**News ‘Attraction’ and Digital Inequalities: Incidental News Exposure and the Equalization or Stratification of Political Information**

A central question in the study of contemporary news environments has been whether digital media are reshaping long-standing inequalities in political news exposure and engagement. While the dominant perspective among scholars and public intellectuals has been that prominent platforms such as Facebook and Google tend to exacerbate these informational inequalities (Prior, 2007), the burgeoning literature on ‘incidental’ exposure complicates the picture by suggesting that even the politically disengaged or uninterested might be exposed to some political news in the course of using digital media platforms for other purposes (Fletcher & Nielsen, 2018). However, recent scholarship has identified a key issue in this literature: It has perhaps overemphasized the role of interest in identifying information gaps to be closed by incidental exposure, and underemphasized the confluence of these ‘demand-side’ factors with changes in ‘supply-side’ dynamics brought about by digital media platforms and the ways they shape information flows.

Based on this observation, Thorson (2020) introduced the metaphor of ‘attracting the news’ in order to describe this confluence of factors and shift the scholarly conversation about informational inequalities toward a deeper consideration of the range individual, social, and technological influences that might produce them. In this article, we develop the idea of *news attraction* as an analytic concept to be used in tandem with incidental news exposure, and we argue that doing so clarifies debates surrounding the equalizing or stratifying effects of digital media on news exposure and engagement. We derive predictions about equalization or stratification based on theory and our explication of the ‘news attraction’ concept, and we then test those hypotheses with data from an online survey of social media users in the United States conducted during the 2020 Presidential Election cycle. Finally, we discuss results in light of extant theory and broader conversations about informational inequalities in contemporary news environments.

**Equalization Versus Stratification in Political News Audiences**

The question of whether the use of digital media reduces or exacerbates inequalities in news exposure and engagement grew out of normative assumptions about the role of news and ‘the press’ in informing the electorate (e.g., Prior, 2007), as well as the functionalist tradition in the study of mass communication, with its assertions that mass media serve important social functions of informing the public and contributing to social integration or cohesion (Wright, 1960), and they largely parallel similar questions regarding broad stratificational effects of the internet (i.e., the ‘digital divide’; c.f., Rogers, 2001). While the field has moved on from functionalism as an organizing framework for understanding media effects on individuals and societies, scholars have continued to grapple with the problem of the stratifying effects of news media, particularly in digital media environments.

Widespread access to journalism and public affairs information should ideally decrease information gaps among groups that are otherwise split along lines of socioeconomic status or other social inequalities. Theoretically, ‘equalizing’ or ‘compensatory’ effects should increase individual and collective knowledge, as access to high-quality information helps people identify problems, coordinate opportunities for solving those problems, and enables participation in civic and political activities (Delli Carpini & Keeter, 1996). But research shows that, historically, individuals with greater political resources (e.g., the wealthy, educated, and politically interested) have been able to not only consume more news content, but reap greater benefits in terms of political knowledge and engagement (Brady et al., 1995; Schlozman et al., 2018), producing a ‘stratificational’ effect or ‘rich-get-richer’ dynamic.

The dominant perspective on digital media has been that prominent platforms such as Facebook and Google tend to create ‘high-choice’ environments, in which the ability of individuals to customize and curate their media diets has deepened inequalities in news consumption (Prior, 2007). According to this view, the politically interested exist in news-rich digital spaces, while everyone else is able to self-select out of news and politics altogether (Karlsen et al., 2020; Thorson, 2020). Empirical research has documented that inequalities in news exposure and engagement persist online (Kalogeropoulos & Nielsen, 2018; Merten et al., 2022), an although evidence that these discrepancies result in knowledge gaps is not consistent across different countries, there are strong indications of growing gaps in the United States (Haugsgjerd et al., 2021).

The growing literature on ‘incidental’ exposure provides a plausible reason to question or temper these claims about informational stratification. *Incidental news exposure* broadly describes encounters with news or political information that occur when individuals are using media for other, non-news purposes (Fletcher & Nielsen, 2018; Weeks & Lane, 2020). Despite the high-choice nature of digital media, the pervasiveness of news online makes it likely that even those who have little interest in news will ‘stumble upon’ it once in a while (Fletcher & Nielsen, 2018; Lu & Lee, 2019; Weeks et al., 2022). In particular, social media seemingly facilitate these encounters with news in “moment[s] of leisure” (Boczkowski et al., 2018) and, some have argued, incidental exposure makes up a substantial portion of news use on those platforms (Antunovic et al., 2018; Fletcher & Nielsen, 2018). Accordingly, some scholars have argued that the sheer abundance of opportunity to encounter news online may actually serve to reduce or temper political inequality by providing opportunities for the disinterested to learn about and participate in the political process (Ahmadi & Wohn, 2018; Weeks et al. 2022; Xenos et al., 2014). Others have argued that, while digital media may facilitate incidental exposure to news, actual *engagement* with news will remain unequal (Kümpel, 2020; Thorson, 2020).

