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Who Is Exposed to News? It Depends on How You Measure: Examining Self-Reported Versus Behavioral News Exposure Measures

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Abstract
Despite the importance of news exposure to political outcomes, news consumption is notoriously difficult to measure, and misreporting news exposure is common. In this study, we compare participants' news behaviors measured on a news aggregator website with their self-reported story selection immediately after exposure. We find that both individual and contextual characteristics—especially the presence of political cues in news headlines—influence reporting of news story selection. As a result, the news audience profiles differ using self-reported versus behavioral measures, creating two different pictures of news exposure. More attention is needed to improve news measurement strategies to address misreporting and to improve the accuracy of news audience profiles.

Keywords
news exposure, self-report measures, website analytics, news audiences, misreporting

Research consistently shows that people misreport their exposure to traditional news, online news, and social media news (Guess, 2015; Prior, 2009a, 2009b; Vraga, Bode, & Troller-Renfree, 2016). This misreporting often takes the form of overreporting or overestimating our exposure to news in general and when exposed to news in controlled experiments. Misreporting has not only implications for validity in research but also broader implications for understanding how news use relates to outcomes like political knowledge and participation (Chong & Druckman, 2012; Dilliplane, Goldman, & Mutz, 2013; Price & Zaller, 1993; Prior, 2009a, 2009b).

Innovations in survey design and digital tools for capturing behavioral data show promise in improving measures of news exposure (Araujo, Wonneberger, Neijens, & de Vreese, 2017).

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Gathering behavioral data by capturing browsing and web histories (e.g., Araujo et al., 2017; Dvir-Gvirsman, Tsfati, & Menchen-Trevino, 2016; Revilla, Ochoa, & Loewe, 2017), downloading mobile phone logs (e.g., Kobayashi & Boase, 2012), and using eye tracking software that follows participants' gaze (e.g., Vraga, Bode, & Troller-Renfree, 2016), combined with efforts to encourage more accurate self-reporting through survey design (e.g., Andersen, de Vreese, & Albæk, 2016; Guess, 2015; Nelson & Webster, 2017) enable researchers to more precisely measure media exposure. These efforts to improve measurement undoubtedly have implications for media effects research.

With this in mind, this study uses an experimental design that manipulates an online news environment to compare self-reported news exposure behavior with actual "clicks" on simulated news aggregator websites. By collecting demographic and individual trait data, self-reported exposure data, and web data, this study addresses how contextual cues on the website and personal characteristics predict self-reported versus actual news exposure, paying special attention to the news audience profiles that emerge depending on the measures used. This study is designed to uncover the conditions under which misreporting of news exposure is more likely to occur and detail how estimates of news audiences might differ if relying on self-reported data of news exposure rather than behavioral measures.

Literature Review

Measuring News Exposure: Self-Reports and Behavioral Data

Measuring and understanding news exposure is an essential part of media effects and political communication research (Chong & Druckman, 2012; Prior, 2009b). News exposure has been linked to both political knowledge and behaviors (Dilliplane et al., 2013; Price & Zaller, 1993). As such, accurately measuring news exposure is fundamental to testing these outcomes. Researchers often rely on self-reports to measure this key variable despite the substantial body of research that shows self-reports are inaccurate and unreliable for traditional media, such as newspapers (e.g., Price & Zaller, 1993) or television (e.g., Prior, 2009a, 2009b), and for online and social media (e.g., Araujo et al., 2017; de Vreese & Neijens, 2016; Vraga, Bode, & Troller-Renfree, 2016).

A substantial body of work has focused on improving self-reports by designing survey measures that make it easier for participants to accurately gauge their news behavior, including questions about news use, political and public affairs knowledge, and exposure to specific current events (e.g., Andersen et al., 2016; Guess, 2015; Price & Zaller, 1993; Prior, 2009b). One alternative is to ask about exposure to a specific story, which avoids conveying information about expected frequencies that could influence participants' response or lead to flawed estimation (Prior, 2009b; Schwarz & Oyserman, 2001). However, even in studies that ask about recent exposure to a specific story or post—as we do in this study—estimations are often inaccurate (Bode, 2016; Jerit et al., 2016; Price & Zaller, 1993; Vraga, Bode, & Troller-Renfree, 2016).

Despite the difficulties in accurately measuring media exposure, digital tools and innovative research designs offer some opportunities for gathering these data and linking them to survey or experimental data (e.g., Araujo et al., 2017; Dvir-Gvirsman et al., 2016; Guess, 2015; Kobayashi & Boase, 2012; Vraga, Bode, & Troller-Renfree, 2016; Wells & Thorson, 2017). Unobtrusively capturing website data provides some measure of Internet use and can be used to accurately measure the kinds of sites that people visit and their behavior on specific sites (Araujo et al., 2017; Barba, Cassidy, De Leon, & Williams, 2013). Both capturing media use and connecting it to demographic and personal characteristics are critical to better understanding who misreports their news behaviors and under what conditions.

