, 77.2% white, and 75% reporting affiliation with a religion. The average respondent has an associate’s or bachelor’s degree ($M = 4.38, SD = 1.71$, where 1 = Some high school and 7 = Post-graduate degree) and lives in a household that makes between $45,000 and $75,000 per year ($M = 4.84, SD = 2.14$, where 1 = Less than $15,000 and 8 = More than $150,000).

A multiple imputation technique (predictive mean matching) was used to impute missing values. Separate imputations were performed for the first and second waves. Predictive mean matching works as follows: First, cases with complete data were used to predict values of variables with missing data, producing a set of coefficients. Next, a random draw was taken from the predictive posterior distribution to produce a new set of coefficients, which were then used to compute predicted values for all cases with at least one missing value. Finally, an observed value close to the predicted value of each missing case was located and assigned as a substitute. This process was repeated 50 times for each of five imputed datasets, which were pooled for analysis.

**Measures**

**User—Journalist Interactions**
The dependent variable was derived from prior research (Gil de Zúñiga, Diehl, and Ardèvol-Abreu 2018). Respondents were first prompted: “Some people like to interact with journalists on Twitter.” They were then asked (1 = Never, 7 = Very often): “How often do you engage in the following activities on Twitter?” Activities included (a) “tweet at specific journalists,” (b) “retweet specific journalists,” and (c) “direct message specific journalists.” Respondents were also asked: “How often do specific journalists engage in the following activities with your Twitter account?” Activities included (a) “tweet back at you,” (b) “retweet your tweets,” and (c) “direct message you.” These six items were averaged to create the scale (Cronbach’s alpha = .98, $M = 1.67, SD = 1.47$). Because the variable was positively skewed, a log transformation was applied for use as a dependent variable in OLS (ordinary least squares) regression analysis ($M = .29, SD = .57$, Min. = .00, Max. = 1.95). An identical variable was created for Wave 2 (Cronbach’s alpha = .97, $M = 1.74, SD = 1.44$), which was also logged ($M = .34, SD = .58$, Min. = .00, Max. = 1.95).

**Political Talk Frequency**
The political talk frequency variable was also based on prior literature (Barnidge 2017; Eveland and Hively 2009). Respondents were first prompted: “From time to time, people talk with others about government, elections, politics, or the news. We’d like to ask you specifically about the conversations you’ve had in face-to-face settings.” They were then asked (1 = Never, 7 = Very often): “In the last 12 months, how often have you talked about government, elections, politics, or the news with the following types of people in face-to-face settings?” Discussant types included: (a) family members, (b) friends, (c) other coworkers or classmates, and (d) other acquaintances. These same four questions
were repeated for three additional communication settings: (1) “mobile messaging apps,”
(2) “social media sites,” and (3) “online (not including social media sites or mobile messa-
ging apps).” These 16 items were averaged to create the final variable (Cronbach’s alpha
= .97, M = 2.31, SD = 1.45).

**News Use**
The news use measure was also based on prior literature (Bakker and De Vreese 2011; Gil
de Zúñiga, Jung, and Valenzuela 2012). The variable was constructed using seventeen
items. Respondents were asked (1 = Never, 7 = Several times a day): “How often would
you say you get news from:” (1) “print versions of national newspapers (e.g., USA Today,
the New York Times, Wall Street Journal, etc.),” (2) “print versions of local or regional
newspapers (daily or weekly),” (3) “print versions of national news magazines (e.g., Time, News-
week),” (4) “broadcasts for national television news (e.g., ABC, CBS, NBC),” (5) “broadcasts
for local television news,” (6) “broadcasts for cable television news (e.g., Fox News, MSNBC,
CNN),” (7) “talk radio (e.g., Rush Limbaugh or Paul Finebaum),” (8) “public radio (e.g., NPR),”
(9) “online-only news sites or blogs (e.g., Politico, BuzzFeed, HuffPo, DrudgeReport, Breit-
bart News Network),” (10) “online sites for news organizations (e.g., nytimes.com, foxnews.
com, cnn.com),” (11) “podcasts (e.g., PodSaveAmerica, RadioLab),” (12) “online message
boards (e.g., Reddit, Digg),” (12) “social networking websites or apps (e.g., Facebook,
Google+, MySpace, or LinkedIn),” (13) “microblogging websites or apps (e.g., Twitter or
Tumblr),” (14) “blogging websites (e.g., Wordpress, Medium, or Blogger),” (15) “photo
sharing websites or apps (e.g., Instagram, Flickr, or Pintrest),” (16) “video sharing websites
or apps (e.g., YouTube, Vimeo, or Periscope),” and (17) “mobile messaging websites or apps
(e.g., Snapchat or What’s App).” These 17 items were averaged to create the final variable
(Cronbach’s alpha = .97, M = 2.87, SD = 1.16).

