

# #Indigenous: Tracking the Connective Actions of Native American Advocates on Twitter

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## ABSTRACT

With fewer than 66% of eligible voters registered and voter turnout rates 5-14 percentage points lower than any other ethnic group, Native Americans comprise the least participatory ethnic group in U.S. political elections [42, 57, 49, 25]. While discourse surrounding Native American issues and interests has increasingly moved to social media [55, 56], there is a lack of data about Native American political discourse on these platforms. Given the heterogeneity of Native American peoples in the U.S., one way to begin approaching a holistic understanding of Native American political discourse on social media is to characterize how Native American advocates utilize social media platforms for connective action. Using a post-structural, interdisciplinary, mixed methods approach, we use theories of connective action [5] and media richness [14] to analyze a Twitter data set culled from influential Native American advocates and their followers during the 2016 primary presidential election season. Our study sheds light on how Native American advocates use social media to propagate political information and identifies which issues are central to the political discourse of Native American advocates. Furthermore, we demonstrate how the bandwidth characteristics of content impact its propagation and we discuss this in the context of pernicious digital divide effects present in Indian Country.

## ACM Classification Keywords

H.5.3 Group and Organization Interfaces: Computer-supported cooperative work; H.3.5 Online Information Services: Web-based services

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## Author Keywords

social network analysis, social media, civic engagement, Native American

## INTRODUCTION

Native Americans comprise an exceptional class of citizenship within the U.S. While many Native Americans are voting members of tribal nations, they are also eligible to vote in local, state, and national elections. However, the historically agonistic relationship between the U.S. federal government and Native American nations, has discouraged Native American individuals from engaging with electoral politics in the U.S. [25, 49, 57]. Moreover, Indian Country<sup>1</sup>, which is associated with some of the largest Native American voting blocs, suffers from a lack of communications infrastructure<sup>2</sup>, limiting Native American individuals' potential for political engagement through digital means. To demonstrate the critical need for Internet infrastructure in Indian Country, it is necessary to understand the discursive qualities and data characteristics of political content disseminated across Internet Protocol (IP) networks. Indeed, the U.S. Government Accountability Office has recently issued a statement outlining the need for data surrounding tribal Internet access [23].

To the best of our knowledge, there have been no network scientific studies of Native American political engagement through social media, although social media uses are observable in Native American policy arenas [4, 15, 29, 37, 56, 30, 38, 20]. Indeed, presidential hopeful Bernie Sanders hired

<sup>1</sup>“Indian Country is a legal term that refers to the federally-recognized tribes, state-recognized tribes, pueblos, rancherias, bands, and Alaska Native villages and corporations within the political boundaries of the U.S. Used colloquially and not in a legal sense whatsoever, Indian Country also refers to Native peoples habits and norms in this somewhat parallel society. As a legal term, the phrase Indian Country has come to have meaning out of the basis of over a century of treaty-making and recognition processes between Native peoples and U.S. federal authorities. It inherently refers to an intertribal state of being for Native peoples in the U.S.” [16].

<sup>2</sup>According to the FCC, 85% of residents living on tribal land lack access to fixed broadband speeds of 3 Mbps [18].

two well-known Native American rights advocates to help craft his social media campaign [36, 41]. The 2016 U.S. presidential elections present a unique opportunity to investigate the political content propagated by Native American advocates<sup>3</sup> representing a diverse swath of Indigenous and tribal interests. As a cursory investigation into the characteristics of Native American political content on Twitter, this research asks:

**RQ1** What political content do Native American advocates share on Twitter?

**RQ2** What are the network characteristics of sub-communities present within the Twitter streams of Native American advocates?

**RQ3** In light of bandwidth restrictions in Indian Country, what are the bandwidth characteristics of content propagated by and from Native American advocates?

To accomplish this, we worked with Indigenous scholars and community-based activists to curate a list of the Twitter hashtags and user accounts they follow to share political information. We culled the most frequent hashtags and top user accounts to generate a data set. We collected and characterized 11,102 tweets generated and/or shared by Native American advocates active on Twitter. We contrast our findings as they pertain to the Twitter activities of Native American advocates to 46.5 million tweets sampled from the general Twitter feed. Using the social connectivity information embedded in the Native American advocates data set, we identify network sub-communities, and highlight ways that dispersed efforts pull from similar bases of support, ultimately providing a characterization of Native American and Indigenous political agendas as manifested by advocates online. Finally, we discuss these findings in the context of on-the-ground realities for Native American people.

## RELATED WORK

A large body of work has explored information and communication technologies (ICTs) and political engagement, and it is clear that the Internet enables new grassroots movements to quickly materialize and operate for a period of time [20, 21, 6, 7, 19]. The Mexican Zapatista movement of the 1990s provides a prime example of the success social movement organizations (SMOs) can achieve by networking over the Internet [20]. Prior studies have commented on the balkanization that occurs in political social networks on Twitter, where actors divide into affiliate networks, reducing exposure to opposing viewpoints [26]. However, for marginalized social groups, sharing political viewpoints within affiliate networks can become a source of in-group validation and motivation for political mobilization [12, 56, 31]. While social media platforms can empower marginalized groups, limited Internet access and connectivity continues to trouble Indian Country. According to the Federal Communications Commission (FCC), fewer than 15% of people living on tribal land

<sup>3</sup>We use the phrase *Native American advocate* to refer to activists, journalists, newsgroups, scholars, and non-governmental organizations that represent North American Indigenous peoples, nations, and individuals.

have broadband access [18]. As is typical for infrastructure-poor, rural areas, many reservations depend on wireless networks to extend residential broadband access [2, 16]. In some communities, this is accomplished through a combination of wireless backhaul links connecting homes to the Internet over Wi-Fi [51, 48] or TV whitespaces [58]; in others, residents rely on cellular network coverage to access the Internet from home [24, 34]; in still others, people must travel what can be tens of miles in order to reach the nearest access point, typically located in private businesses bordering tribal land or in tribal libraries and media centers [34]. The dependence on wireless technology leads to connection opportunities that are either limited because of their financial expense (in the case of data subscriptions), attenuated performance over long distance operations (in the case of microwave and satellite), or excessive time requirements (in the case of opportunistic transactions made from a municipal cellular or Wi-Fi hotspot).