Thus, significant scholarly attention has been devoted to understanding the process and frequency with which incidental exposure occurs (Ahmadi & Wohn, 2018; Antunovic et al., 2018; Barnidge, 2020; Bergström & Jervelycke Belfrage, 2018; Boczkowski et al., 2018; Fletcher & Nielsen, 2018; Hermida et al., 2012; Weeks et al., 2017), the conditions under which people cognitively and behaviorally engage with the news they encounter incidentally (Oledorf-Hirsch, 2018; Karnowski et al., 2017), and the effects of incidental exposure on political knowledge and participation (Bode, 2016; Lee & Xenos, 2022; Lee et al., 2022; Nanz & Matthes, 2020; 2022; Valeriani & Vaccari, 2016).

Empirical findings are generally mixed when it comes to equalization versus stratification in news exposure and engagement. For example, Fletcher and Nielsen (2018) find relatively strong evidence for equalizing effects in terms of exposure. Using survey data from four countries (Italy, Australia, United Kingdom, United States), they find that people who use social media for purposes other than news are exposed to significantly more online news sources, and the effect is stronger among those with lower levels of political interest. In another cross-national sample, semi-structured interviews suggest that equalizing effects may occur while stumbling across content that other people post on the platform (Mitchelstein et al., 2020). Additionally, other studies have found some support showing that incidental exposure is positively related to political learning and participation (Heiss & Matthes, 2019; Weeks et al., 2022). However, a meta-analysis of incidental exposure research noted that these effects tend to be small and contextual (Nanz & Matthes, 2022).

Despite these findings, there continues to be robust scholarly debate over the role of incidental exposure in shaping inequalities in news exposure and engagement due to evidence for stratifying effects. While some studies have found equalizing effects for exposure to news, other studies have found that people who are interested in the news are much more likely to expend the extra effort to engage with content they come across (Kümpel, 2020), and these behaviors are read by news selection algorithms as indicators of future interest (Thorson et al., 2021), which create stratificational effects in future exposure (Barnidge, 2021). Additionally, inequalities in social networks embed some individuals immersed in ‘information-rich’ networks while others are left in so-called ‘social media news deserts’ (Barnidge & Xenos, 2021), as individuals’ social contacts also inform content selection algorithms on social media platforms (DeVito, 2017). Thus, while there is some evidence for equalizing effects, the antecedent individual- and meso-level factors—like news interest, network characteristics, and algorithms—tend to create a reciprocal relationship between exposure and engagement, where some groups are left in information landscapes that are only sporadically populated with politically relevant information (Barnidge & Xenos, 2021; Lee & Xenos, 2022; Thorson, 2019).

**From Incidental Exposure to News Attraction**

Advancing our understanding of digital inequalities in political news audiences requires addressing a key issue that has arisen in the incidental exposure literature. This work has primarily focused on the ‘demand side’ of news exposure. Studies have operationalized incidental exposure as instances in which an individual was exposed to news when they were not motivated to do so. In foregrounding the role of individual motivation, incidental exposure becomes primarily a function of the psychology of news consumers. Yet the novelty of digital media lies in the confluence of ‘demand-side’ factors with changes in the ‘supply side’ of the equation. Here, the very opportunity to incidentally encounter news (i.e., the supply of news) is shaped by a host of social, strategic, and algorithmic forces (Thorson & Wells, 2016; Thorson, 2020). As Kümpel (2020) argued, there is a need to focus on how the very opportunity for incidental exposure may be unequally distributed. This requires considering not only individual motivation, but also social and algorithmic forces as well (Weeks & Lane, 2020; Thorson, 2020).