Misreporting News Exposure

Although underreporting media use and exposure does occur (Guess, 2015; Revilla et al., 2017; Scharkow, 2016), research has largely focused on overreporting—indicting more exposure than actually occurred—which is particularly common for news exposure (Dilliplane et al., 2013; Price & Zaller, 1993; Prior, 2009a, 2009b; Scharkow, 2016). For example, Vraga, Bode, and Troller-Renfree (2016a) found that participants in an experiment did not accurately recall the content of a simulated Facebook feed in a question immediately following that exposure and tended to over-report how many political posts they saw. In addition, Jerit and colleagues (2016) show this imprecision in reporting extends over time with misreporting and overestimation occurring days after exposure. In their study, 57% of participants in the control condition responded "yes" to seeing a news story that they did not see, while 33% in the experimental condition responded "no" despite being previously exposed to the story. Given what we know about overreporting, we propose the following hypothesis:

Hypothesis 1: Self-reports of news story selection will be higher than actual story selection.

Story Cues and Misreporting

Less is known about how news exposure in different environments affects the accuracy of self-reports. Measuring news exposure is further complicated by imprecise categorization of what should count as "news" (e.g., Dilliplane et al., 2013; Vraga, Bode, Smithson, & Troller-Renfree, 2016). Some scholars distinguish between "soft" and "hard" news content, which may have different civic and political relevance (e.g., Bakshy, Messig, & Adamic, 2015; Baum, 2002; Prior, 2003), whereas others debate whether political content should count as a meaningful subset of hard news or a separate type of content (Bode, 2016; Dilliplane et al., 2013; Prior, 2013a; Vraga, Bode, Smithson, & Troller-Renfree, 2016). Thus, more attention needs to be paid to story cues (e.g., headlines, images, sources) that may influence self-reported exposure.

In the current study, we examine story-level factors that may influence misreporting. First, we explore how the story type will impact misreporting in different news environments. We examine reporting of exposure to political news, including partisan content, in one simulated news environment and exposure to nonpolitical hard and soft news stories in another to assess how story characteristics affect reporting and behavior. While many of the factors that predict overreporting—such as inaccurate recall or flawed inference in estimating exposure (Prior, 2009b)—may apply for a range of content, story cues are likely to activate different motivations in responding to questions about that exposure. Given the research emphasis on overreporting, our hypotheses make predictions about *overreporting*, while our research questions focus on *misreporting*:

Research Question 1a: Will misreporting story selection be higher in a political or nonpolitical news environment?

Research Question 1b: Will misreporting story selection be higher depending on the type of news story (e.g., hard, soft, partisan) presented?

News Media Literacy (NML) and Misreporting

Second, we examine the effect of messages designed to promote critical news consumption on self-reported exposure. We draw on NML education and research, which promotes critical engagement with news content and consumption of news from a variety of sources (Craft, Ashley, & Maksl, 2016; Potter, 2018). NML messages designed to accompany news content on websites and social media have been shown to influence perceptions of partisan and nonpartisan news and news habits (Vraga & Tully, 2015, 2016). NML education focuses on building knowledge and skills across a range of domains including knowledge of journalistic constraints and processes, the financial incentives behind news decisions, and the role of individual biases in coloring news perceptions and consumption (Craft et al., 2016; Maksl, Ashley, & Craft, 2015; Vraga & Tully, 2016). Designing effective NML messages that promote the critical news consumption tailored for online environments, then, requires simplifying and distilling these topics into short messages that can be embedded on websites and social media platforms (Vraga & Tully, 2016).

In addition, we manipulated the presence or absence of popularity cues in the NML messages. The cue, which invited participants to "join the more than 12,000 people who like us [Media Literacy Coalition] on Facebook" and included social media logos (e.g., Twitter, YouTube, Instagram), was intended to suggest popularity of the message and organization sponsoring it. Given the importance of such cues in influencing credibility and news selection behaviors (Messing & Westwood, 2014; Metzger, 2007), we examine whether the NML messages with a cue are more effective at promoting accurate self-reporting than those without a cue.

While NML messages have not been studied for their effect on misreporting news exposure, there are several potential mechanisms by which this might occur. NML messages that encourage people to be critical and engaged news consumers may promote careful consideration of their news behaviors (Vraga & Tully, 2015), therefore leading to more accurate recall of their story selection. In addition, NML messages may encourage people to actually consume more stories as these interventions promote news consumption, lessening the opportunity to overreport. In short, if participants are thinking about themselves through the lens of "news consumer," they should be more likely to pay attention to their news behaviors and to report accurately. Conversely, the opposite may apply: Reminding people of the value of news consumption may heighten social desirability related to reporting story selection, if it is perceived as a pro-social behavior (Kahn, Ratan, & Williams, 2014; Revilla et al., 2017), without changing actual behaviors, which are more difficult to change than intentions or attitudes (Ajzen, 1985), leading to more overreporting. Therefore, we ask the following questions:

> **Research Question 2a:** How will exposure to different NML messages influence misreporting story selection?
>
> **Research Question 2b:** How will the presence of a popularity cue in NML messages influence misreporting story selection?

