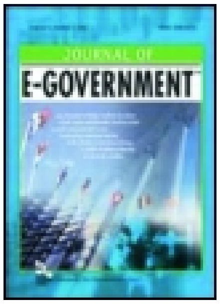

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Quantifying Political Behavior on Mobile Devices over Time: A User Evaluation Study

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Abstract

The way citizens use technology has changed dramatically in just the last decade; nearly a third of American adults own tablets and almost a half own smartphones. But it’s not just ownership that’s on the rise, citizens are increasingly using such technology to communicate about and participate in politics. The present study utilized a multi-method approach to tap into how technology affects citizens’ political behaviors online in the context of the 2012 U.S. Presidential primary season. Compiling survey data with tablet-tracking behavior in a field experiment, results showed that users spent more days with online aggregators (like Google and Yahoo), recreational sites (like games), and social interaction sites than news and politics. But when they did spend time with news and politics, they spent an average of 10 minutes on each news page, and National/Regional news was the most visited subtopic. User-specific descriptive analyses provide portraits of each user's demographic makeup and online political behavior. Finally, we linked user ideology to their user behavior through accurate, real-time behavioral observations. Results suggest that participants are more likely to view news from their own ideological perspective than the other, demonstrating evidence for selective exposure.

Keywords: political behavior, big data, mobile technology, selective exposure, user evaluation, tablets

To say that the Internet has radically changed the way people get their news in the new digital era is an understatement. Not only is news readily available, often for no cost, Web 2.0 has enabled individuals to share and exchange information through social media websites such as Facebook, Twitter, and blogs. Moreover, the mobile market has exploded in recent years, with more than half of Americans saying they now own a smartphone and 34% with a tablet (Pew Internet & American Life Project, 2013). But what are users actually *doing* when they are browsing the Internet via their mobile devices? Although some reports tell us what users *say* they do on their devices, there exist no data that track actual user behavior, in combination with self-report social science data. This manuscript describes the results of four months of tracking 20 users, examining overall use as well as patterns in individual user behavior.

Methodological and Theoretical Framework

Scholars in a variety of disciplines have been actively exploring how and why citizens use technology for political purposes (e.g., De Vreese, 2007; Di Gennaro & Dutton, 2006; Shah, et al., 2005; Xenos & Moy, 2007). Although the technology is often changing faster than we can monitor its uses and effects, there is some evidence to suggest that new technologies can create polarized ideological enclaves (Brundidge & Rice, 2009) with increasing selective exposure (e.g., Stroud, 2010).

At the same time, public opinion polls demonstrate that Americans have become increasingly active online. Recent research shows that 85% of Americans go online, and while they are there, 78% of them get their news online and 61% specifically look for news or information about politics (Pew Internet & American Life Project, 2013). Although the primary online activity was using a search engine to find information, after email and social networking the fourth most frequently cited activity was getting news: 45% of Americans reported doing this on an average day. Growing at a fast rate, too, is the use of mobile technologies to access the news online; 64% of tablet owners and 62% of smartphone owners say they access news at least weekly on their devices. This shift represents a sea change in how Americans consume news, and polling data suggest that mobile technology can actually add to the amount of time people spend with news content (Mitchell, et al., 2012).

The Trouble with Survey Data and Self-Report

While these figures are compelling—especially when one examines how quickly adoption and use rates have exploded over the last decade—they lack some certainty because they rely solely on self-reported data. This is by no means a new challenge; scholars in the social sciences have for decades developed more and more accurate question wording and sampling techniques to gain an accurate picture of media use. And although Nielsen has long relied on user diaries to provide information to advertisers about what exactly people are watching on TV and online, these data are difficult for scholars to obtain (c.f., Taneja, et al., 2012; Yuan & Webster, 2006). As a result, many social scientists interested in media use and Internet behavior must rely on self-reports in surveys or in a less ecologically valid setting like an experiment (e.g., Wilson, Gosling, and Graham, 2012). Yet, as Prior (2009) noted, self-reported news consumption was exaggerated by more than three times on average compared to estimates obtained from objective data.