To address this challenge, we turn to Thorson's (2020) concept of ‘news attraction.’ Thorson introduced the concept of ‘news attraction’ in order to better characterize the “shift in power toward a broader assemblage of actors” that play a role in the process of exposure to news and political information on social media platforms” (p. 1073). Drawing from dictionary definitions of ‘attraction’ that define the term as a force that attracts two objects or an evocation of interest, she argues concept more accurately reflects the dynamics of news exposure in which platforms and curation algorithms play a critical role in the shaping news exposure through the datafication of user activity. In other words, individual activity creates a ‘force’ or ‘evocation’ that ultimately ‘attracts’ news and political information to the user. Thus, much of what scholars have considered to be incidental exposure is not necessarily encountered accidentally. Rather, these encounters often reflect individual’s previous news-related choices and behaviors, as platforms and news organizations use digital traces of these actions to classify users as interested, and subsequently draw on this classification to select content for them to view (Thorson et al., 2021). Therefore, while news may be encountered in the course of doing something else on a platform, these encounters may not entirely non-elective in that people previously have made choices that lead to these encounters. Thus, on social media platforms, the object of choice, as well as the temporality of choice, is often displaced, and choices themselves may not pertain to specific pieces of news content but rather to ‘types’ or categories of content (Barnidge & Xenos, 2021).

While Thorson (2020) offered ‘news attraction’ as a metaphor, we argue that it may also prove fruitful to develop the idea as an analytic concept in conjunction with incidental exposure. There is a need for such a conceptualization in the literature, because, as we previously discussed, most models testing the equalizing or stratifying effects of incidental exposure focus solely on ‘demand-side’ factors such as individual’s self-reported interest in politics or the news as an antecedent factor, and generally consider incidental exposure (or its subsequent outcomes) among individuals with low interest to be evidence of equalizing effects (Barnidge, 2021). Yet, in line with the ‘news attraction’ metaphor, we know from prior literature that the factors shaping incidental exposure go beyond personal interests, and include environmental perceptions (Weeks & Lane, 2020), characteristics of ego-centric social networks (Barnidge & Xenos, 2021), and processes of algorithmic classification based on prior user activity such as engaging with news and political information or following news organizations and/or information actors like journalists and politicians (Thorson et al., 2021). Therefore, there is a need to systematically develop a concept that incorporates these various influences on the process of news exposure and also separates those factors from ‘incidentality’ associated with exposure to any given story or piece of content (Michelstein et al., 2020). We believe that doing so will bring clarity to the debate over equalization versus stratification and provide leverage over the question of whether incidental exposure closes or widens gaps in exposure to and engagement with news and political information.

The ‘news attraction’ metaphor is quite clear about two factors that shape news exposure: individual preferences and the curation algorithms that social media platforms use to select content for users. Prior research shows the individual interest and other preferences do play large role in shaping the extent to which individuals are incidentally exposed (e.g., Barnidge, 2021), helping to create what Kümpel (2020) has called ‘Matthew Effect’ (i.e., a ‘rich-get-richer’ dynamic) of news on social media platforms. While the capacity of research to directly observe curation algorithms is limited, prior research has provided some evidence that is algorithms play a large role in shaping incidental exposure (e.g., Thorson et al., 2021). In addition to these two factors, prior research has identified several other influences on the process of news exposure on social media. For example, Weeks and Lane (2020) theorize that ‘environmental perceptions’—that is, individuals’ perceptions of whether social media platforms are suitable venues for obtaining news and political information—play a primal role in processes of exposure by shaping how people approach and use particular platforms. Additionally, recent research shows that characteristics of individuals’ ego-centric networks such as network size and diversity (Barnidge & Xenos, 2020), as well as the extent to which people follow accounts to get news content (Thorson et al., 2021), also affect processes of news exposure, in large part because content is not only selected by news algorithms, it is also curated by social contacts (Thorson & Wells, 2016).

Thus, prior literature has identified at least five dimensions of influence on processes of news exposure that are related to the ‘news attraction’ concept, which is to say they reflect individual’s interest in news and politics, and they contribute to the ‘force’ that draws news content toward them: (1) personal preferences; (2) environmental perceptions; (3) social network characteristics, particularly those that shape flows of information; (4) social news curation; and (5) the datafication of user behavior by social media platforms and/or news organizations. Therefore, we can conceptually define *news attraction* as follows: the force that results from user interactions with social media platforms, and which affects the likelihood of encountering news or political information on those platforms. Operationally, this definition implies that we need indicators not just of individual preferences such as interest, but also of the other ways in which individuals interact with social media platforms in a way that increases the chances of news exposure.