Individual Factors Predicting Misreporting

A number of demographic factors have been shown to affect the accuracy of reporting across different media types; however, there is less agreement about the nature of these associations. While many studies suggest that age, income, and education are linked to misreporting media exposure, others have found no relationship (e.g., Araujo et al., 2017; Guess, 2015; Kahn et al., 2014; Kobayashi & Boase, 2012; Prior, 2009a, 2009b). For example, Prior (2009b) found that people with higher education were more likely to overreport news exposure, while Guess (2015) suggests that those with higher education underreport (see also Araujo et al., 2017). Similarly, whether political orientations are related to misreporting, and the direction of that relationship, remains a source of debate (Dilliplane et al., 2013; Guess, 2015; Prior, 2009b). Considering the competing findings on the role of these individual characteristics in misreporting, we ask the following questions:

Research Question 3a: Will an individual's demographic characteristics influence misreporting story selection?

Research Question 3b: Will an individual's party affiliation and partisan strength influence misreporting story selection?

Next, we consider three news attitudes and related traits: political news interest, need for cognition (NFC), and tendency toward selective exposure. Research suggests that high interest and use of a particular media type is often associated with overreporting exposure to media that may be considered pro-social, like news, while underreporting is more common for less desirable media, like video games or certain websites (Kahn et al., 2014; Revilla et al., 2017). Kahn, Ratan, and Williams (2014) suggest that how people view themselves (e.g., as a video gamer, as a regular news consumer) will influence self-reports about their behavior, so that their views and actions align as a means of resolving any potential cognitive dissonance. In addition, the strong association between political interest, knowledge, and media use has led some to debate as to whether such measures are in fact distinct (e.g., Dilliplane et al., 2013; Price & Zaller, 1993), which may contribute to overreporting of news consumption among the politically interested (Prior, 2009b). Considering this, we propose the following:

Hypothesis 2: People more interested in news will be more likely to overreport story selection.

Second, NFC, which measures enjoyment of critical thinking and complex tasks (Cacioppo & Petty, 1982), may not only influence news behaviors and NML but also accurate reporting on such behaviors (Hobbs, 2017; Maksl et al., 2015; Tully & Vraga, 2017). Individuals with high NFC have been shown to think more critically about media messages and tend to respond more positively to NML messages (Austin, Muldrow, & Austin, 2016; Hobbs, 2017; Tully & Vraga, 2017). Although one study found no relationship between NFC and overreporting (Jerit et al., 2016), it did not consider cues in the news environment, suggesting the need for further research.

We introduce a third variable: tendency toward selective exposure, which gauges news preferences for like-minded content or news that supports our worldviews (Stroud, 2011; Tsfati, 2016). Although the preference for like-minded news and political content is well established (e.g., Garrett, 2009; Stroud, 2011), to our knowledge, it has not been tested with regard to *accuracy* in self-reported news exposure. Given its relationship to news behaviors, as well as its association with other variables such as NFC and media trust (Tsfati, 2016), it seems reasonable to conclude it may influence accurate reporting as well. Considering these factors associated with news exposure, we propose the following questions:

Research Question 3c: Will need for cognition influence the likelihood of misreporting story selection?

Research Question 3d: Will a tendency toward selective exposure influence the likelihood of misreporting story selection?

The individual characteristics that matter for overreporting exposure may also depend on the *type* of story being considered. Examining these potential differences allows us to explore the role of news cues and individual traits in misreporting. For example, educated individuals may be more likely to overreport their exposure to "hard" news stories—which we define as referencing public affairs information or current events—but not their exposure to "soft" news stories that focus on personal stories or come from entertainment sources (e.g., Bakshy et al., 2015; Baum, 2002; Vraga, Bode, Smithson, & Troller-Renfree, 2016). Likewise, individual traits, especially political party identification, may predict exposure to news stories that are congruent or incongruent with one's beliefs. Previous research suggests that Republicans may be more likely to engage in selective exposure (e.g., Garrett, 2009), although this assumption has not been tested in relationship to misreporting exposure. With this in mind, we ask the following questions:

> **Research Question 4a:** How will the individual differences that predict misreporting news story selection depend on the type of news story (e.g., hard, soft, partisan) being reported?
>
> **Research Question 4b:** How will the individual differences that predict misreporting news story selection differ for congruent versus incongruent politically partisan news stories?

Method

Participants were recruited from Qualtrics panels in March 2017 using quota sampling based on gender, age, race, and education to approximate the U.S. population. For the website to function and load properly, participants were asked in the informed consent to take the survey on a computer, which created some skew in our stratification, particularly for gender (see below). Participants were also asked to disable their ad blockers and enable cookies as part of the informed consent, although this was not required.