This (over)reliance on self-report emerged with the cognitive revolution of the 1970s and 1980s, which saw an emphasis on developing stronger methodologies in asking questions, taking into account the many limitations of human mental capacity (Hoffman & Young, 2010). Tourangeau, Rips, and Rasinksi's (2000) seminal volume on the subject cited at least four hurdles over which respondents must leap before providing a simple response: comprehension of the question, retrieval of information, judgment of memories, and what response to give. Yet with such methods, we are still relying on an individual's memory, his or her perception of the activity, estimation of the time spent doing the activity. This goes without mentioning issues of social desirability, which may cause respondents to over- or underreport behaviors.

Research from a variety of disciplines has demonstrated that the correspondence between self-report and objective data is often questionable. For example, advertising research has found that buyers are susceptible to over-reporting purchasing behaviors (Woodside & Wilson, 2002). Other everyday behaviors, such as driving distance and number of trips made, are often misreported in self-report data compared with objective GPS-tracking methods (e.g., Blanchard,

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Myers, & Porter, 2010). When it comes to news media use—including Internet use—self-report data offer similar, if not more, challenges.

Because the tradition of media-effects research has relied on self-report data, the discipline has long grappled with the question of how to measure the impact of media exposure on attitudes, cognitions, and behaviors. Yet, even as some scholars have established precedence for indicators that could be used across paradigms of research (e.g., Eveland, Hutchens, & Shen, 2009), little agreement exists on optimal procedures. Slater (2004) suggested that the vast number of methodological designs and statistical analyses made the operationalization of media use a "messy business" (p. 168). Valkenburg and Peter (2013) argue that the number-one in media-effects research is to improve measurement of media exposure. They note that misreporting of media exposure can result from cognitive reasons (e.g., using heuristics to recall behavior) or motivational reasons (such as a desire to over-report some behaviors). Yet this type of data collection continues to be commonplace in the study of Internet and politics (e.g., Zhong, 2013).

Moreover, as Valkenburg and Peter (2013) argue, "people are not only exposed to much more media content than ever before, but this exposure also happens nearly everywhere, any time, and even simultaneously" (p. 200). The authors offer two important suggestions relevant to the present research: 1) we must avoid measuring only time spent with a medium because of the poor validity of such items; 2) scholars must also examine the *type* of content being consumed in as detailed a way as possible.

Along with changing media habits among Americans, there has been a concurrent advance in technological tools that can track behaviors with more accuracy than self-report data. As such, it is incumbent upon social scientists to triangulate methods to get the most accurate and detailed information as possible. The promise of such research is that we can make more precise judgments about Internet users' behavior—and effects—when combining this data with traditional research methods. As a result, we obtain a fuller portrait of online political behavior. One area of research, in particular, that can benefit from such precise measurement is the study of selective exposure.

An Application of Objective Measurement: Selective Exposure

The proliferation of personal technology that allows users to filter information based on personal interests has reignited the debate on selective exposure—that tendency to gravitate towards information that agrees with one's existing views and values (for a review of selective exposure, see Bennett & Iyengar, 2008; Festinger, 1957; Frey, 1986; Garrett, 2009; Iyengar & Hahn, 2009; Knoblock-Westerwick & Meng, 2009). Prior (2005) suggested that the way people make decisions is affected by the number of options available, and those options have increased dramatically in the digital age. Because citizens have multiple choices, they can polarize themselves by consuming only content that shares, rather than challenges, their point of view (Mutz & Martin, 2001).

Survey research suggests that, users prefer to visit web sites that share their point of view; 54% of online political users gravitated towards news that shares their political point of view (Pew Research Center for the People & the Press, 2011). This is particularly true among those with strong political leanings; both Republicans and Democrats were more likely than Independents to say that they typically get online political news from sources that share their view. Moreover, Iyengar and Hahn (2009) concluded that selective exposure is much more likely to manifest itself in the new media environment simply because of the multitude of options available. Yet no studies have examined selective exposure in a real-world field experiment that tracks user behavior. We examine selective exposure among a small group of users who were tracked on their tablets for four months.