Theoretically, news attraction should have a reciprocal relationship with both news exposure and news engagement (see Figure 1). That is, news attraction is an important antecedent of exposure as well as key predictor of engagement, while at the same time exposure to and, in particular, engagement with news likely increases news attraction. But critically, our conceptualization of news attraction separates its observable implications from the incidentality of exposure to any given piece of news content. Thus, we recognize the possibility that incidental encounters with the news could occur among individuals who are both ‘high’ and ‘low’ in news attraction, and doing so allows us to isolate incidentality and assess the extent to which incidental exposure occurs among each group. The logic of this assessment can be used to derive three predictions about equalizing or stratifying effects. First, and in an effort to provide predictive validity for the news attraction concept, news attraction should be positively correlated with news use *via any medium or platform*, as the preferences, perceptions, connections, and behaviors that makeup news attraction likely reflect a generalized habit of or preference for news consumption. Hence, we propose the following hypothesis:

H1: News attraction will be positively related to non-social media news use.

Second, if incidental exposure on social media platforms truly closes exposure gaps by drawing in potential news audience members who would not otherwise encounter news, we would expect to see (a) higher levels of incidental exposure among people who score low on news attraction and (b) roughly equal levels of overall exposure among those who are high and those who are low in news attraction. We expect the opposite pattern if incidental exposure widens the exposure gap. These predictions can be summarized with two competing hypotheses:

H2a: Incidental news exposure will close exposure gaps between people who are low in news attraction and people who are high and news attraction.

H2b: Incidental news exposure will widen exposure gaps between people who are low in news attraction and people who are high and news attraction.

Similarly, if incidental exposure closes engagement gaps, then we would expect to observe an interaction effect between incidental exposure and news attraction—that is, people who are low in news attraction but high in incidental exposure should have roughly equal levels of engagement to those who are high in news exposure. On the other hand, if incidental exposure widens engagement gaps, we might expect to see the highest levels of engagement among those who are high in news attraction and high in incidental exposure. Thus, we can formulate the following competing hypotheses:

H3a: Incidental news exposure will close engagement gaps between people who are low in news attraction and people who are high and news attraction.

H3b: Incidental news exposure will widen engagement gaps between people who are low in news attraction and people who are high and news attraction.

**Methods**

**Survey Design**

This study relies on a novel design featuring an online rolling cross-sectional survey of adult social media users in the United States. The survey was administered in 17 sampling frames of 3-4 days each (with Saturday/Sunday counted as one day). This approach affords a unique opportunity to link survey responses and social media content, because it is possible to ‘locate’ responses in temporal proximity to actual content known to be circulating on social media. The research team collected external media data from Facebook’s proprietary platform, CrowdTangle. In each sampling frame we embedded a screenshot of (one of) the most popular news articles in the previous three day with source cues photoshopped out of the image. Because most of the stories came from a single news organization (Fox News), we balanced this dynamic by also including the most popular story from any other news organization (e.g., CNN, *New York Times*, *Washington Post*, etc.), and, thus, in each sampling frame respondents were randomly presented with either the most popular Fox News story or the most popular story from some other organization that was circulating immediately prior to the sampling frame. Respondents were told the story had been “recently circulating on Facebook”—a true statement. Based on this method, we developed several cued recall measures, which form key outcome variables.

**Sample and Data**

Data were collected between September 3 and November 1, 2020. Quotas for age, race, gender, and census region were based on the 2018 American Community Survey. The survey has an incidence rate of 100% and a cooperation rate of 70%. It has an overall sample size of *N* = 2,008 with at least *n* = 100 for each sampling frame. The sample reflects the target population on the quota criteria (see Table A1 in the online appendices). The average respondent is between 45 and 54 years old (measured on a 7-point scale where 1 = *18-24* and 7 = 85 or older). Approximately 40% of the sample are persons of color, and 51% are female. Census regions were defined according to the U.S. Census Bureau’s map, and in our sample ~22% of respondents live in the Midwest, ~19% live in the Northeast, ~37% live in the South, and ~23% live in the West. In terms of non-criterion demographics, the average respondent has either some college or a 2-year associate’s degree or trade school diploma (*M* = 4.5 on a 7-point scale where 1 = *Some high school* and 7 = *Post-graduate degree*), and lives in a household that earns between $45,000 and $75,000 per year (*M* = 4.7 on an 8-point scale where 1 = *Less than $15,000* and 8 = *More than $150,000*). The sample underrepresents low-education and low-income individuals, and therefore the data were weighted by education and income (see Table A2 online for the weighting scheme). Missing values were imputed using a chained equations technique (Fully Conditional Specification; see van Buuren & Groothuis-Oudshoorn, 2011).