Participants answered demographic questions before being asked to review a news aggregator website under development "as if they found it online." Participants were asked to spend at least 4 min on the site and told they would answer questions about their experience. The websites featured eight short video news stories. A pretest in March 2017 was used to select these news stories. Participants recruited from Mechanical Turk ($N = 299$) were randomly assigned to view 8 (out of a possible 26) news headlines with leads, as they would appear on the news website. Participants rated on 7-point scales whether each headline was liberal/conservative, serious/not serious, informative/not informative, political/not political, and dull/entertaining (see Online Appendix located in the online supplement to this article for descriptive statistics). For the nonpolitical news condition, we selected four "hard" and four "soft" news headlines on the basis of these evaluations, as well as for a diversity of content. For the political news condition, we choose six political news stories—which offered clear cues about the political valence (e.g., liberal or conservative) of the story—across three controversial issues (e.g., gun control, climate change, and abortion). We then identified whether these stories are congruent versus incongruent with party affiliation (e.g., stories that lean Democratic are congruent to Democrats and incongruent for Republicans, and vice versa), dropping the neutral stories and independents from this analysis of the partisan stories. Two neutral stories, which were about political topics but did not include partisan cues, were selected for comparison.

Participants were randomly assigned to either the political or nonpolitical news website. These two websites, including story order, were held constant across participants and can be seen in the Online Appendix. After 4 min, the "continue" button appeared and participants continued the survey ($M = 461$ s, median $= 344$, $SD = 636$ on portal page).

A second manipulation incorporated the NML message into the websites. As participants entered the site, they watched one of the five videos as "sponsored content." Four NML videos were designed to mimic public announcements (PSAs) and focused separately on (1) news production practices and journalists' responsibility to construct accurate stories ("Journalism PSA"), (2) citizens' role to be critical news consumers and the ways in which personal biases color interpretation of news stories ("Citizen PSA"), (3) the importance of a free press for democratic society ("Democracy PSA"), (4) a video that briefly combines these three ideas ("Combination PSA"), or (5) a control video, which was taken from the Ad Council on the danger of texting and driving ("Texting PSA"). These videos ran 31–42 s in length, and the four NML videos were pretested to ensure they adequately conveyed the targeted messages (Vraga & Tully, 2016). The main NML message was reinforced in sidebar ads throughout the website. The third manipulation involved the presence or absence of popularity cues at the end of the NML videos and reinforced on the "about" page of the website. In total, there were 20 experimental conditions: (1) two website contexts (political vs. nonpolitical), (2) five PSAs (Journalism, Citizen, Democracy, Combination, and Texting), and (3) two social media cues (present vs. absent).

Participants' behavior on the news sites was unobtrusively tracked using website analytics software to determine which stories they clicked on. After visiting the site, participants rated their perceptions of the site overall before self-reporting which stories they viewed. Participants were shown a screenshot of the headline, image, and lead of each of the eight stories on the website and were asked to answer whether they had clicked on that news story (yes/no), similar to yes/no measures used by Jerit et al. (2016) and Price and Zaller (1993). A total of 3,211 participants completed the survey with behavioral data recorded for 2,463 participants.

We examine the differences between participants with ($N = 2{,}463$) and without ($N = 748$) behavioral data. A series of t tests reveal meaningful differences between these groups. Younger ($p = .04$), wealthier ($p = .04$), and more educated ($p = .01$) participants were significantly less likely to have behavioral data recorded, as were more Republican individuals ($p = .02$). Likewise, participants without behavioral data reported clicking on more stories total ($M = 3.69$) than those with behavioral data ($M = 3.46$, $p = .04$). These differences may result from variations in digital literacy (Hargittai, 2010; Park, 2013), especially as related to use of ad blockers or "do not track" software. Indeed, we find that people who did not have behavioral data recorded were more likely to report having used an ad blocker ($p = .00$) and disabled or blocked cookies ($p = .00$) and less likely to have signed into a web browser ($p = .01$). Limiting our analyses to those participants with behavioral data, our sample averaged 45 years in age ($M = 45.73$, $SD = 16.41$), 54.6% women, 72.2% White, median education was "some college," and had a median income of US$25,000–49,000. All analyses are limited to those for whom we have behavioral data.

Measures

Exposure measures. Our key dependent variable is misreported story exposure, which measures the gap between self-reported and behavioral click data. First, we created a composite measure of *self-reported exposure* by adding the number of stories participants reported clicking on, ranging from 0 to 8. This measure was also subdivided by story type for subsequent analyses (e.g., hard vs. soft news stories in the nonpolitical condition; liberal, conservative, and neutral stories in the political condition). We then created a measure of *behavioral exposure* by summing the total number of stories a participant clicked according to the website data, ranging from 0 to 8. The measure of behavioral clicks was subtracted from the self-reported clicks to create a difference score, with a positive sign signaling more overreporting of story exposure and a negative sign signaling underreporting ($M = 1.42$, $SD = 2.34$, min $= -6$, max $= 8$).

Personality measures. In addition to the demographic variables noted above, we measure personality factors that may affect news exposure. *NFC* was measured using 2 items which rated agreement on a 7-point scale with the statements: "I prefer complex to simple problems" and "I prefer to do something that challenges my thinking abilities rather than something that requires little thought" ($r = .53$, $p < .001$, $M = 4.89$, $SD = 1.27$).

We used 2 items to gauge *political news interest*, which combined measures of interest in (a) politics and government and (b) news and current events on 5-point scales ($r = .69$, $p < .001$, $M = 3.88$, $SD = 0.94$).