Research Questions

Our first goal is to examine not just the amount of time users spend online and with news, but what exactly they are doing when they are engaged with their mobile devices. Using objective rather than subjective self-report measures, we ask:

RQ1: How much time are people spending online? How is this allocated over major topics and subtopics?

Relatedly, previous social science research has demonstrated that self-reported behavior often differs from objective observations, but media scholars have yet to adequately determine what Internet users are actually doing with mobile devices beyond self-reported data.

RQ2: How consistent is this method of examining user behavior with self-report?

Moving beyond comparisons of objective and subjective data and descriptives of overall behavior, a second goal of this study was to examine if individuals engaged in selective exposure. Although several scholars (e.g., Stroud, 2010); Valentino, et. al., 2009) have concluded that numerous factors—such as an individual's political beliefs, predispositions or environmental context—influence their news choices, Iyengar and Hahn (2009) concluded that selective exposure is much more likely to manifest itself in the new media environment simply because of the multitude of options available. Yet no studies have examined selective exposure in a real-world field experiment that tracks user behavior. Because our users also answered survey questions, we were able to compare their responses to their actual behavior (measured by coding all URLs visited for ideological leaning) over the data-collection period. Thus, we ask:

RQ3: Do users of different ideologies look at sites from the same and/or different sides of the ideological spectrum? Is there a difference in how people at opposite ends of the ideological spectrum engage in selective exposure?

Methods

Research Design

This study used a three-phase research design, beginning with a telephone survey of a random sample of panelists in Delaware who had previously agreed to participate in research conducted by a well-known state university. Of 1,000 panelists, 708 agreed to participate in the survey, which was conducted by a survey research center, July 21 – August 9, 2011. The final sample included 708 voting-age adults.

The next phase involved selecting 20 participants to take part in a field experiment that would track their use of one of 20 university-provided tablets. We purposively selected each of the participants to include a variety of racial and ethnic backgrounds, as well as age, education, geographic location (within the county), and reported comfort level with technology.[1] None of the 20 participants reported previously owning a tablet. A Washington, D.C. research facility specializing in focus groups and surveys assisted in selecting and recruiting participants. Demographic details for each participant can be found in Table 1.

The third and final phase provided each participant with a Samsung Galaxy 10.1 tablet (Samsung, 2013) that they could use for any purpose, November 15, 2011 – March 13, 2012. Each device was configured by a software development company to track the user's Internet behavior with a proprietary tracking method that recorded web pages visited and time spent on each. Participants signed a consent form to agree to have their tablet activity recorded and used for data analysis purposes. A 20-minute training session, a user booklet, and 24-hour telephone assistance were provided for technical support.

Survey Data Measurement

We utilized self-reported ideology to analyze selective exposure. In the telephone survey, ideology was measured on a five-point scale, with 1 indicating more conservative and 5 indicating more liberal. The full sample (n = 708) averaged slightly liberal (M = 2.87, SD = 1.02). The average among the 20 tablet users was slightly more liberal than the random telephone sample (M = 3.25, SD = .79). We then examined the survey data of only the 20 users

[1] We did not include respondents who did not use much or any technology—such as cell phones or cable TV—and who reported being very low on comfort with technology.

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in the tablet-tracking study to compare their self-reported data with objective data. To compare self-reported data with the tracking and answer RQ2, we asked how many days in the last seven days users had viewed news or politics on 1) a news organization's site, 2) a blog or personal site, and 3) a social networking site. These responses were averaged for each participant (M = 3.05, SD = 1.94).

Field Experiment Measurement and Coding

Filtering

From the tablet data emerged a large number of URLs that were not relevant to the present study, so the first step was to clean these data by filtering out unneeded information. One graduate assistant (GA) and four undergraduate assistants (UA) conducted the filtering. Each root URL was entered into a web browser, including those that were recognized. If the loaded site was blank or showed an error, then the site was recorded as one to "filter" out of the data. If the root site fully loaded, then site content was assessed for whether it met criteria for inclusion. Advertisers, advertisements, marketing companies, and analytics companies were filtered. During filtering, coders were careful not to filter sites associated with major websites. An attempt was also made to keep content delivery networks (CDN) associated with legitimate websites but not the filtered websites.