**Group Membership**
Based on prior literature (Rojas, Shah, and Friedland 2011), the group membership variable
was measured with 13 questionnaire items (0 = Not member, 1 = Inactive member, 2 =
Active member). Respondents were prompted:

Below is a list of different types of organizations. For each one, please indicate whether you are
an active member (i.e., belong to and participate in the organization), you are a member but
not active (i.e., belong to but do not participate), or you are NOT a member.

The following types of groups were included: (1) social group or club; (2) sports team; (3)
aristic, musical, or cultural organization; (4) educational organization or after-school
program; (5) union; (6) church or religious organization; (7) environmental or ecological
organization; (8) professional association; (9) charitable or service-based organization;
(10) neighborhood association; (11) political party or movement; (12) human rights or
animal rights organization; and (13) health or disability organization. These items were
summed to create the final variable (Cronbach’s alpha = .83, M = 3.76, SD = 4.59), and
the variable was then logged (M = 1.16, SD = .91, Min. = .00, Max. = 3.30).

**Political Talk Network Size**
This variable is also based on prior literature (Bartridge 2017; Eveland and Hively 2009), and
it used the same prompt as for the talk frequency measure. Respondents were asked “In
the last 12 months, about how many people have you talked to about these subjects in the following settings?” Setting included (1) “face-to-face,” (2) “mobile messaging apps (e.g., Snapchat, What’s App, SMS text),” (3) “social media site (e.g., Facebook, Twitter, Instagram, YouTube),” and (4) “online (not including social media or mobile messaging apps).” Combined, these four items create the network size measure, which was capped at 200 to reduce skew (Cronbach’s alpha = .63, $M = 43.42$, $SD = 156.38$), and the variable was then logged and the variable was then logged ($M = 2.34$, $SD = 1.54$, Min. = .00, Max. = 7.74).

**Political Knowledge**

Using six fact-based survey items derived from prior research (Delli Carpini and Keeter 1996), respondents were asked about political actors, parties, and processes. Questions included: (1) “Will you tell me who the Vice President of the United States is?” [Mike Pence], (2) “Can you tell me the name of the President of Russia?” [Vladimir Putin], (3) “Do you happen to know which political party has a majority in the US House of Representatives?” [Republican], (4) “Which party is generally more liberal on most political issues?” [Democrat], (5) “How much of a majority in both the House of Representatives and the Senate is requires for the US Senate and House to override a presidential veto?” [Two-thirds], and (6) “Whose responsibility is it to determine if a law is constitutional or not?” [Judicial branch]. Correct answers were tallied, with a minimum score of 0 and a maximum score of 6 ($M = 4.74$, $SD = 1.52$).

**Political Efficacy**

The variable for political efficacy was measured using three items borrowed directly from prior research (Niemi, Craig, and Mattei 1991). Respondents were asked the extent to which they agree or disagree (1 = Strongly disagree, 7 = Strongly agree) with the following statements: (1) “People like me can influence what local government does,” (2) “I believe that the national government cares about what people like me think,” and (3) “City government responds to the initiatives of individuals.” These three items were averaged to create the final variable (Cronbach’s alpha = .70, $M = 3.89$, $SD = 1.19$).

**Political Interest**

Political interest was measured with three items based on prior literature (Verba, Schlozman, and Brady 1995) and asked respondents: “How interested are you in” (1) local or regional politics, (2) national politics, and (3) international politics (1 = Not at all, 7 = Very). These items were averaged to create the final variable (Cronbach’s alpha = .89, $M = 4.35$, $SD = 1.72$).

**Demographics**

Analyses also controlled for age, gender, race, education, and income. See above for measurement scales and descriptive statistics.

**Analysis**

All analyses were performed on the pooled dataset. Ordinary least squares (OLS) regression models were used to test each of the hypotheses outlined above. Both
cross-sectional models and autoregressive panels models were fit to the data. Separate models were fit for each hypothesized interaction.

Results

Table 1 shows results for the cross-sectional analyses. The first model in the table shows estimates without interactions, while the next four models test each of the four hypothesized interactions in separate models. Table 2 shows parallel analyses for the longitudinal analyses, and these models control for the autoregressive term.