**Measures**

***Exposure and Engagement***

Prior literature suggests that news exposure has both ‘trait-like’ and ‘state-like’ properties (Weeks & Lane, 2020), and we included both kinds of indicators in our study. On the trait-like side, *total exposure* to political information was measured with six questionnaire items asking respondents how often in the past week they have encountered the following types of information (0 = *Never* and 4 = *Several times a day*): information critical of a candidate they support; information critical of a candidate they oppose; information supportive of a candidate they support; information supportive of a candidate they oppose; information that disagrees with their political views; and information that agrees with their political views (c.f., Weeks et al., 2017). These items were averaged for each respondent, and the resulting scale is reliable (Cronbach’s alpha = .96). The variable has a mean of 1.8 (*SD* = 1.3).

It is important to clarify whether exposure was incidental (Nanz & Matthes, 2020). Therefore, immediately after answering the above battery of questions, respondents were asked a follow-up question: “On social media, some people intentionally search for news or political information, but others come across such information accidentally. What about you?” (0 = *Always intentionally* and 4 = *Always accidentally*). To create a measure of *incidental exposure*, this item was multiplied by the total exposure scale, and then the square root was calculated to maintain the original 5-point metric. The variable has a mean of 1.5 (*SD* = 1.1).

The state-like measures centered on the embedded story stimuli. Once shown the story, respondents were asked whether they had seen it on Facebook. A follow-up question asked whether they had seen it on some other social media platform, and answers to these two items were recoded so that 1 = *Exposed* and 0 = *Not exposed*. Approximately 42% of the sample reported *story exposure*.

Those respondents who reported exposure were asked a series of additional follow-up questions, from which our measures of *incidental exposure* and *engagement* are created. First, this subset of respondents was asked: “When you say the story, were you purposefully seeking information on this topic?” (1 = *Yes* and 0 = *No*; 54% of subset and 23% of full sample said yes). Next, they were asked: “When you saw the story, did you engage in any of the following activities?” (1 = *Yes* and 0 = *No*): click on the story; scan the headline of the story; read the entire story; seek out additional information about the topic; comment on the post; discuss the story; and share the story. Responses were summed for each respondent (Cronbach’s alpha = .79; *Min*. = 0 and *Max*. = 7), and the variable has a mean of 3.5 (*SD* = 2.2). Additionally, a *high-effort engagement* variable was created to isolate those activities that relatively higher amounts of cognitive or behavioral effort, including information seeking, commenting, discussing, and sharing (Cronbach’s alpha = .76; *Min*. = 0, *Max*. = 4, *M* = 1.5, *SD* = 1.5).

***Non-Social Media News Use***

Non-social media news use was measured with four survey items measured on 5-point scales (1 = *Never*, 5 = *Several times a day*) asking respondents how often they got news directly from the following sources in the past week: online websites for mainstream news; online-only news websites; print versions of newspapers; and broadcast or television news. These four items were averaged for each respondent (Cronbach’s alpha = .80, *M* = 2.6, *SD* = 1.1).

***News Attraction***

The study includes four indictors of news attraction. First, the study measures respondents’ perceptions of *social media as news source* (Weeks & Lane, 2020) by asking them which choice best describes their “reason for accessing [their] social media accounts”: to follow news and public affairs information; for some other reason; do not think very much about the reason. This three-level factor was recoded into a binary variable (1 = *News source* and 0 = *Not news source*). A little more than one-third of the sample (35%) views social media as a news source. Second, the study measures *self-reported interest* with a three-item scale. Questions asked respondents how interested they are (1 = *Not at all interested* and 5 = *Very interested*) in news, politics, and local community. These three items were averaged for each respondent (Cronbach’s alpha = .83) and the variable has a mean of 3.5 (*SD* = 1.0). Third, the measures the extent which respondents *follow accounts for news* with a three-item scale. Items ask how often respondents follow accounts on social media because they are interested in what they post about news or current affairs, politics, and community events (1 = *Never* and 5 = *Very Frequently*). These three items were averaged for each respondent (Cronbach’s alpha = .91), and the scale has a mean of 2.7 (*SD* = 1.2). Finally, we measured *algorithmic categorization* using a technique pioneered by Thorson and colleagues (2021). With the aim of obtaining an observable indicator of Facebook’s classification algorithm, we asked respondents at the end of the survey to open a web browser, navigate to the Settings menu of their Facebook accounts, and locate their Ad Interests section. We then asked them whether they saw the following categories included in their interests: (a) politics; (b) news or specific news organizations (e.g., the *New York Times*); or (c) neither. We coded this item into a binary variable (1 = *News or politics* and 0 = *Neither*). A little less than half (41%) of the sample was categorized as interested in news or politics. Finally, social news curation is a concept taken from Thorson and Wells’ (2016) influential work on curated flows. The variable relies on 5 items that ask respondents how much (1 = *None at all* and 5 = *Almost all*) of the content their friends post is about the following topics: the 2020 election; politics or current affairs; social or community issues; racial or social justice issues; and COVID-19. The items were averaged for each respondent (Cronbach’s alpha = .92), and the variable has a mean of 2.9 (*SD* = 1.1).