This process was developed by the GA with assistance from a software-development company and the principal researcher. The GA was available to UAs for questions during the entire filtering process. Once filtering was complete, each UA copied the root URLs, redirected URLs, and errors in a document that the GA checked for accuracy, then worked with the UAs to revise and make changes. The second author then wrote a script to apply the filters to the raw data. This process resulted in a data file that included 4,459 unique root URLs.

Categorization

Once the filtered data were removed from the file, an iterative categorization process began, which involved two UAs and two GAs going through batches of URLs to decipher what category each represented. Once a base list of categories was developed, the GA developed a coding scheme with 9 major topics and 31 sub-topics.[2] Multiple topics and subtopics could be selected for each URL.

For the purposes of the present study, we will focus on the News and Politics category as well as its sub-topics. Coding the ideology of the sites was admittedly more difficult for the coders than simply labeling a site "National News" or "Blog." The two GA coders identified news as liberal and conservative on the basis of the source's presidential endorsement in the 2008 and 2012 elections. Sources that did not make an endorsement, or who split their

[2] The nine major categories were: Online Aggregator, Recreational Usage, Social Interaction Site, Professional Networking and Job Search, News and Politics, Financial, Informational Resource, Blog, and Filter (which were removed). News and Politics subcategories were: Liberal, Moderate-to-Liberal, Moderate, Moderate-to-Conservative Conservative, International, National, Delaware region, Regional, and Financial. Other subtopics available upon request.

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endorsement, were coded as moderate. Sources were also coded based on their stated political affiliation on their site. The GA coders trained the UG coders on this scale and provided them with examples of each type of site.

In order to establish that the coding was reliable across the coders for ideology, we conducted a reliability analysis. Ten percent of the total URLs were randomly selected and coded by two GA and two UA coders, which resulted in a reliability sample of 447 URLs. Sites categorized as news or politics were coded 1) conservative / moderate-to-conservative, 2) moderate, and 3) liberal / moderate-to-liberal. Krippendorf's alpha was used to assess intercoder reliability among the four coders, as this measure can be used with multiple coders and varying levels of measurement and sample sizes (Hayes & Krippendorf, 2007). For sites coded conservative, Krippendorf's alpha was 0.73; for sites coded moderate, Krippendorf's alpha was 0.84, and for sites coded liberal, alpha was 0.70, all suggesting appropriate levels of inter-coder reliability. This file was then merged with survey data on each of the 20 users to examine overall patterns of use as well as specific indicators of the individuals.

Results

The most days were spent on 1) Online Aggregators (like Google or Yahoo); 2) Recreational sites (such as shopping or games); 3) Social Networking sites; and 4) News and Politics. Users spent more time on News and Politics sites in the middle of weekdays (Tuesday, Wednesday, and Thursday) and Sunday than other days, with an average of 10 minutes on each news page. See Table 1 for a breakdown of demographics and total hours spent with News and Politics.

RQ1 asked about overall time spent online and with News and Politics as a main topic and its subtopics. Eight of the users were active[3] nearly every day (88 to 120 days); 7 users were moderately active (34 to 67 days); while the remaining 5 participants rarely used the device (6 to 19 days). Of the major topics, users spent the most days on Online Aggregator sites like Google and Yahoo (M = 62.80, SD = 42.11) and the least days on Professional Networking and Job Sites (M = 10.80, SD = 23.91). However, when measuring *time* spent in hours, News and Politics was the most frequent major topic on average (M = 10,145.80, SD = 33,232.41), followed by Online Aggregator (M = 5,119.05, SD = 7,975.12). The least amount of time, as in days, was spent on Professional and Job Networking sites (M = 99.35, SD = 357.02). For subtopics of News and Politics, the most frequently visited category (in hours) was National/Regional News (M = 5,154.14, SD = 17,641.56). The next most frequent category was International News (M = 1,506.61, SD = 3,929.08).[4] The average for State and Local News was 763.34 (SD = 2,971.60). The least frequently visited were Campaign sites (M = .01, SD = .03). (See Figure 2.)