Prior studies of Indigenous approaches to social media provide examples of tribes and tribal groups applying ICTs toward cultural revitalization, strengthening community relationships, language revitalization, art and aesthetics, gaming and storywork, and political mobilization [4, 15, 29, 37, 56, 30, 38, 20]. Most of these studies are qualitative and focus on discerning relationships between Indigenous practices and ICTs. Scholars have written about the difficulties federally-recognized tribes in the U.S. face as they seek licensing, subsidies, and rights to build Internet infrastructure across sovereign reservation lands [32, 39]. These studies are in accord with research on the structural inequalities between federal and state policy institutions and tribal policy institutions [13, 17, 46, 55]. A small number of studies utilize Census data and case studies to ascertain Internet access and uses among Native Americans in rural and urban locations [43]. This research discerns the characteristics and qualities of the propagation of Native American political content through Twitter.

## THEORETICAL FRAMEWORKS

Our work is best understood through the combination of two theories: connective action and media richness.

### Connective Action

For heterogeneous Native American groups, hosting political “diffuse conversations [9]” through social media contributes to media salience in spite of mass media marginalization of Native American political issues [55]. Agarwal et al. examine the role of Twitter in the Occupy movement, using the constant comparative method and with empirical analysis of network artifacts (specifically, tweet records collected using the Twitter Streaming API) [1]. Characterizing the networks that allow for successful Internet-based SMOs, Gloor defined Collaborative Innovation Networks (COINs): “a cyberteam of self-motivated people with a collective vision, enabled by the Web to collaborate in achieving a common goal by sharing ideas, information, and work” [21]. Similarly, through analysis of the online uses of collective action networks—brick-and-mortar institutions and face-to-face groups—Bennett and Segerberg identified *connective action networks*, groups of

individuals who may only encounter each other through online spaces and who are unaffiliated with SMOs or brick-and-mortar institutions, yet who mobilize toward common goals [5]. In that sense, we approach Native American advocates' uses of social media as the connective tissue binding multiple political action environments, where actors who may or may not know each other and who may or may not belong to SMOs nevertheless agree to propagate content and adopt discourses related to certain issues.

### Media Richness

Daft and Lengel's Media richness theory (MRT) defines *media richness* as "the relative ability of information to influence or change mental representations and thereby to facilitate learning [14]." More specifically, the richness of each medium is based on the following: "the use of feedback so that errors can be corrected; the tailoring of messages to personal circumstances; the ability to convey multiple information cues simultaneously; and language variety [35]." As an online social media platform, Twitter is capable of posting users' content and responses to content. The platform supports embedded multimedia content including audio, photo, and video in addition to 140 characters of text. While Twitter operates as a broadcast medium where tweets are visible to any other user on the platform, tweets can be personalized and directed leveraging usertags and hashtags. In particular, we interpret the impact of media richness from the perspective of Twitter audiences connecting from Indian Country, where persistent digital divide effects likely impact the Internet access and connectivity capacities of some of the largest Native American voting blocs.

### METHODOLOGY

By applying decolonizing and post-structural methods with network analysis, we follow an approach similar to Garrido, who, in tracing the Zapatista movement, reconstructed a network from digital artifacts, applied categorizations based on domain knowledge, and used network analysis to determine relationships among actors and topics in the network [20]. Thus we surface, describe, and quantify what Smith refers to as the "[networking] process which indigenous peoples have used effectively to build relationships and disseminate knowledge and information" [50].

### Statement of Positionality

The research team consists in part of Native American advocates and educators with a combined record of over 20 years of experience working with Native American SMOs, cultural revitalization efforts, and Native American political theorists. Results that pertain to political engagement are analyzed from within an Indigenous political science paradigm, which is premised on the assumption of colonizing logics in modern Westphalian nation-states, the politics of recognition, and theories of tribal sovereignty and self-determination [13, 17, 46, 55].

For Native Americans, sovereign rights refer to the rights they bear within their tribe as it is recognized by the U.S. federal government. At present, there are 586 federally-recognized

tribes within U.S. borders, and U.S. congressional representatives acknowledge tribal rights occasionally, and not as a matter of course. Many social scientists interpret Indigenous peoples' social movements as entirely identity-based movements, which is technically erroneous, as many Indigenous peoples' movements are also expressions of the sovereign autonomous rights of federally-recognized tribal governments [55]. This study is designed to reveal the propagation of Native American political content through network analysis of Twitter data sets, with conscientious regard to issues affecting Native American peoples, given their limited access to the Internet, limited resources for Internet infrastructure innovation, and the constraints of democratic political participation for Indigenous peoples.

### Definitions

For this study, we defined *political content* as data exchanged over technical network channels that pertains to political engagement. We define *political engagement* as human activities that contribute to awareness of justice in governmental affairs and moral or ethical behavior of government officials or institutional authorities, mostly as consciousness-raising, protest strategies, or sustained critique. Political engagement can include *political action*, which refers to direct and indirect methods that individuals utilize to change a governmental status, including political participation through voting, registering to vote, donating to campaigns, and petitioning.

We define *content propagation* as the transmission of data across the Twitter platform through the intentional user techniques of tweeting, retweeting, and embedding artifacts (i.e. photos, videos, and URLs) into the tweet. We also distinguish the *actor* from the *user*, in which the actor is a human or non-human node in a time interval within a network map, while a user is an individual or organization with a unique identifying Twitter account. Additionally, we define *sub-communities* as clusters of actors identified using the Louvain measure of density of Jaccardian similarity edges between hashtag-centric ego networks.

### Data Curation

Functioning as participant observers, the research team created a list of search terms based on their own Facebook newsfeeds, groups, and friends lists and Twitter streams. In addition, the team reached out to fifteen associates, also Native American activists, advocates, educators, and journalists, who likewise contributed Twitter hashtags and usernames. The team queried individuals across a range of advocacy roles, from individuals in prominent institutional policy roles to individuals working in remote reservation areas and focusing on local issues. The process of manual curation resulted in a list of 45 hashtags and 33 user accounts.

### Data Collection

Between February 11 and March 31, 2016 (during the height of the U.S. presidential primary election season), the team queried the Twitter Streaming API using a list of 45 hashtags and 33 user accounts, specifically tracking the number of original tweets, retweets, and users associated with these hashtags and user accounts. We provide an example

	Native American Advocates	General
Total tweets	11,102	46,495,733
Unique tweets	5,172	24,619,723
Retweets	5,930	21,876,010
Users	5,019	13,879,253
Content creators	2,086	3,064,395

Table 1: Overview of the Twitter data sets collected between February 11, 2016 and March 31, 2016.

to demonstrate how our query methodology functioned. Using the hashtag *#mmiw*<sup>4</sup>, we captured all original tweets and retweets containing the string “mmiw.” The Twitter Streaming API is not case sensitive, so all possible letter-case combinations (e.g. “MMIW,” “Mmiw,” “mmiW”) were captured in our sample.