We also measured *tendency toward congruent selective exposure*, adapted from Tsfati (2016) with 2 items measuring agreement on a 7-point scale: "I try to avoid exposure to media outlets expressing irritating opinions" and "I don't find much use in reading articles expressing views that are different from my own" ($r = .49$, $p < .001$, $M = 4.35$, $SD = 1.28$).

Political orientations. We used a single item on a 7-point scale from *strong Republican* to *strong Democrat* ($M = 4.06$, $SD = 1.87$) to measure *party affiliation*. This was folded to create a measure of *partisan strength*, which ranged from "0" for independents to "3" for someone who "strongly" affiliates with the Democratic or Republican party ($M = 1.56$, $SD = 1.04$).

Results

Descriptive Measures of Validity

Before testing our hypotheses and research questions, we explore the validity of participants' self-reported behavior compared to their measured behavior. The descriptive statistics for the percentage of people who *self-reported* clicking on a news story versus the percentage of people whose behavioral data *confirmed* that they clicked on a story demonstrate that self-reported exposure is consistently higher than behavioral measures (see Online Appendix). This pattern is especially pronounced for stories that appeared later on the page, largely because the behavioral data suggest fewer people clicked on these stories.

To better understand this gap between self-reported and behavioral measures, we examine three types of validation: simple validation, validation of nonclicks, and validation of clicks for each story. Simple validation (e.g., calculated when the behavioral data match the self-reported data by story) suggests high levels of reliability across the stories (78%). Subsequent analyses suggest this number is inflated by high match (91–99%) between self-reported *nonclicks* (e.g., reporting they did not click a story) and measured behavior (see Online Appendix). In contrast, self-reported *clicks* were validated 33–78% of the time, with most stories closer to 40–50% validation. In other words, people who self-reported not clicking a story were nearly always accurately reporting their lack of exposure, whereas those who reported clicking a story were often misreporting their behaviors. The failure to validate self-reported click data with behavioral data is especially prominent for earlier news stories, likely because these stories were more often clicked.

Examining the Extent of Misreporting

We formally test the first hypothesis—that self-reported story exposure would be higher than behavioral exposure—using a paired sample t test. Hypothesis 1 is supported. Across both websites, people self-reported clicking on 3.51 stories, but behavioral data found an average of 2.01; this difference is statistically significant (see Table 1). Overall, paired sample t tests show people over-report their story selection across the nonpolitical and political site and for all types of stories. However, an independent sample t test demonstrates that the gap between self-reported and measured behavior (e.g., overreporting) was significantly larger for the political news site than the nonpolitical site ($t = 4.68$, $p = .00$), answering Research Question 1a. While actual story selection behavior was equivalent across sites (t=.54, p=.59), self-reported story selection was significantly higher (t=5.06, p=.00) for the political site. In contrast, paired t tests revealed there were no differences in overreporting for hard versus soft stories ($t = 0.82$, $p = .41$) or between congruent and incongruent stories ($t = 0.11$, $p = .92$), therefore suggesting that people are equally likely to overreport their exposure across story types, per Research Question 1b.

We next compare how three contextual features—whether the site focused on political or nonpolitical stories, the type of NML message, and the presence of a popularity cue, which we

Table 1. Comparing the Means for Self-Reported Versus Behavioral Measures of Story Choice, by Story Characteristic.

Story Characteristic	Self-Reported	Behavioral	Difference	*t* Test	Degrees of Freedom	*p* Value
Total	3.46	2.04	1.42	30.06	2,462	.000
Nonpolitical	3.21	2.02	1.19	18.78	1,210	.000
Political	3.69	2.06	1.63	23.68	1,251	.000
Nonpolitical environment						
Hard	1.57	0.99	0.58	17.10	1,210	.000
Soft	1.64	1.03	0.61	17.46	1,210	.000
Political environment						
Congruent	1.56	0.89	0.67	20.17	953	.000
Incongruent	1.42	0.74	0.67	19.21	953	.000

Note. Cells shaded in gray indicate a significant difference between the gap scores across two story types. An independent sample *t* test was used to test the difference between the nonpolitical and political story types; hard versus soft and congruent versus incongruent were tested using a paired sample *t* test.

experimentally manipulate—and individual characteristics influence misreporting exposure using a series of linear regression models (see the Online Appendix for the zero-order correlations). We test overreporting overall, then explore the factors that predict overreporting by story characteristic—comparing hard versus soft stories in the nonpolitical condition and congruent, incongruent, and neutral stories in the political condition (Research Question 4).[1]

Across the models, we find little evidence that the NML messages altered misreporting for any story type or context, in response to Research Question 2 (see Table 2). Only one case is significant, with the combination PSA boosting overreporting exposure to soft news stories.

We do find a range of individual characteristics that predict overreporting across all types of news content. We support Hypothesis 2: Those who report greater interest in news and politics were significantly more likely to overreport story selection in five of six analyses. Answering Research Question 3a, young adults, men, minorities, and wealthier individuals were significantly more likely to overreport story exposure across the models. In addition, Democrats were less likely to overreport their exposure across story types, per Research Question 2b, while the relationship between partisan strength and overreporting is only significant for political news stories. Likewise, we observe that those with higher selective exposure tendencies also tended to self-report greater story exposure for both political and nonpolitical stories, per Research Question 3d, with the exception of neutral political news stories. Only a few characteristics—most notably, education—did not produce consistent effects across story type. However, the direction and magnitude of effects were similar, suggesting these relationships are largely consistent across story types (even if statistical significance differs in some cases). Overall, the factors that contribute to overreporting appear largely consistent across story type, per Research Question 4.