RQ2 asked how consistent users would be in their average new use online compared with self-reported measures. Days using News and Politics were converted to a weekly average, and while users *reported* spending an average of 3.05 days a week (SD = 1.94) with news online, *actual* user statistics revealed that they spent an average of 2.02 days (SD = 1.93) with news on the

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[3] Active was measures as a user visiting at least one non-filtered site that day.

[4] Sites could be coded as either National or Regional or BOTH, as was the case with State and Local News.

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tablets. There was not a statistically significant correlation between self-reported behavior and actual behavior ($r = .30$, $p > .05$).[5] The results confirm previous research, and suggest that users appear to over-estimate how much time they spend with news online.

Regarding ideological News and Politics sites, users spent similar overall number of hours on conservative / moderate-to-conservative sites (M = 13,932.51, SD = 5,023.18)[6] and liberal / moderate-to-liberal sites (M = 12,664.04, SD = 3,684.74)[7] and the least time on strictly moderate sites (M = 32.50, SD = 117.53).[8] Self-reported Conservatives (combined with moderate Conservatives) spent more time on News and Politics sites (M = 38,076.88 hours) than Liberals / Moderate Liberals (M = 3,976.14) or Moderates (M = 2,700.30). However, this is likely because one Conservative user (18) spent a large amount of time with news compared to other participants (see Table 1).

To examine selective exposure, RQ3 asked if users of different ideologies looked at sites from their own and/or different ideologies, and which ideology has more of a tendency to view information from the other side of the ideological spectrum. Figures 2 and 3 demonstrate

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[5] Although this should be interpreted with caution since there are only 20 subjects.

[6] These categories were combined for ease of analysis. The average hours per day per user on Conservative and Mod-to-Conservative sites was 5.80 hours.

[7] The average hours per day per user on Liberal and Mod-to-Liberal sites was 5.28 hours.

[8] User 10 was excluded from these analyses because no ideological sites were visited.

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selective exposure among those who identify with a liberal or conservative ideology.[9] Figure 2 shows that these users visited sites that agreed with their own ideologies more frequently than those that agreed with the other side. Sometimes this was to the extent that no moderate or other-sided sites were viewed at all during the 120-day period. Notably, there were very few visits to moderate sites even by the self-identified moderate users (see Figure 3).

We also examined what sites preceded and followed visits to News and Politics sites. We segmented all the activities into 30-minute sessions; if there was no new activity within 30 minutes of the previous one, we started a new session. We then went through each session to identify activities that were adjacent to News and Politics. The majority of users visited News and Politics sites after having been on an Online Aggregator (30%), followed by Social Interaction Sites (20.2%), and other News and Politics sites (17.8%). Sites visited after News and Politics took on much the same pattern. As far as ideological patterns, Figure 4 demonstrates that URLs visited had a strong ideological pattern. A liberal site was followed by another liberal site about 96% of the time, as were conservative sites. Moderate sites were followed by moderate sites less frequently (82.9%) and went to liberal sites 14.9% of the time.

Discussion

The goals of this study were to extend research on online political behavior beyond self-report data and to apply these methods to the study of selective exposure. Twenty users were given

[9] This included participants who reported being "somewhat" liberal or conservative.

tracked tablets for a four-month period, after which their behaviors were analyzed and matched to self-reported data. Overall, we discovered several patterns of use, as well as preliminary, objective evidence of selective exposure.

The first goal of the study was to answer Valkenburg and Peter's (2013) call to examine, in addition to time spent, the *type* of content that is being consumed in as detailed a way as possible. By combining survey data with observational data, we were able to determine that, while the estimates were close, our participants overestimated the time they spent with online news by about one day. However, we only measured News and Politics use on the tablet; users could have been accessing news on a computer or smartphone, which may have made up that one-day difference. However, the results align very well with recent Pew data that show the primary online activity is using a search engine (or "online aggregator") to find information, and the fourth most frequently cited activity is getting news (Pew Internet & American Life Project, 2013). This is precisely the same pattern that emerged in our data. Future research will need to conduct similar comparisons to evaluate self-report of online news use with observational data.