One of the limitations of the Twitter Streaming API is that it does not allow API users to filter by specific hashtags, meaning the hashtag symbol (“#”) is ignored in the query. Thus, the API interprets the hashtag as a keyword. This becomes problematic when filtering for acronym hashtags such as *#mmiw* because they can be matched to tweets in non-English languages. In order to ensure that the tweets used in our analysis reflect our targeted hashtags, we imposed our own post-filtering process. This process includes translating the original tweet text to a lowercase string, parsing the string into whitespace-separated tokens, then using regular expression matching across each token to assess whether any of the desired hashtags were included in the text of the resulting tweet or retweet. All tweets that included at least a single match with a hashtag in our list of hashtags are included in the data set.

The details of this data set are presented in the “Native American Advocates” column of Table 1. In order to provide a larger context for the Native American advocates data set, we use the sampling mechanism of the Twitter Streaming API to procure a data set that represents a random 1% sample of all tweets generated between our study dates of February 11 and March 31. We filter this data set down to English-language tweets and report the details of the data set in the “General” column of Table 1. The original JSON files collected for this research, query terms used to seed the Twitter Streaming API, and software used to collect and analyze data are available for public access at <https://github.com/mvigil90/IndianCountryTweets>.

### Data Analysis

The Native American advocates data set resulted in a list of 5,019 users, including the preliminary 33 recommended user accounts. The 5,172 unique tweets (not including retweets) were generated by 2,086 users, or content creators. The data set consists of 11,102 total tweets. We apply our combined experience with Native American political issues to identify the topics in the most frequently propagated content. cursory qualitative review of randomly selected subsets of this data set includes topics such as: news about missing Indigenous women, presidential campaign messaging, notices about environmentally damaging projects, and updates about the Indian Child Welfare Act.

<sup>4</sup>“Missing and murdered Indigenous women.”

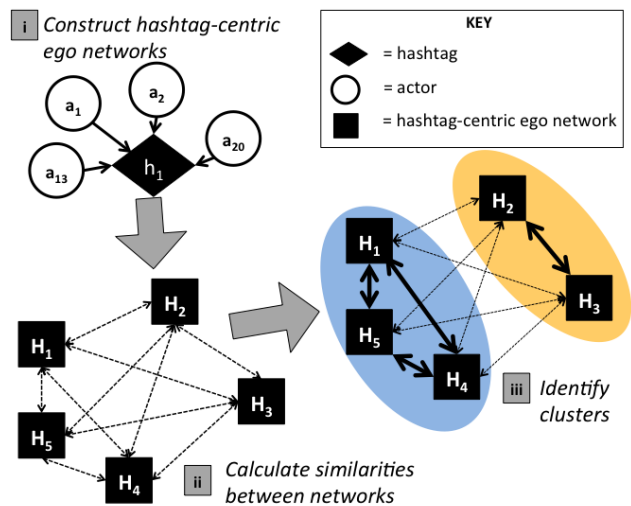


Figure 1: Network analysis methodologies used to identify sub-communities in the Native American advocates data set.

We also examine the types and sizes of media embedded within the tweets we collect. We identify tweets with embedded media as those that contain the full URL associated with linked media. We label each tweet record as containing either an embedded photo, embedded video, or no media. We discern photos by searching the embedded media URL for the substrings associated with embedded image types on Twitter, namely PNG (“.png”) and JPEG (“.jpeg”). We also discern tweets that link to videos by searching the tweet body for regular expressions mentioning videos (“video”) or containing URLs to popular video sites (“youtube.com”, “vimeo.com”, and “vine.co”). Finally, we examine the sizes of the embedded content. To do this for photos, we use cURL<sup>5</sup> to download the photo from the URL embedded in tweets and ascertain the file size. For videos, which are streaming content, we first manually identify the temporal length of each video and then find the file size by multiplying the video time by various data rates that Twitter supports.

Finally, we applied network analytic approaches—specifically social graph analysis, descriptive statistics, sequence analysis, and cluster analysis—to characterize network structures in the Native American advocates data set. We do this according to the process outlined in Figure 1: (i) We create hashtag-centric ego networks ( $H_i$ ) where hashtags ( $h_i$ ) represent ego nodes and the actors ( $a_i$ ) that tweet and retweet a hashtag are the neighbor nodes, then (ii) we use the Jaccard index to calculate how similar each hashtag-centric ego network is to each other [28], and finally (iii) we use the Louvain method to identify sub-communities of actors that tend to form around clusters of hashtags [8].

### Critique of Methodology

In a recent study, Tufekci asserted a number of methodological and inference issues commonly associated with social media big data analysis including: limited platform representation, selection on dependent variables, unrepresentative sampling, ignorance of wider social ecology of interaction, am-

<sup>5</sup>cURL. <https://curl.haxx.se/>

biguous interaction sentiment, disparity between actual and theoretical usage, inappropriate application of network methods, ignorance of field effects, and skews caused by human self-awareness [53]. Similarly, Morstatter et al. presented a critique of the sample quality provided by Twitter’s Streaming API [40]. Here we provide a critique of our collection methodology in light of the most common methodological criticisms.

### Representation

Although the data sets resulting from our collection methodologies are not representative of Native American social media activity as a whole, it does represent the social media interactions between a collection of Native American advocates, Native American political issues, and users who follow them. As a highly interdisciplinary team representing research expertise in computer science, Indigenous information systems, and Native American public policy, we have thoughtfully applied domain knowledge in discerning methodologies for data collection and analysis. We deliberately limited our analysis to a single social media platform for two reasons. Our initial objective was to investigate directed information propagation patterns that occurred between Native American advocates, their audiences, and their information sources. Twitter proved to be the best platform for observing this type of propagation. Second, there was a lack of data from the outset regarding Native American online political engagement and it made sense to begin with a platform that enabled public visibility to a wider portion of user accounts and content [23]. There is indeed a greater social ecology not fully captured by the study of a single platform; however, when attempting a cursory investigation into the relationship between network infrastructure and the propagation of minority perspectives online, it is reasonable to begin by understanding interactions as they take place over a single platform.