***Covariates***

Prior research has shown that social networks structures are predictors of incidental exposure, and they also related to news involvement (Barnidge & Xenos, 2021). Therefore, it is important to include indicators of social network structures as covariates in the analysis, and we included four such variables. First, network size was measured by asking respondents how many people or accounts they are “friends with,” “follow,” or “subscribe to” on six social media platforms (1 = *None* and 7 = *2,001 or more*). Respondents’ answers to these items were averaged to create a scale (Cronbach’s alpha = .91), which was then unobtrusively logged to correct for skew (*Min*. = 0 and *Max*. = 1.9). The final variable has a mean of 0.7 (*SD* = 0.5). Second, a structural measure of *network diversity* was borrowed directly from prior literature (Hampton et al., 2011). The measure uses a standardized list of 22 occupations and asks respondents whether they are connected someone on social media who belongs to each (1 = *Yes* and 0 = *No*). An averaged scale was created from these items (Cronbach’s alpha = .92), which has mean of 0.3 (*SD* = 0.3). Third, *group activity* on social media was measured with an 8-item scale, where questions asked respondents whether they had discussed news or related topics during the past month in various types of groups. These items were summed for each respondent, and the resulting index was then unobtrusively logged to normalize the distribution. The final variable has a mean of 0.5 (*SD* = 0.6).

***Controls***

In addition to *age*, *race*, *gender*, *education*, and *income* (see above for descriptive statistics), the analyses control for *political ideology*, *party identity*, and *frequency of social media use*. Political ideology was measures with a single 11-point L-R scale where -5 = *Very liberal* and 5 = *Very conservative* (*M* = 0.2, *SD* = 3.0). Party identity was measured with three questionnaire items borrowed from the American National Elections Survey. The first asked about party identity (*Democrat*/ *Republican*/ *Other*/ *None*). The second, shown only to those who selected *Democrat* or *Republican* asked about the strength of identity (*Strong*/ *Not that strong*). The third, shown only to those who selected *Other* or *None*, asked about party lean (*Closer to Democrat*/ *Closer to Republican*). These items were then coded to create a 7-point scale where -3 = *Strong Democrat* and 3 = *Strong Republican* (*M* = -0.3, *SD* = 2.0). Finally, frequency of social media use was measured with a single item asking respondents how much time per day they spend actively using social media (1 = *Less than 10 minutes* and 6 = *More than three hours*. The variable has a mean of 3.5 (*SD* = 1.6).

**Analysis and Results**

**Latent Class Analysis**

In the first stage of the analysis, the five indicators of involvement were entered into a Latent Class Analysis (LCA). The correlations among the four variables are relatively strong (.34 < *r* < .72, *p* < .001 for all coefficients, see Table B1 online for a full correlation matrix), indicating that they may be empirical manifestations of a common underlying construct—that is, they arise from related dimensions of involvement with the news and political information. To establish the best number of latent classes, we compared the fit statistics for models ranging from 2 to 5 classes, using the BIC as the primary criterion for model selection (lower BIC indicates better model fit). The BIC is generally better than *G*2 or χ2 for establishing model fit, as these statistics almost always decrease when the number of classes increases, regardless of concern for overfitting. Additionally, the BIC typically outperforms the AIC for model selection, as it presents a stronger penalty for adding parameters (i.e., classes). Based on these considerations, we selected the model with the lowest BIC, which has 4 latest classes (see Table B2 online).