This research provides supplemental evidence for selective exposure: these citizens actively visited sites that shared their point of view, while avoiding sites that were of the opposite ideological side. Figures 2 and 3 indicate that nearly every user engaged in selective exposure; only three of the 13 users visited sites from the other side more than 5% of the time, but all visited their own side's sites at least 55% of the time. The liberals in this group were more likely to engage in selective exposure than conservatives. Moderates were the most likely to visit sites on both sides of the ideological spectrum.

Of course the study has limitations, namely that we only examined 20 users' behavior. But the methodological choices were made in such a way as to generate strong social science data with survey methods, followed by more nuanced, objective analyses of individual behavior. Moreover, this research is primarily of an exploratory nature, and thus does not include inferential statistics. While this poses limitation in the generalization of results, our objective is to demonstrate new methods for answering existing research questions. Additionally, respondents were free to use other devices such as smartphones or laptops, which we did not track, and could show different behavior patterns. Nevertheless, we hope this research spurs other scholars to examine "big data," even if it comes from a smaller number of subjects.

Overall, our results suggest that citizens do exhibit different behaviors in self-reports versus objective observation. Additionally, we found some evidence that selective exposure exists, particularly among self-identified liberals and conservatives. But perhaps most importantly, we have demonstrated new methodological techniques for gauging actual online political behavior. As users increasingly rely on mobile devices for news and information (Duggan & Smith, 2013), scholars must be prepared to establish new methods for examining user behavior. In 2013, 63% of adult cell-phone owners reported using their phones to go online—double that of 2009. And 45% of Americans report getting news on mobile devices on an average day (Pew Internet & American Life Project, 2013). As technology use changes, so must our methodologies to advance research and theory in information technology and politics.

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Figure 1. Average number of days users viewed major subtopics over the 120-day data collection.

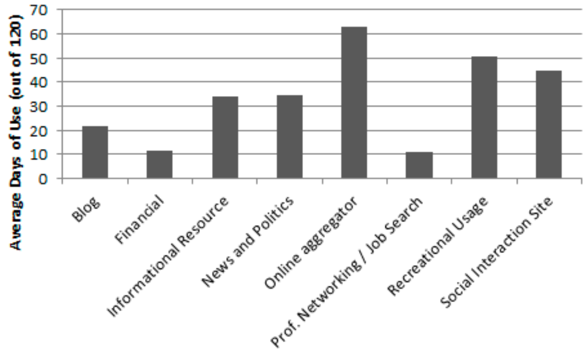

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Figure 2. Selective exposure by self-identified ideological users.

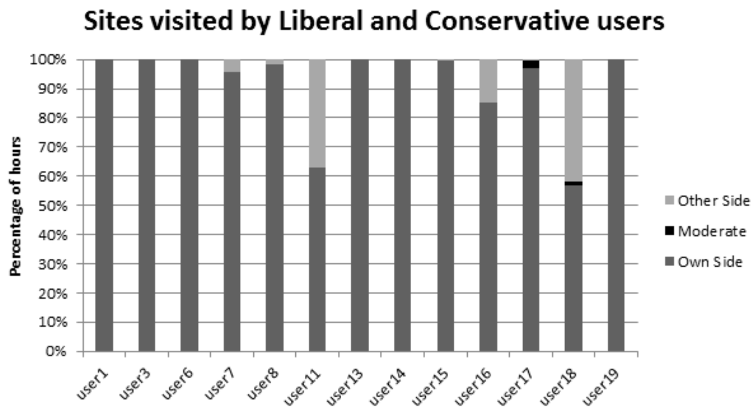

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Figure 3. Ideological sites visited by type of user.