### Sampling

Morstatter et al. suggest mitigating the sampling effects in Twitter’s Streaming API by generating more specific parameter sets with different users, keywords, and geographical bounding boxes [40]. In our own methodology, we attempt this in several ways. First, we curated as specific a list of hashtags and user accounts as possible using our connections to Native American advocates, then queried the Twitter Streaming API using two different application keys, one for hashtags and the other for user accounts (generating two overlapping samples that are  $\leq 1\%$  of all simultaneous Twitter activity). Our final Native American advocates data set is a union of these two data sets. While it was possible for us to impose geographical restrictions on the samples, we decided to forgo these restrictions for two reasons. First, the bounding box we required to capture tweets about Native American political issues was too large to function as a practical filter. Second, because Native American and Indigenous political engagement explicitly revolves around transnational sovereign relationships between nations, studies of Indigenous political engagement are not bound by state borders, but rather are shaped by Indigenous social and cultural practices, issues,

Tag	Original tweets	Retweets	Users
#indigenous	2,303	3,042	2,839
#mmiw	607	1,054	1,031
#airp	358	987	527
#nativelivesmatter	311	278	305
#nativeamerican	205	85	97
#idlenomore	189	199	193
#ndn	184	51	66
#hiring	177	1	9
#colonialism	151	136	259
#cdnpoli	140	176	186

Table 2: Top 10 most posted hashtags in the Native American advocates data set.

and affiliations that occur in the margins of national and state borders [55].

## RESULTS

### Native American Political Content on Twitter

Our first research question investigates the types of content Native American advocates post on Twitter and contrasts this content to content present in the general Twitter stream. We also examine the Native American advocates data set for content pertaining to political action and compare it to a general data set.

#### Hashtags

We begin our analysis of topics by examining the hashtags associated with the posts in our Native American advocates data set. Overall, we observe 2,885 unique hashtags. We report the top 10 most posted hashtags in Table 2. While many of the top tags pertain to Indigenous and Native American identity (*#indigenous*, *#colonialism*, *#airp*<sup>6</sup>, *#nativeamerican*, and *#ndn*<sup>7</sup>), a few of the tags represent specific causes, including femicide awareness (*#mmiw*) and murder/suicide awareness (*#nativelivesmatter*). For the top hashtags that correspond to identity, we find that they are more likely to be paired with other hashtags than to be used as standalone hashtags ( $P(c_t > 1 | t_{identity}) = 0.90$  where  $c_t$  represents the number of hashtags associated with a tweet,  $t$ ). This is in contrast to the top hashtags that emphasize specific issues, which are more likely to exist as standalone hashtags ( $P(c_t > 1 | t_{issues}) = 0.42$ ).

**Categories.** Next, we examine the top 100 most frequently occurring hashtags in both the Native American advocates and general Twitter data sets and categorize them with one of the topic labels described in Table 3, which represent: identity (I), civil rights (CR), current events (CE), environmental issues (EI), and other (O). We note that for the general data set, the identity category refers to hashtags that signify and promote group identity. We then report the percentage of tweets associated with each of the top 100 hashtags that fall into each category in Figure 2. For the Native American advocate data set, the category with the most associated hashtags is the identity category (I) with 55% of the hashtags, followed by the civil rights category (CR) with 32% of the hashtags. In contrast, the top category for the general data set is other (O) with 59%, of which 69% pertain to popular awards (e.g. Nickelodeon’s Kids’ Choice Awards or the

<sup>6</sup>“The American Indian Red Power.”

<sup>7</sup>“[American] Indian.”

Topic	Description	Examples
I	Relevant to Indigenous, Aboriginal, or Native American peoples and promotes Indigenous identity through acknowledgement of Indigenous language, art, culture, and education.	<i>#indigenous, #ndn, #nativeamerican, #metis</i>
CR	Promotes political and social justice for minorities, particularly rights while engaging with law enforcement and the legal system.	<i>#nativelivesmatter, #mmiw</i>
CE	Highlights news events or campaigns that occur during or near the observation window.	<i>#nativevote16, #nativesforbernie, #caucus</i>
R	Points to resources including job advertisements and health services.	<i>#ihs, #jobs, #hiring</i>
EI	Related to environmental issues and concerns, either current or longstanding.	<i>#pipeline, #saveoakflat, #climatechange</i>
O	Miscellaneous tags that do not fit into the above categories.	<i>#love, #facebook</i>

Table 3: Description and examples of topical categories that are applied to the top 100 hashtags in each data set.

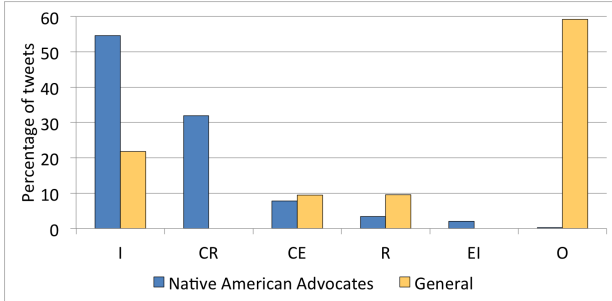


Figure 2: The percentage of tweets from the Native American advocates data set that fall into each topical category defined in Table 3.

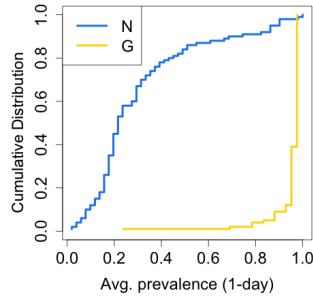


Figure 3: Cumulative distribution of hashtag prevalence over day-long intervals where “N” corresponds to the Native American advocates and “G” represents the general data set.

iHeart Radio Music Awards) and entertainment. The identity category in the general data set has 22% of the top hashtags and 97% of these refer to celebrity fan bases. It is also worth noting that the general data set contains no civil rights or environmental hashtags in the top 100 hashtags.

**Circulation.** In addition to overall tweet count, we evaluate the circulation of topics in the data sets by examining the prevalence and persistence of hashtags. Defined by Paxson when characterizing the presence of routes in the Internet, prevalence and persistence are metrics that can be used generally to characterize churn [44]. Churn refers to the levels of instability surrounding a hashtag or network structure that manifests in the flow of information. In Figure 3, we show the distributions of prevalence over one-day intervals for the top 100 hashtags in the Native American advocates and general data sets. In this context, we define *prevalence* as the portion of day-long time segments in which a hashtag is present relative to all time segments. For the Native American advocates data set, the median prevalence is 0.22, meaning that at least half the hashtags are present across 22% of the days contained in our observation period. Only 5 hashtags are present for more than 90% of the observation period. These include three hashtags that denote Indigenous identity (*#indigenous*,

Time scale	%	Notes
minutes	5.2	“Ephemeral.” These hashtags are retweeted for only minutes after the original post and represent transient topics.
hours	0.8	“Event-driven.” These topics represent reactions to specific events and headlines.
days	2.9	“Recurrent.” These topics represent recurrent issues and causes in the Native American advocates data set.
all	1.7	“Pervasive.” These are topics pervasive to the Native American advocates data set.