H1a predicts that association membership will be positively related to user—journalist interactions, while H1b predicts that network size will be positive related. H1a is supported in the cross-sectional analysis (\(B = .03, SE = .01, p < .05\)), but the relationship is not statistically significant in the longitudinal analysis. For H1b, the cross-sectional analysis shows a negative relationship: network size (\(B = -.02, SE = .01, p < .05\)), but, once again, this relationship is not significant in the longitudinal analysis. Taken together, these results show mixed results for the relationship between social ties and user—journalist interactions. People who belong to more associations are more likely to interact with journalists, but so are people who talk politics with fewer discussion partners (these cross-sectional relationships are illustrated in Figure 1). Neither of these variables has an over-time effect on user—journalist interactions.

News use and talk frequency are also positively related to user—journalist interactions. For news use, the effect estimate is \(B = .17\) in the cross-sectional analysis (\(SE = .01, p < .001\)) and \(B = .07\) in the longitudinal analysis (\(SE = .03, p < .05\)). For talk frequency, the estimates are \(.11 (SE = .01, p < .001)\) and \(B = .06 (SE = .02, p < .01)\), respectively. Thus, results show that

<table>
<thead>
<tr>
<th>Variable</th>
<th>User—Journalist Interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>(-.22 (.08)**)</td>
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<tr>
<td>Age</td>
<td>(-.01 (.00)***)</td>
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<tr>
<td>Gender</td>
<td>(-.10 (.02)***)</td>
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<tr>
<td>(1 = Woman)</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>(-.01 (.01))</td>
</tr>
<tr>
<td>Income</td>
<td>(.00 (.01))</td>
</tr>
<tr>
<td>Race</td>
<td>(-.02 (.02))</td>
</tr>
<tr>
<td>Social Trust</td>
<td></td>
</tr>
<tr>
<td>Political Knowledge</td>
<td>(-.03 (.01)***)</td>
</tr>
<tr>
<td>Political Efficacy</td>
<td>(.05 (.01)***)</td>
</tr>
<tr>
<td>Political Interest</td>
<td>(-.01 (.01))</td>
</tr>
<tr>
<td>Association Membership</td>
<td>(.03 (.01)*)</td>
</tr>
<tr>
<td>Network Size</td>
<td>(-.02 (.01)*)</td>
</tr>
<tr>
<td>News Use</td>
<td>(.17 (.01)***)</td>
</tr>
<tr>
<td>Talk Frequency</td>
<td>(.11 (.01)***)</td>
</tr>
<tr>
<td>Assoc. Membership * News Use</td>
<td>(.05 (.01)***)</td>
</tr>
<tr>
<td>Assoc. Membership * Talk Frequency</td>
<td>(.03 (.01)***)</td>
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<tr>
<td>Network Size * News Use</td>
<td></td>
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<tr>
<td>Network Size * Talk Frequency</td>
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</tbody>
</table>

\(R^2 \quad .53***\)

Note: Cell entries are coefficients (B) and standard errors (SE, in parentheses) from pooled ordinary least squares (OLS) regression models. Multiple imputation performed using predictive mean matching. Five datasets produced using 50 iterations each. \(N = 1493\). *\(p < .05\), **\(p < .01\), ***\(p < .001\).
people who use the news and talk about politics more frequently are more likely to interact with journalists on Twitter, and they also show an overtime effect of these communication behaviors. The cross-sectional relationships are visualized in Figure 2.

H2a predicts a positive interaction between association membership and news use, while H2b predicts a positive interaction between association membership and talk frequency. Table 2 presents the hierarchical regression model showing the longitudinal predictors of user—journalist interactions.

**Table 2.** Hierarchical regression model showing the longitudinal predictors of user—journalist interactions.

<table>
<thead>
<tr>
<th>Variable</th>
<th>User—Journalist Interactions W2</th>
<th>Intercept</th>
<th>User—Journalist Interactions W1</th>
<th>Age</th>
<th>Gender (1 = Woman)</th>
<th>Education</th>
<th>Income</th>
<th>Race</th>
<th>Social Trust W1</th>
<th>Political Knowledge W1</th>
<th>Political Efficacy W1</th>
<th>Political Interest W1</th>
<th>Association Membership W1</th>
<th>Network Size W1</th>
<th>News Use W1</th>
<th>Talk Frequency W1</th>
<th>Assoc. Membership W1 * News Use W1</th>
<th>Assoc. Membership W1 * Talk Frequency W1</th>
<th>Network Size W1 * News Use W1</th>
<th>Network Size W1 * Talk Frequency W1</th>
<th>R²</th>
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<tr>
<td></td>
<td></td>
<td>.00 (.15)</td>
<td>.08 (.16)</td>
<td>.06 (.15)</td>
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<td>.49***</td>
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<tr>
<td>User—Journalist Interactions W1</td>
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Note: Cell entries are coefficients (B) and standard errors (SE, in parentheses) from pooled ordinary least squares (OLS) regression models. Multiple imputation performed using predictive mean matching. Five datasets produced using 50 iterations each. N = 576.