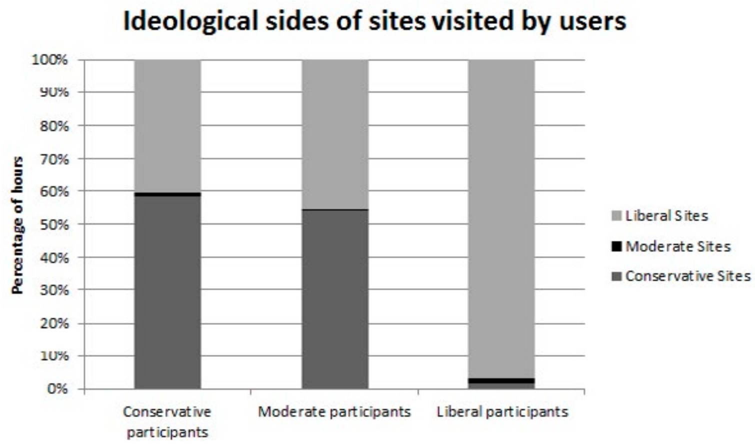

Figure 4. Session patterns of ideological News and Politics sites visited.

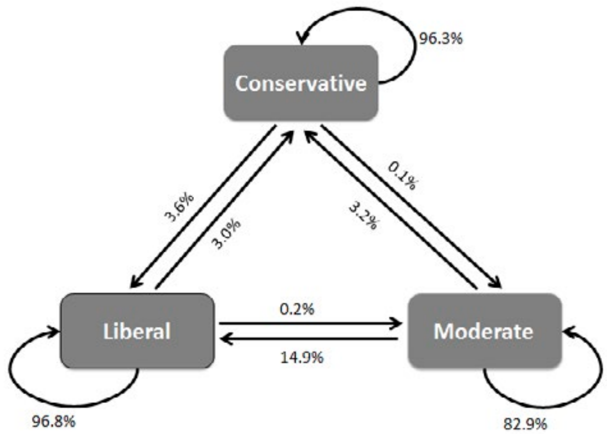

Table 1. Demographics of users and time spent with News and Politics.

ID	**Race** *80% W*	**Gender** *50% M*	**Education** *M = 4.15 ~ college grad, SD = 1.46 on a 6-point scale*	**Employment status** *65% Full-Time*	**Age** *M = 54.0, SD = 13.2*	**Ideology** *45% Lib, 35% Mod, 20% Cons*	**Observed News and Politics** [b]	**Self-Reported News and Politics** [c]
1	W	M	4 year college graduate	Full-time	34	Liberal	2.98	5.33
2	B	M	4 year college graduate	Full-time	36	Moderate	2.10	6.33
3	W	F	4 year college graduate	Full-time	61	Liberal	1.63	2.33
4	W	F	Graduate degree	Full-time	37	Moderate	1.93	2.67
5	W	F	4 year college	Full-time	55	Moderate	5.66	3.00

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			graduate					
6	B	F	HS graduate	Homemaker	51	Conservative	1.52	1.00
7	W	F	Some college [a]	Full-time	60	Liberal	0.70	2.33
8	W	M	Some college	Part-time	62	Liberal	1.34	.00
9	W	F	Graduate degree	Full-time	51	Moderate	0.29	2.00
10	W	M	Graduate degree	Full-time	58	Moderate	0.06	3.67
11	W	F	Graduate degree	Full-time	71	Liberal	2.39	4.67
12	B	M	HS graduate	Part-time	28	Moderate	4.61	2.67
13	W	M	Some college	Full-time	69	Liberal	0.93	4.67

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14	W	F	Graduate degree	Full-time	56	Liberal	0.12	.00
15	W	F	4 year college graduate	Full-time	37	Conservative	0.18	.00
16	W	M	HS graduate	Full-time	61	Liberal	0.70	5.00
17	W	M	Some graduate school	Retired	68	Liberal	4.32	6.33
18	W	M	4 year college graduate	Retired	64	Conservative	6.83	3.00
19	W	M	Some college	Retired	67	Conservative	0.88	2.33
20	B	F	Some college	Retired	-	Moderate	1.28	3.67

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Notes. [a] also includes community or junior college.

[b] Days on average per week from tablet data (M = 3.05, SD = 1.94).

[c] Days reported in "last seven days" from average of "news on a news organization's site," "news on a blog or personal site," and "news through updates on a social networking site like Facebook" (M = 2.02, SD = 1.93).