Table 4: Summary of topic persistence at different time scales for Native American advocates data set.

*#nativeamerican*, and *#airp*), one hashtag raising awareness for violence against Native women (*#mmiw*), and *#jobs*. On the other hand, the median prevalence for the top 100 general hashtags is 0.97. Thus, it is apparent that identity-based hashtags are the ones with the greatest longevity in the Native American advocates data set, whereas most hashtags in the general data set are highly prevalent (meaning most hashtags appear in each day of our sample window—see Figure 3). An explanation for this is the much larger volume of tweets in the general data set and the fact that a significantly larger portion of the population is represented in that data set.

We next characterize the persistence of each hashtag. We define *persistence* as the number of consecutive time segments in which a hashtag appears. For the Native American advocates data set, we examine persistence at the magnitude of minutes, hours, and days. We calculate persistence by identifying the initial appearance of a tag and counting the consecutive time intervals at which it is present. For hashtags that appear more than once, we report the average persistence across all appearances. In Table 4, we provide an overview of the percentage of hashtags that are persistent at each time interval, meaning they are present in the data set for more than one consecutive interval. In addition to the interval categories, we add a category that corresponds to content that is persistent across all time scales. Content that is persistent only at the scale of minutes is classified as “ephemeral” content. The ephemeral hashtags with the longest persistence were associated with Bernie Sanders (*#wearbernie*, *#tularipforbernie*, and *#bernieinseattle*), larger social justice movements (*#brownlivesmatter* and *#seniorcitizens*), and calls to mobilization (*#urgentaction* and *#sign*). The most persistent ephemeral hashtag (*#wearbernie*) lasted for 6.5 consecutive minutes and was retweeted 31 times. We also identify hashtags that are persistent on the order of hours, or “event-driven” hashtags. These account for a small portion of the hashtags, and are exemplified in posts that refer to specific events, including Internet Friendship Day (February 13), the death of U.S. Supreme Court Justice Antonin Scalia (Febru-

Native American Advocates				General			
Username	Tweets	Users	1-day prevalence (%)	Username	Tweets	Users	1-day prevalence (%)
@POTUS	39	67	29.4	@realDonaldTrump	75,629	63,237	97.6
@BernieSanders	24	38	35.3	@tedcruz	27,420	23,729	97.6
@zhaabowekwe	15	25	21.5	@HillaryClinton	21,356	24,704	97.6
@HillaryClinton	10	3	3.9	@BernieSanders	20,831	21,507	97.6
@goldmanprize	5	3	1.9	@marcorubio	12,885	12,997	95.2
@indiancountry	7	6	7.8	@FoxNews	11,172	11,958	95.2
@SenSanders	6	8	9.8	@POTUS	9,048	13,174	97.6
@BarackObama	6	11	7.8	@YouTube	7,589	7,490	95.2
@WinonaLaduke	5	22	13.7	@CNN	6,883	8,518	95.2
@realDonaldTrump	5	6	5.8	@JohnKasich	5,877	7,140	95.2

Table 5: Statistical overview of the most mentioned users in political action tweets.

Keywords	
	bernie, bern, sanders, hillary, clinton, barack, obama, donald, trump, cruz, rubio, kasich, senator, president, caucus, primary, democrat, republican, ballot, vote, debate, register, convention, elect, incumbent, poll, political, politics, gop, liberal, conservative, congress, potus, supreme court, senate, representative, delegate

Table 6: Keywords used to identify political action content.

ary 13), and a march to raise awareness for missing and murdered Indigenous women (February 14). The most persistent of the event-driven hashtags (#mmiw) lasted 2 hours and was retweeted 7 times. “Recurrent” hashtags correspond to persistence on the order of days. These hashtags are associated with more intersectional Indigenous concerns, most predominantly violence against women, environmental issues, and cultural appropriation. The most persistent of these hashtags (#mmiw) lasted for 3 consecutive days and was retweeted 8 times. Finally, we examine hashtags that are persistent at all intervals (minutes, hours, and days). We refer to these hashtags as “pervasive,” since the issues they address represent some of the most ubiquitous topics we encounter. Pervasive hashtags are predominantly associated with Indigenous and Native American identity, femicide, murder/suicide awareness, and political action. The most persistent of the pervasive hashtags (#indigenous) lasted 49 consecutive days. At the scale of hours, it persisted 7 hours and at the scale of minutes it persisted 2.54 minutes. Overall, it was retweeted 3,042 times.

**Political action hashtags.** We identify hashtags in the top 100 that are related to political action. For the Native American advocates data set, 8 of the top 100 hashtags are associated with political action, including: #cdnpoli<sup>8</sup>, #auspol<sup>9</sup>, #fnpoli<sup>10</sup>, #feelthebern, #wearebernie, #nativesforbernie, #nativevote, and #nativevote16. The median day-long prevalence for these hashtags is 0.33 ( $\sigma = 0.25$ ). For the general data set, 7 of the top 100 hashtags are associated with political action. These include: #trump2016, #trump, #feelthebern, #cruzcrew, #gopdebate, #demdebate, and #pjnet<sup>11</sup>. The median prevalence for these hashtags is 0.98 ( $\sigma = 0.01$ ). As mentioned previously, an explanation for the significant difference in political action hashtag prevalence is the fact that the general data set is much larger than the Native American advocates data set. When comparing the top hashtags in

these two data sets, it is also worth noting that both Democratic and Republican presidential candidates and debates are represented in the general data set. This is a contrast to the Native American advocates data set where the top political action hashtags are used in tweets that are non-opinion bearing statements (typically associated with news sources and voter registration campaigns) or highlight Democratic presidential candidate Bernie Sanders.

#### Political action

One of the distinguishing characteristics of our data set is the fact that it was collected in the midst of the 2016 presidential primary election season in the U.S. Knowing this, we filter tweets that contain keywords associated with political action (see Table 6).

We identify 528 unique tweets (938 total tweets) in the Native American advocates data set that contain these keywords, which represents 10.2% of all 5,172 unique tweets we observe in the data set. In comparison, we identify 2,063,583 unique tweets (2,919,275 total tweets) that contain these keywords in the general data set, which represents only 5.7% of all 3,608,8642 unique tweets we observe in the general data set.