Audience Profiles for Self-Reported Versus Behavioral Measures

To better understand the mechanisms behind overreporting story selection, we use the same models to predict self-reported exposure separately from behavioral story selection. These models suggest our picture of the audience differs depending on whether self-reported versus behavioral measures are used. A series of t-tests were used to probe whether the differences in the beta coefficients is significant between conditions (e.g., Hardy, 1993).

Our results suggest that the predictors of self-reported story selection are often distinct from those predicting actual behaviors. A few findings stand out. First, the models are often more successful in explaining variance in self-reported as compared to behavioral measures of exposure—except for

Table 2. Linear Regression Predicting Misreporting Story Selection, Depending on Story Characteristic (All Participants).

	Total		Nonpolitical Website				Political Website					
	Total		Soft Stories		Hard Stories		Congruent Stories		IncongruentStories		Neutral Stories	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Contextual characteristics												
Environment (partisan)	.02	.11	—		—		—		—		—	
Combination	.05	.14	.09*	.10	.02	.10	.04	.10	.06	.10	.02	.06
Citizen	−.00	.14	.04	.10	.01	.10	−.03	.11	−.03	.11	−.02	.07
Democracy	.01	.14	.05	.11	.02	.10	.03	.10	.00	.10	−.05	.06
Journalist	−.02	.14	−.00	.11	−.02	.10	−.05	.10	−.06	.10	−.01	.06
Social	−.01	.09	.00	.07	−.03	.07	.04	.06	.03	.07	.00	.04
Individual characteristics												
Education	−.04*	.03	−.01	.03	−.04	.02	−.04	.02	−.02	.03	−.08**	.02
Age	−.10***	.00	−.11***	.00	−.06*	.00	−.09**	.00	−.13***	.00	−.11***	.00
Gender (female)	−.09***	.09	−.07*	.07	−.09**	.07	−.10**	.07	−.11***	.07	−.07**	.04
White	−.16***	.11	−.11***	.08	−.20***	.08	−.16***	.07	−.13**	.08	−.11***	.05
Income	.10***	.04	.11**	.03	.12***	.03	.07	.03	.07*	.03	.09**	.02
Need for cognition	.05*	.04	.05	.03	.06	.03	.05	.03	.05	.03	.03	.02
Selective exposure	.11***	.04	.13***	.03	.09**	.03	.08**	.04	.07*	.05	.04	.03
Political/news interest	.10***	.05	.10**	.04	.13***	.04	.08*	.04	.03	.04	.07*	.03
Party affiliation (Democrat)	−.13***	.03	−.09**	.02	−.10***	.02	−.10**	.02	−.20***	.02	−.13***	.01
Partisan strength	.09***	.05	.04	.03	.04	.03	.12***	.05	.11***	.05	.10**	.02
R^2	.128		.089		.115		.103		.124		.083	
N	2,457		1,209		1,209		951		951		1,247	

Note. Higher category indicated in parentheses. For congruent and incongruent stories, independents are excluded from our analysis. Table reports standardized β coefficients and standard errors.
$^{*}p \leq .05$. $^{**}p \leq .01$. $^{***}p \leq .001$.

exposure to incongruent political stories, in which more variance is explained for the behavioral measure of exposure (see Table 3). Second, the NML PSAs (particularly the citizen and democracy PSAs) appear to *depress* story exposure to neutral news stories, both for self-reported and behavioral measures of exposure. While the NML PSAs did not influence misreporting, the fact that they may have depressed story exposure is unexpected and merits additional consideration. Third, we find that the popularity cue boosted exposure to incongruent stories, regardless of measurement.

Finally, the individual factors that explain exposure often differ across the models. Using self-reported measures of story selection, minorities, wealthy individuals, and Republicans *report* viewing more news stories, as are those who are interested in news and politics and who engage in selective exposure. However, the behavioral measures suggest that it is older adults and nonpartisans who *click* on more news stories. Moreover, the size of the effects of political interest and party affiliation on story selection may be exaggerated when relying on self-reports. These models

Table 3. Linear Regression Comparing Self-Reported and Behavioral Measures of Story Selection.