There are important qualitative differences among the four groups, which can be described according to differing response probabilities on the five criteria variables in the analysis. These probabilities are visualized in Figure 2. Respondents in the first latent class, which we have labeled the *low-attraction group*, are unlikely to perceive social media as news sources or to be categorize as interested in news or politics by Facebook’s algorithm. They are less likely than the other groups to follow accounts for news or report social news curation in the past week—the most probable response category on both of these variables is ‘*1 = Never*’ for both variables. There is a relatively normal probability distribution on self-reported interest, but this distribution actually skews lower than it does for the other groups. The low-attraction group is the second-largest latent class (*n* = 594); it makes up 38% of the sample and has a predicted probability of group membership of .40 (see Table B3 online).

The second and third latent classes are somewhat similar in that they can be characterized as having ‘moderate’ levels of news attraction. However, they also differ in important ways. Although both groups are more likely than the low-attraction group to perceive social media as a news source and to be categorized by Facebook’s algorithm as interested, the probability of a ‘*Yes’* score on both variables is considerably lower in the second group as compared to the third. Additionally, the most common response category on the other three criterion variables (self-reported interest, following news accounts, and social curation) is ‘3’ in the second group but ‘4’ in the third. Thus, while both groups display moderate levels of news attractiveness, respondents in the third group appear to be more motivated to attract the news than respondents in the second. Therefore, we have labeled the second group, which is larger (*n* = 805; 31%; predicted probability = .30), the *moderate—unmotivated group* and the third group, which is smaller (*n* = 416; 21%; predicted probability = .21), the *moderate—motivated group*.

The final group, which we have labeled the *high-attraction* *group*, displays the strongest tendencies toward news attraction on all criteria variables. The most likely response category on the two binary criteria—environmental perceptions and algorithmic categorization—is ‘*1 = Yes*’ and the most likely response on the three interval-like scales is ‘*5 = Very Often/Very Interested*’. This group is the smallest (*n* = 193); it makes up only 10% of the sample with a .10 predicted probability of group membership.

**Regression Analyses: Non-Social Media News Use**

Conceptually, news attraction should reflect general tendencies and orientations toward news that shape not only patterns of exposure and engagement on social media platforms, but also elsewhere. Therefore, and by way of establishing the external validity of the news attraction variable, H1 predicts that news attraction will be positively associated with non-social media news use. We test this prediction using multi-level modeling (MLM). This approach allows us to estimate differences between the attraction groups while controlling for measurement invariance introduced by the data structure—that is, the data were collected in 17 sampling frames, and therefore the means of the outcome variables could vary across frames. The analysis accounts for this structure by including random intercepts for each sampling frame. Results are reported in Table 1, and they support H1. The table shows a linear model in which the covariates have been group-mean centered by frame. Therefore, the intercept can be interpreted as the adjusted grand mean of the reference group, which in this case is the ‘low-attraction’ group, and the coefficients for the other groups can be interpreted as adjusted mean differences from the reference group. Thus, the model shows the ‘low-attraction’ has a mean of 1.86, and the means for the other groups are all significantly higher (*p* < .001 for all comparisons). The model estimates an adjusted mean of 2.43 for the ‘moderate—unmotivated’ group, 3.32 for the ‘moderate—motivated’ group, and 3.84 for the ‘high-attraction’ group. These differences are visualized in Figure 3, and the pattern shows that each successive group has a higher mean than the next, validating the idea that news attraction reflects general tendencies and orientations toward news.

**Regression Analyses: Exposure**

If incidental exposure closes gaps in news exposure, we should expect to observe (1) higher incidental exposure in the low- and moderate-attraction groups than in the high-attraction group *and* (2) roughly equal amounts of overall exposure among the groups. We test these criteria using multi-level modeling (MLM). Linear models are used for the trait-like variables, reflecting their interval-like properties, while quasibinomial (Poisson) models are used for the state-like variables, which are appropriate for weighted binomial outcomes. Results of these analyses are presented in Table 2.

The first model in the table tests the trait-like incidental exposure outcome variable. Because the model is linear and the covariates are group-mean centered by frame, the intercept can be interpreted as the adjusted grand mean (*M* = 1.15) of the low-attraction group, and the coefficients as differences from this mean. The estimated adjusted means for the two moderate-attraction groups are significantly higher (*p* < .001) than the mean of the low-attraction group (*M* = 1.77 for unmotivated and *M* = 1.51 for motivated). Meanwhile, the estimate for the high-attraction group (*M* = 0.99) is not significantly different than the estimate for the low-attraction group. These means are visualized in Figure 4 (upper-left).