We begin our analysis of political action by examining the top 10 most frequently mentioned users in the subset of tweets that match keywords in from Table 6. In Table 5, we report the number of tweets that mention a username, the number of unique users who tweet or retweet posts mentioning a username, and the prevalence of the mentioned username (on a one-day scale). Of the top 10 most mentioned usernames for the Native American advocates data set we observe 6 individuals, 1 NGO, and 1 Native American news network. With the exception of two, the individuals represented in Table 5 are all politicians. This includes current U.S. president, Barack Obama (@POTUS<sup>12</sup> and @BarackObama), as well as current U.S. presidential candidates: Bernie Sanders (@BernieSanders and @SenSanders), Hillary Clinton (@HillaryClinton), and Donald Trump (@realDonaldTrump). Winona LaDuke (@WinonaLaduke) is a former politician, tribal activist, and environmentalist. Tara Houska (@zhaabowekwe) was the Native American advisor to Bernie Sanders during the time of this study. The Goldman Environmental Prize (@goldmanprize) is the world’s largest award for recognizing grassroots environmental activists [22]. Finally, Indian Country Today Media Network (@indiancountry

<sup>8</sup>“Canadian politics.”

<sup>9</sup>“Australian politics.”

<sup>10</sup>“First Nation politics.”

<sup>11</sup>“Patriot Journalist Network.”

<sup>12</sup>“President of the United States.”



try) is a news media network that provides a platform for Native American journalism and issues [27].

When examining the users mentioned in the general tweets filtered with the keywords<sup>13</sup>, we find that the users who are mentioned are much more prevalent in the general data set than in the Native American advocates data set. Moreover, a more substantial collection of the U.S. presidential candidates are represented, including Republican candidate Donald Trump (@realDonaldTrump), Senator Ted Cruz (@tedcruz), Senator Hillary Clinton (@HillaryClinton), Senator Bernie Sanders (@BernieSanders), Senator Marco Rubio (@marcorubio), and Senator John Kasich (@JohnKasich). Similar to the most-mentioned users in the Native American advocates data set, news media is represented, including the mainstream mass media networks (@FoxNews and @CNN).

### Identifying Sub-communities

To address the second research question, we use clustering methods and sequence analysis to ascertain comprehensive sub-communities (as defined in the Definitions section) based on connections between actors and hashtags in addition to topical sub-communities that exhibit stability over time. We examine these sub-communities across all hashtags in the Native American advocates data set and across political action hashtags identified in the “Political action hashtags” section.

#### Topical sub-communities

When characterizing the content prevalent to the Native American advocates data set, we identify the top 100 most circulated hashtags and use a codebook to classify the tags into six topical categories (see Table 3). In order to identify how different topical issues might unite through similar bases of support, we identify all the actors tweeting or retweeting posts that contain at least one of the top 100 hashtags. We then construct an egocentric graph wherein the hashtag acts as the ego node and all actors who tweet or retweet a post containing the hashtag act as the neighbor nodes in the graph. We then perform a pairwise comparison between the egocentric graphs associated with each hashtag using the Jaccard similarity index:

$$jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

where  $A$  is the ego network associated with one hashtag and  $B$  is the ego network associated with the other hashtag [28]. Thus, Jaccard similarity indices range from 0 to 1 where an index of 0 represents no similarity and 1 represents absolute sameness. From these individual ego networks, we create a graph where the nodes represent each of the top 100 hashtags and the edges represent the Jaccard similarity between each of the hashtags. Next, we identify sub-communities present

<sup>13</sup>While the majority of the 15 most mentioned user accounts in the general data set referenced U.S. political action, we found that the “vote” keyword captured content that pertained to irrelevant votes and polls (e.g. for Nickelodeon’s Kids’ Choice Awards for entertainers or Radio Disney’s poll for top artists). To ensure that our comparison of mentioned usernames in both data sets makes contextual sense, we discard a total of 6 irrelevant usernames that were captured by our keyword filters (Table 6) when applied to the general data set.

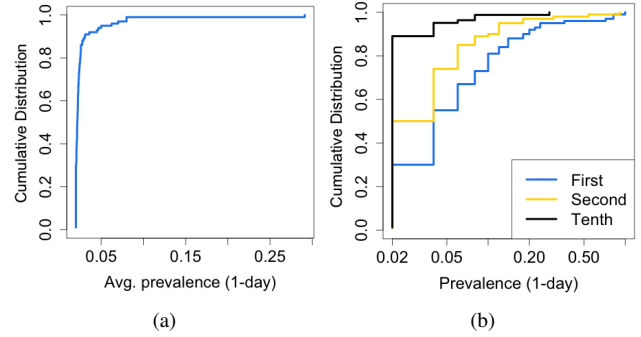


Figure 4: Cumulative distributions of (a) the average prevalence of actors associated with the top 100 hashtags and (b) the prevalence of the first-, second-, and tenth-most prevalent actors associated with the top 100 hashtags in the Native American advocates data set.

ID	Hashtags	Avg. Jacc. Index	Avg. # actors
1	#tairp, #freeleonardpeltier, #indigenous	0.006	591.17
2	#mniw, #idlenomore, #cdnpoli, #turtleisland	0.009	183.38
3	#nativelivesmatter, #blacklivesmatter	0.006	96.25
4	#facebook, #india, #colonialism	0.009	61.17
5	#art, #appropriation, #closethegap, #culture, #lawyers	0.008	56.10

Table 7: Overview of the five largest topical sub-communities in the Native American advocates data set as identified by the Louvain method.

in the graph using the Louvain method, which attempts to partition the graph in such a way that optimizes the *modularity*, or the relative density of edges inside each community as compared to the density of edges between communities [8]. With this technique, we identify 29 sub-communities that exist between the top 100 hashtags with a modularity of 0.81. The median sub-community consists of 3 hashtags ( $\sigma = 2.7$ ) and the median Jaccard similarity present within a community is 0.18 ( $\sigma = 0.11$ ). We provide an overview of the five sub-communities that have the largest average actor bases in Table 7.

We next examine the stability of topical sub-communities over time. To do this, we create hashtag-centric ego graphs for each of the top 100 hashtags as they exist in each day of our data set. We examine the presence of each ego’s neighbor at each of the time-periods to determine the actor prevalence throughout the entirety of our observation period. As with our analysis of hashtags, actor prevalence indicates the comprehensive degree of churn surrounding each hashtag. Figure 4a plots the distribution of the average actor prevalence associated with each of the top 100 hashtags. The average prevalence is 0.022 ( $\sigma = 0.029$ ). #hiring has the greatest average actor prevalence with 0.29. We also plot the distributions of the prevalence associated with the first-, second-, and tenth-most prevalent actors associated with each of the top 100 hashtags in Figure 4b.