	Nonpolitical Website								Political Website											
	Soft Stories				Hard Stories				Congruent Stories				Incongruent Stories				Neutral Stories			
	Self-Report		Behavior		Self-Report		Behavior		Self-Report		Behavior		Self-Report		Behavior		Self-Report		Behavior	
	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*	β	*SE*
Experimental features																				
Combination	.03	.10	−.06	.09	.01	.10	−.01	.09	.02	.09	−.02	.08	.00	.10	−.08	.08	−.06	.06	−.10*	.05
Citizen	.02	.10	−.03	.09	.01	.10	−.00	.09	−.03	.10	.00	.09	−.04	.10	−.02	.09	−.09*	.07	−.08*	.06
Democracy	.02	.10	.03	.09	.01	.10	−.01	.09	.01	.09	−.03	.08	−.03	.10	−.04	.08	−.10**	.06	−.07*	.05
Journalist	−.02	.10	−.02	.09	−.04	.10	−.03	.09	−.04	.09	.01	.08	−.07	.10	−.01	.08	−.01	.06	.00	.05
Social	.04	.06	.05	.06	−.00	.07	.03	.06	.06	.06	.02	.05	.08*	.06	.07*	.05	.04	.04	.05	.04
Observational characteristics																				
Education	.01	.02	.03	.02	.02	.02	.08*	.02	.00	.02	.05	.02	.02	.02	.05	.02	−.04	.01	.05	.01
Age	−.08*	.00	.04	.00	.05	.00	.15***	.00	−.05	.00	.04	.00	−.02	.00	.14***	.00	−.02	.00	.11***	.00
Gender (female)	.02	.07	.11***	.06	−.05	.07	.05	.06	−.06*	.06	.05	.06	−.03	.07	.11**	.05	−.05	.04	.02	.04
White	−.03	.08	.10**	.07	−.18***	.08	−.01	.07	−.07*	.07	.12**	.06	−.13***	.07	.01	.06	−.09**	.05	.02	.04
Income	.06*	.03	−.05	.03	.07*	.03	−.05	.02	.00	.03	−.08*	.02	.06	.03	−.02	.02	.03	.02	−.07*	.02
Need for cognition	.04	.03	−.01	.02	.07*	.03	.03	.02	.02	.03	−.03	.02	.04	.03	−.01	.02	.07*	.02	.04	.02
Selective exposure	.08*	.03	−.06*	.02	.07*	.03	−.01	.02	.05	.04	−.04	.04	.00	.04	−.09**	.04	.02	.03	−.03	.02
Political/news interest	.07*	.04	−.04	.03	.17***	.04	.08*	.03	.17***	.04	.11**	.04	.10**	.04	.10**	.03	.04	.02	−.03	.02
Party affiliation (Democrat)	−.05	.02	.05	.02	−.13***	.02	−.06*	.02	−.21***	.01	−.13***	.01	−.06	.02	.18***	.01	−.11***	.01	.02	.01
Partisan strength	.04	.03	.00	.03	.02	.03	−.02	.03	.06*	.04	−.07*	.04	.03	.04	−.11**	.04	.07*	.02	−.04	.02
R^2	.024		.029		.106		.033		.093		.047		.046		.093		.037		.023	
N	1,209		1,209		1,209		1,209		951		951		951		951		1,247		1,247	

Note. Higher category indicated in parentheses. Cells shaded in gray indicate a significant difference in the β coefficients in the self-reported versus behavioral measure tested using *t* tests; for congruent and incongruent stories, independents are excluded from our analysis. Table reports standardized β coefficients and standard errors.
**p* < .05. ***p* < .01. ****p* < .001.

demonstrate that when researchers rely on self-reports, they may get a very different picture of who is exposed to news than when behavioral indicators are available.

Discussion

This study set out to investigate the ways in which self-reported and behavioral measures of news story exposure may be shaped by individual predispositions, contextual cues, and story characteristics. Using website data, we observe which news stories individuals click and compare these behaviors with their self-reported exposure to the same stories immediately after the experience. Our results suggest that overreporting of story selection is rampant and that it is responsive both to contextual and individual cues. This study confirms the importance of integrating digital trace data and survey data to more accurately capture news exposure and behaviors, as relying on self-report data may present a very different picture of the news audience than behavioral data indicate.

First, this study suggests that the context in which news consumption habits are measured matters for estimates of exposure. While overreporting occurs both in nonpolitical and political environments, it is more prominent when people confront political stories rather than nonpolitical topics. Although other research has suggested that social desirability biases are not the best predictor of inflated news exposure measures (e.g., Jerit et al., 2016; Prior, 2009b), the presence of political cues may enhance social desirability pressures to engage in a perceived pro-social behavior such as consuming political news. Alternatively, these salient political cues may hinder accurate recall given the importance of political beliefs to personal identity (Green, Palmquist, & Schickler, 2002) creating pressures toward group conformity (Guilbeault, Becker, & Centola, 2018), although the lack of differences in overreporting for congruent versus incongruent stories may undermine this explanation. Pairing digital trace data with qualitative interviews that explore motivations may provide insight into these mechanisms.

The other contextual cues—the NML messages, with or without popularity cues—did not affect misreporting but may have influenced actual news consumption. Videos that reference the popularity of the message on social media platforms boosted exposure (both self-reported and behavioral) to incongruent political stories, in line with previous research suggesting these cues can be powerful for overcoming selective exposure biases (Messing & Westwood, 2014). This study demonstrates such cues may not only guide choices about whether to read a particular story but affect behaviors on the platform more broadly. As such, popularity cues may be an important avenue to mitigate selective avoidance of incongruent political content.