*p < .05, **p < .01, ***p < .001. W1: Wave 1. W2: Wave 2.

**Figure 1.** The cross-sectional relationships between user—journalist interactions and association membership (left) and network size (right).
Results from both cross-sectional and longitudinal analyses support these predictions. For the interaction with news use, the effect size is $B = .05$ in the cross-sectional analysis ($SE = .01$, $p < .001$) and $B = .03$ in the longitudinal analysis ($SE = .015$, $p < .05$). For the interaction with talk frequency, the effect estimate is identical in both sets of analysis ($B = .03$, $SE = .01$), with the only difference being the $p$-value (cross-sectional: $p < .001$; longitudinal: $p < .05$), which is, ostensibly, due to the difference in sample size. These results suggest that the overtime of social ties (association membership, network size) are conditional on communication (news use, talk frequency). The more people communicate about public affairs with their existing social ties, the more likely they are to interact with journalists on Twitter. These conditional relationships (cross-sectional) are illustrated in Figures 3 and 4, respectively.

H3a and H3b predict positive interactions between network size and news use, and between network size and talk frequency. This prediction is supported by both sets of analysis for first interaction (cross-sectional: $B = .02$, $SE = .00$, $p < .001$; longitudinal: $B = .03$, $SE = .01$, $p < .01$). The second interaction, on the other hand, is supported only by the cross-sectional analysis ($B = .01$, $SE = .00$, $p < .01$), but it is non-significant in the longitudinal analysis. These conditional relationships (cross-sectional) are shown in Figures 5 and 6, respectively.

**Discussion**

Based on the idea that individuals with more social capital will be more likely to interact with journalists, we predicted that individuals with more social ties—both in terms of formal association membership and informal talk networks—will report higher levels of initiating and receiving communications with journalists on Twitter. Both cross-sectional and longitudinal analyses are supportive of these predictions. Additionally, we drew from the idea that communication is the primary mechanism by which benefits of
social capital are derived from social relationships (Rojas, Shah, and Friedland 2011), and we hypothesized interactions between indicators of social ties and indicators of communication on user—journalist interactions. Cross-sectional results supported all four of these interaction hypotheses, and longitudinal results supported three of four.

Based on this evidence, we conclude that individuals with more social capital—operationalized as having and communicating with social ties—is positively related to user—journalist interactions. In other words, people who are relatively more connected to

Figure 3. The cross-sectional relationship between association membership and user—journalist interactions at three levels of news use.

Figure 4. The cross-sectional relationship between association membership and user—journalist interactions at three levels of talk frequency.
formal and informal groups and networks are more likely to interact with journalists on Twitter, and journalists are likewise more likely to engage with them. Thus, while Twitter presents the possibility of opening up discourse between journalists and new audience members, our evidence suggests that it is the “usual suspects” who are most likely to engage journalists in these spaces, which means that Twitter is more “business as usual” than it is a new connection point for journalists. These conclusions advance theory on social capital by shedding light on the ways in which journalists in the social media age

**Figure 5.** The cross-sectional relationship between network size and user—journalist interactions at three levels of news use.

**Figure 6.** The cross-sectional relationship between network size and user—journalist interactions at three levels of talk frequency.
are technologically embedded in and often reinforce existing structures of social connection and power. They also advance the study of user—journalist interactions by highlighting social inclusion and exclusion in these processes.

This study advances social capital theory by illuminating the ways in which journalists in the social media age are technologically embedded in formal and informal social structures. Both voluntary associations (formal groups) and informal talk networks are critical to communicatively integrating citizens into social structures that are connected to institutions of government and civil society (Friedland 2001; Rojas, Shah, and Friedland 2011). News media have always played a critical role in this integrative process by providing the informational resources necessary to build and sustain civic involvement (Brehm and Rahn 1997; Shah 1998). But Twitter changes the dynamics of news media’s relationship to citizens by providing a space in which they can interact directly with the public (Molyneux, Holton, and Lewis 2018). This study finds that citizens who have more social capital are more likely to interact with journalists, which means that, in the social media age, journalists themselves are closely and personally intertwined in processes of community integration and mobilization. Thus, journalists likely play an even greater role in shaping public conversations than they did before the rise of social media, and these conversations can have a real impact in communities because they carry over into the deliberative and discursive processes in both formal groups and informal networks.