We find that only 26% of the hashtags have an actor that is prevalent for at least 10% of the observation period and only 5% of the hashtags have an actor that is prevalent for at least 25% of the observation period. The four hashtags that have at least one actor that is prevalent for the majority of the observation period (i.e. more than 24 days) are: *#indigenous*, *#ndn*, *#nativeamerican*, and *#hiring*. It is also worth noting that 3% of the 2,839 actors involved with *#indigenous* interacted with the tag on at least two different days between February 11 and March 31.

#### Political action sub-communities

As in the Content Analysis section, we separate the political action hashtags associated with the top 100 hashtags in the Native American advocates data set in order to better understand actor engagement around political action. When examining the sub-communities identified via clustering of hashtag-centric ego graphs, we find one sub-community that contains half of the political action hashtags identified in the Content Analysis section. The hashtags that comprise this community include: *#nativesforbernie*, *#feelthebern*, *#apachestronghold*, *#nativevote*, *#nativevote16*, *#saveoakflat*, and *#israel*. *#saveoakflat* and *#apachestronghold* represent a movement spearheaded by tribes in Southern Arizona that challenges Congress’ right to distribute sacred land to a foreign copper mining company without conducting environmental impact studies or consulting tribes [3]. The topics in this sub-community consist of an average of 28.1 unique actors and the average Jaccard similarity index between hashtags comprising the sub-community is 0.15.

When examining the stability of political action topical sub-communities using the day-long prevalence, we find that political action hashtags exhibit relatively low stability over time. The political action hashtag with the highest level of stability is *#cdnpoli* with the most stable of its 162 actors having a day-long prevalence of 0.22 (mean prevalence is 0.023). One explanation for the large number of one-time actors is the fact that many of the tweets tagged with *#cdnpoli* are also tagged with the hashtag that boasts the most prevalent actors; 31% are co-tagged with *#indigenous*. In contrast, top political hashtags linked to campaigns (*#nativevote16*, *#nativevote*, *#wearebernie*, *#feelthebern*, and *#nativesforbernie*) have a collective mean prevalence of 0.02, which translates to an actor tweeting/retweeting that hashtag for only a single day in the data set. For these hashtags, the most prevalent actors are associated with *#feelthebern*, which has one actor with a prevalence of 0.04 and the remaining 54 actors have a prevalence of 0.02. Given the relatively low prevalence of these campaigning hashtags, it is noteworthy that on average, only 1.4% of tweets containing them are co-tagged with *#indigenous*.

#### Bandwidth Characteristics

We address RQ3 in light of Indian Country’s infrastructural limitations described in the Introduction and Related Works sections. We investigate the impact media richness has on the propagation of individual tweets in the Native American advocates data set. We argue that all tweets are essentially bulletins that enable asynchronous interaction between

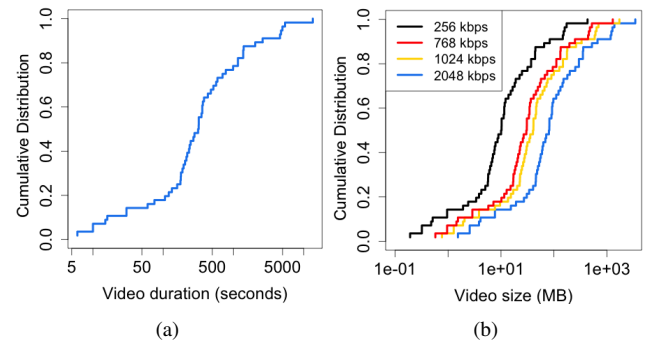


Figure 5: Cumulative distributions associated with (a) durations and (b) sizes of videos embedded in tweets from the Native American advocates data set.

the poster and audience. However, the richness of individual tweets can vary considerably depending on the presence, type, and size of media embedded in the tweet. Of the 5,172 unique tweets we observe in the Native American advocates data set, 1.7% contain embedded video content, 35.8% contain embedded photo content, and 62.5% do not contain any embedded content. Per Daft and Lengel’s definition, we consider tweets with embedded media to be richer than those that lack embedded media [14, 35]. Moreover, we consider tweets with embedded videos or GIFs to be richer than tweets with embedded photos based on the fact that such media offers the “simultaneous transmission of multiple information cues” [35]. Similarly, we consider tweets with embedded videos to be richer than tweets with embedded GIFs, as the audio component lends the expression of a greater “variety of languages” [35].

Overall, we were able to obtain the length of 56 (64%) of the embedded videos; 28 (32%) of the videos corresponded to GIF content that did not have any associated length of time and 3 (3.4%) of the videos were no longer accessible on the Web. In Figure 5a, we plot the distribution of the duration of accessible embedded videos. We find that the median duration of embedded videos is 5.3 minutes ( $\sigma = 35.4$  minutes). With guidance from the Twitter developer documents, we also report on the sizes of embedded video.

Since Twitter serves various types of devices, the playback rate of video content ranges from 256 kbps to 2048 kbps (depending on screen size and screen orientation)<sup>14</sup>. In Figure 5b, we plot the distributions of the sizes of embedded videos as they would correspond to various playback rates. Depending on which playback rate is used, the median video size ranges from 10.1 MB ( $\sigma = 68$  MB) to 81.2 MB ( $\sigma = 543.7$  MB). Given the highest bandwidth playback rate of 2048 kbps, only 7.9% of the videos were larger than 1 GB; at the next highest bandwidth playback rate, only 1.3% of the videos were larger than 1 GB. We also use the Twitter developer guidelines to estimate the range of sizes of the 28 GIFs we observe, which defines the minimum GIF duration as 0.5 seconds and the maximum duration as 30 seconds. Given these specifications and the aforementioned playback rates,

<sup>14</sup>Video Specifications and Recommendations. <https://dev.twitter.com/rest/media/uploading-media#videorecs>

a GIF can range from 16 KB<sup>15</sup> to 7.7 MB<sup>16</sup>. When examining the sizes of the 1,852 embedded photos, we find that the median photo size is 50.4 KB ( $\sigma = 32.9$  KB), and the largest observed photo is 269.7 KB. We demonstrate the impact these data sizes have on a hypothetical network infrastructure. Assuming a connection to the Internet that allows for download speeds of 3 Mbps with 100% goodput (which is faster and higher performing than what 85% of Native Americans living on tribal land can access at home [18]), the average video would take between 26.9 and 216.5 seconds to download; the average GIF would take between 42.7 milliseconds and 20.5 seconds to download; and the average photo would take 0.13 seconds to download. Considering that the average length of a Twitter session is 107 seconds [11], waiting for embedded media from a single tweet to download could potentially take a significant portion of the session (if not the entire session).