In contrast, several of the NML messages depressed exposure to neutral political stories, an unanticipated effect. Previous research suggests these NML messages can reduce selective exposure to congruent election stories among Republicans (Vraga & Tully, 2017), but the relationship here is significant only for neutral political stories. Future efforts to use NML messages to promote diverse news consumption and accurate self-reported behaviors should consider these difficulties and tailor their messages to the intended audience and context. If NML messages do not promote more news consumption, critical engagement with news, or accurate reporting of news exposure, they fail to deliver on their intended goals of promoting the application of media literacy skills (Bulger & Davison, 2018; Potter, 2018).

Our study allows us to speak to the mechanisms by which misreporting news exposure can occur. Our results echo previous research: Young adults, men, wealthier individuals, minorities, and those interested in news and politics overreported the number of stories that they clicked on the news aggregator site (Guess, 2015; Prior, 2009b). But for some—like younger adults—overreporting was driven by their *lower* levels of actual exposure as measured by behavioral data rather than higher self-reported exposure. In other words, these individuals self-report clicking on the same number of stories as older adults but do not actually do so. For other characteristics—like income and race—it is a combination of inflated self-reports and unreported behaviors that contributes to misreporting. Considering how overreporting occurs provides valuable insight into the mechanisms of misreporting and may help resolve disputes about the nature of these effects (Dilliplane et al., 2013; Guess, 2015; Prior, 2009b).

We explore the political predispositions that contribute to misreporting. Of particular note is the relationship between a tendency toward congruent selective exposure (Tsfati, 2016) and overreporting news exposure. Our results found those who report they engage in select exposure are less likely to click on incongruent news stories, although this relationship is not significant for self-reported data. Amid concerns about selective exposure and its influence on democratic society (Prior, 2013b; Stroud, 2011), these results suggest that those relying on self-reported measures may be overestimating the amount of news and political content these individuals are exposed to and potentially overstating the magnitude of the problem of selective exposure. This may also be reflected in the difference in the amount of polarization in news consumption uncovered by studies using self-reports (e.g., Garrett, 2009; Rodriguez, Moskowitz, Salem, & Ditto, 2017; Stroud, 2011) versus those relying on aggregate data (Nelson & Webster, 2017; Webster & Ksiazek, 2012; see Dvir-Gvirsman et al., 2016, for a similar argument).

Our results also raise questions about how political beliefs contribute to misreporting. We find that Democrats were generally less likely to overreport their story selection compared to Republicans. Notably, Democrats appear more likely to click on incongruent political stories and less likely to click on congruent political stories (Prior, 2013b; Stroud, 2011). Additionally, partisan strength tends to consistently produce overreporting for political news stories, driven by a combination of higher self-reported exposure and lower actual exposure. Moving away from self-reported data appears especially important for answering questions of selective exposure and inequalities in political news consumption (e.g., Guess, Nyhan, & Reifler, 2018; Nelson & Webster, 2017; Webster & Ksiazek, 2012).

Our study has several limitations. First, although efforts were made to recruit a nationally representative sample using stratified quota sampling, combining survey responses with trace data limited generalizability. While we may not be able to precisely estimate population parameters for demographic variables (although many of our relationships echo previous research; see Guess, 2015; Prior, 2009; Stroud, 2011), this study provides insights into the contextual cues likely to matter for overreporting and indicates when self-reported and behavioral measures of exposure are likely to be substantively different.

Second, participants were asked about their news exposure on a simulated news website created for this study. To create a consistent experience across conditions, we selected enduring and timeless news stories and avoided breaking news events. We attempted to produce realistic content by using actual news stories presented on a site that claimed to be in progress. As such, participants were aware they would be asked about their experience immediately after their exposure—likely understating the extent of misreporting. Future research should also test whether the same factors that predict overreporting are maintained over a longer time frame.

Additionally, we acknowledge the need to respect people's privacy and personal data. Participants consented to participating in this study, and no personally identifiable data are connected to a specific individual. The data are used in aggregate. Studies that collect personal web or mobile data from participants should uphold the highest ethical standards.

This study confirms the importance of integrating digital trace data and survey data to more accurately capture news exposure and behaviors. The difficulty of obtaining digital trace data leaves many reliant on self-reports to estimate news exposure; our study helps show that self-reported data may present a very different picture of the news audience as compared to behavioral measures of actual exposure and provides guidance on when such self-reported data may be more accurate. Moreover, overreporting news exposure occurs frequently, and such overreporting depends on personal differences and contextual cues. Specifically, those interested in political news should exercise special caution when relying on self-reported measures of exposure. Research needs to consider the type of news content being examined, especially its political nature, when evaluating the validity of self-reported data and constructing interventions to improve accurate reporting.

Authors' Note

For access to the SPSS syntax used in this project, please contact Emily Vraga at evraga@gmu.edu.

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Note

1. To ensure these numbers are not artificially inflated by individuals who substantially under or overreport exposure, a logistic analysis compared those who had perfect match between self-reported and behavioral data (e.g., reported clicking on "4" stories and have behavioral data confirming clicking on "4" stories) versus those who had a mismatch of any amount. These analyses largely replicate those reported in the paper (see Online Appendix).

Supplemental Material

Supplemental material for this article is available online.

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