The study also expands knowledge about user—journalist interactions by helping us to understand social inclusion and exclusion in conversations with journalists. Social capital theory has primarily focused on the benefits individuals can reap from investing in social relationships (Burt 1992; Coleman 1990; Portes 1998). But social capital itself is not inherently good or bad. Rather, it describes resources embedded in social relationships, and these resources, like any resources, can be distributed equitably or not. Therefore, many outcomes of social capital can be interpreted as both good or bad depending on one’s normative assumptions about the distribution of resources. With that idea in mind, social capital provides a useful lens for determining whether journalists fill “structural holes” (Burt 1992) via engagement with less connected members of society. The findings of this study suggest that they do not. Rather, they are more likely to reinforce existing inequities inherent in structures of social connectivity and power (Tichenor, Donohue, and Olien 1973; Tuchman 1973) than they are to draw underrepresented voices into their conversations. From a normative perspective, this could be interpreted as a form of social exclusion—one aspect of the “dark side” of social capital (Van Deth and Zmerli 2010) that arises from the same resources from which social benefits are derived.

Finally, this study engages the ongoing public conversation about the role of Twitter in journalists’ work routines. The findings imply that the unbounded optimism regarding the potential for Twitter to connect journalists and audience members may be overstated. This disenchantment with social media is becoming increasingly prominent among journalists themselves for a variety of reasons (Bossio and Holton 2018), including polarized and hostile discourse (Manjoo 2019), personal harassment from online trolls (Molyneux 2019), and the general difficulty of identifying “Twitter bots,” or automated accounts who are not actually audience members (Ferrara et al. 2016). This study gives one more reason for journalists not to interact on Twitter: Even if the people they interact with are “real,” their interactions may do more harm than good by reinforcing social inequities (see also Molyneux and Mourão 2019; Usher, Holcomb, and Littman 2018). Therefore,
for journalists it is worth considering whether these interactions are worth the time and energy it takes to engage in them, especially considering their potentially negative outcomes (Molyneux 2019).

The conclusions outlined above are limited in important ways. While the study relies on a longitudinal survey design, readers should take caution when using these results to make causal inferences, as the study has not eliminated all potential “third factors” as an experiment would. That said, the study does establish (a) correlation and (b) time order, and it therefore brings us closer to making causal claims than cross-sectional surveys are able to do. Additionally, the opt-in online panel is, strictly speaking, not a true probability sample, which limits its representativeness. However, the goal of the study is not to provide a precise snapshot of the target population, but rather to estimate the strength of the relationship between social capital and journalist—audience interactions. AAPOR notes that online panel samples are more appropriate for this purpose than they are for providing precise point estimates of single variables (Baker et al. 2010). The reason for this is that even if two point estimates are biased, the relationship between them will not change so long as that bias is systematic. Thus, while the survey may not be precisely representative, the evidence is generalizable to the phenomenon of interest. That said, research based on these samples has become increasingly common in the social sciences, and the current sample does reflect the population of interest along key criteria, including age, race, gender, and census region.

The study is also limited by the fact that it only examined interactions with journalists on Twitter. Although Twitter is important because of its popularity with politicians, media professionals, and opinion leaders, only a small proportion of the US population actively uses the platform. By contrast, other platforms such as Facebook and Instagram have much broader user bases. Thus, future research could study social capital and user—journalist interactions on other social media platforms. Another important limitation is that the study relies on self-reported measures of both Twitter behavior and social capital. There is a danger that people cannot accurately recall either of these things. However, research shows these measurement errors are not a major issue for estimating relationships, so long as each respondent consistently overestimates or underestimates their responses (King, Keohane, and Verba 1994). That said, future research could combine these data with observational or computational studies of user—journalist interactions on Twitter. A related limitation relates to the external validity of our survey measures. While external validity is certainly a concern, our measures are based on prior literature of both social capital (Rojas, Shah, and Friedland 2011) and journalist—audience interactions (Gil de Zúñiga, Diehl, and Ardèvol-Abreu 2018). Future research could focus on validating these measures.

Despite these limitations, this study has provided relatively strong evidence that people with more social capital are more likely to interact with journalists on Twitter and that journalists are more likely to interact with them. Thus, our evidence suggests that Twitter tends to reproduce patterns of social connectivity and communicative power between journalists and audiences.

**Disclosure Statement**

No potential conflict of interest was reported by the authors.
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References


## Appendix

**Table A1.** Demographic profiles of Wave 1 survey sample and target population.

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