We next examine the relationship between embedded media and content propagation. We base our comparisons on tweets from the Native American advocates data set containing embedded content and tweets from the Native American advocates data set that do not contain embedded content using two-sample Kolmogorov-Smirnov tests. Overall, we observe that 66% of tweets with embedded media receive at least one retweet while only 41% of tweets without embedded media are retweeted at least once. Additionally, we find that tweets with embedded media (photo or video) receive higher levels of user engagement ( $p < 2 \times 10^{-16}$ ); on average, tweets with embedded media reach 2.6 users and tweets without embedded media only reach 1.8 users. When examining the prevalence (on a one-day scale) of tweets containing embedded media, we find no significant difference between tweets with and without embedded media; however, we do note that 7 of the top 10 most prevalent tweets contain embedded media. As with the hashtags, we measure churn of specific tweets using the persistence metric at the scale of minutes, hours, days, and weeks. Most tweets do not exhibit persistence at any scale. We find that only 1.8% of all tweets are persistent on the scale of days (i.e. “recurrent”) and of these, 66% contain embedded media (of which all but one are photos). Moreover, when analyzing the 0.4% of tweets that are persistent on a week-long scale, we find that 85% contain embedded media.

## DISCUSSION

### Issues of Life and Death

Our analysis of Native American political discourse online reveals that the most pressing issues are those with life and death consequences. With respect to “issue-based” hashtags, *#mmiw* and *#nativelivesmatter* garner the largest number of supporters. It is also noteworthy that our analysis of topical sub-communities revealed that three of the top five topic clusters that garnered the largest number of supporters involved hashtags referring to issues of life and death for Native Americans, including *#mmiw*, *#nativelivesmatter*, and *#freoleonardpeltier*. This is reflective of daily realities for Native American peoples in the U.S. Data collected by the

<sup>15</sup> Assuming a 0.5 second GIF with a playback rate of 256 kbps.

<sup>16</sup> Assuming a 30 second GIF with a playback rate of 2048 kbps.

U.S. Department of Justice finds that 34% of Native American and Alaska Native women will be raped or sexually assaulted in their lifetime—more than any other ethnicity group in the country—and on some reservations, Native American women are murdered at a rate 10× the national average [52, 45]. Moreover, a study based on data collected by the CDC found that Native Americans comprised the racial group most likely to be killed by law enforcement [33]. Additionally, violence (including intentional harm, homicide, and suicide) accounts for 75% of deaths for Native American youth between 12 and 20 years old [10]. While these life and death issues loom large in the consciousness of Native American peoples, they are largely absent from the campaigns of major party political campaigns in the U.S. and activists wishing to engage these issues have few outlets in the traditional political sphere.

### Mechanisms of Connective Action

While we acknowledge Tufekci’s assertion that the topics referenced by the hashtags may be ongoing despite the ephemerality of the hashtag [53], our study of Native American political engagement on Twitter affirms observations made by Bimber and Garret regarding the ephemeral nature of Internet-based political engagement—we observe high churn rates associated with most hashtags, both with respect to occurrence in the data set and with respect to the sub-communities that form around them [7, 19]. In contrast to our general findings of hashtag and sub-community ephemerality, we find that the most enduring hashtag is *#indigenous*, which was tweeted over 5,345 times by 2,839 users. This hashtag was present in every day of our data set and received some form of interaction from 85 users multiple days through the course of data collection. These observations confirm assertions made by Tully [54]: that Indigenous solidarity is a political movement (based on cultural identity rather than particular issues, grievances, campaigns, or events) towards self-governance. Moreover, *#indigenous* was paired with at least one other hashtag in 90% of its occurrences. These observations lead us to believe that Indigenous solidarity hashtags function as a mechanism for connective action between Native American advocates by stitching together a diverse collection of transitory topics for a relatively stable group of actors over time. Thus, the connective action enabled by content dissemination and annotation (i.e. adding hashtags or user mentions to content already circulating) strengthens the voice of Native American advocates and increases momentum for the potential formation of the highly influential Internet-based SMO’s described by Bimber [7]. It is important for campaigns to take note of these connective actions and to understand that merely identifying an issue as an Indigenous issue (even if it is also a general issue) can encourage Native American advocates and their followers to connect around it.

### Social Media and Infrastructure

Lack of communications infrastructure continues to be a problem for Indian Country that prevents many Native Americans from fully engaging with political discourse that increasingly takes place on media rich platforms [55, 4, 56].

Our results demonstrate that the content that reaches the largest audiences and is the most enduring in Native American advocates' political conversations on Twitter is content that has qualities of greater media richness (i.e. includes embedded media). We find that 66% of the most persistent tweets in the Native American advocates data set contain a photo. Similarly, tweets containing photos receive 24% more retweets than tweets containing video (104% more retweets than tweets without embedded media). While this finding is consistent with what is observed on Twitter in general [47], investigation into circulation with respect to tweets' persistence and prevalence further highlights the value of embedded photos. Only 1.1% of the most persistent tweets in the Native American advocates data set contain video, whereas 65% of the most persistent tweets contain a photo. Overall, our findings with respect to embedded media agree with Daft and Lengel's assertion that some media is superior to others for communicating information (as measured by propagation and circulation metrics), but it also demonstrates that there are limits to the benefits of increasing media richness, namely the cost of resources required to support richer media might make "less rich" media a more appropriate communication tool. While Native American advocates may not consciously craft and propagate content with bandwidth requirements in mind, the fact that limitations of the underlying IP network may impact information diffusion across the relatively bandwidth-light Twitter platform [53] is worth consideration, particularly if the desired audience for content is connecting from areas with limited ICT infrastructure.

## CONCLUSION

Native Americans represent a politically marginalized group in the U.S., and are also likely to have limited Internet access and connectivity—reducing capacity for political engagement via digital means. We use a post-structural mixed-methods approach to analyze Twitter data culled from influential Native American advocates during the 2016 primary presidential election season. This study reveals that the content propagated by Native American advocates tends to orient around Indigenous solidarity and life-and-death issues for Native American peoples. We find that the most durable sub-communities are those that center on *#indigenous* and we demonstrate how hashtags that denote Indigenous solidarity are the mechanisms through which political connective actions take place between Native American advocates and their followers. Finally, our analysis of Tweets containing embedded media suggests that advocates wishing to propagate content to audiences in Indian Country should enhance communications by embedding small photos rather than larger media files to ensure that richness of communication is balanced with consideration for infrastructural limitations.

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