The second model in the table tests the state-like indicator of incidental exposure, which is quasibinomial (Poisson), and therefore differs slightly from the linear models in terms of the interpretation of the coefficients. In this model, the exponentiated intercept can be interpreted as the adjusted proportion of respondents in the reference group who report incidental exposure, and its exponentiated differences with the comparison coefficients as the adjusted proportions for the other groups. Thus, the model estimates that 13% of respondents in low-attraction group report incidental exposure. The proportions for the two moderate groups are significantly (*p* < .001) higher at 25% (unmotivated) and 28% (motivated), respectively, but the proportion for the high-attraction group is not (19%). These proportions are visualized in Figure 4 (upper-right).

The third model reported in Table 2 tests the trait-like indicator for overall exposure. As this is a linear model, the interpretation of the coefficients is similar to those for the trait-like indicator of incidental exposure (Model 1). The model shows an adjusted mean of 1.12 for the low-attraction group. Meanwhile, the means for all other groups are statistically higher (*p* < .001) at 1.91 for the moderate—unmotivated group, 2.34 for the moderate—motivated group, and 2.71 for the high-attraction group. These means are visualized in Figure 4 (lower-left).

The last model in the table tests the state-like variable for overall exposure. This model is quasibinomial and therefore similar to the model for the state-like incidental exposure outcome (Model 2). The model estimates that the adjusted proportion of respondents in the low-attraction group reporting exposure is 18%, while the adjusted proportions for the other groups are significantly higher (*p* < .001) at 38% for the moderate—unmotivated group, 58% for the moderate—motivated group, and 57% for the high-attraction group. These proportions are visualized in Figure 4 (lower-right).

Putting these results together, we can draw two different conclusions for the low- and moderate-attraction groups. Respondents in the former do not report higher levels of incidental exposure than the other groups, and they also report significantly lower levels of overall exposure than the other groups. Therefore, the low-attraction groups meet neither of our observational criteria for closing exposure gaps (H2a). That said, we have no evidence that exposure gaps between the high- and low-group are attributable to incidental exposure (H2b), specifically, as these groups report roughly the same amount of incidental exposure. Thus, for the low-attraction group, incidental exposure does not close or widen the gap in news exposure.

On the other hand, results tell a different story for the two moderate-attraction groups. These groups (and particularly the ‘motivated’ group) report significantly more incidental exposure than either the low- or high-attraction groups, and their reported levels of overall exposure are also relatively close to the high-attraction group. For one outcome (the state-like overall exposure variable), the estimated proportions for the high-attraction and moderate—motivated groups are statistically equivalent (between 55% and 60%). Therefore, we have evidence that incidental exposure closes (H2a) rather than widens (H2b) exposure gaps, especially the ‘motivated’ group but also, to a lesser extent, the ‘unmotivated’ group.

**Regression Analyses: Engagement**

If incidental exposure closes gaps in *engagement* with the news, we be able to observe an interaction between attraction and incidental exposure, wherein we should observe fewer differences between the attraction groups among those reporting incidental exposure than we do among those reporting purposeful exposure. We tested this prediction on two measures of engagement—the general metric includes low-effort behaviors such as clicking and scanning whereas the high-effort metric isolates behavior that require more effort, such as information seeking and sharing. The tests once again rely on weighted linear multilevel models with covariates group-mean centered by frame. Results are reported in Table 3.

For overall engagement, we observe greater differences among the attraction groups among those who report incidental exposure than among those who report purposeful exposure—essentially the opposite of what we would expect if incidental exposure closes engagement gaps. The estimated adjusted means can be calculated from the model coefficients in the same manner as before, only this time the calculations include not only the intercept and comparison coefficients, but also the relevant interaction term. Using this method, we can compare the group differences between those who report purposeful and incidental exposure. Among those reporting purposeful exposure, the difference between the low- and high-attraction groups is 1.82, and the difference between the low-attraction group and its nearest neighbor (moderate—unmotivated) is 0.77. Substantially greater differences are reported among those reporting incidental exposure. The difference between the low- and high-attraction groups is 3.54, and the difference between the low-attraction group and its nearest neighbor is 2.27. These differences are visualized in Figure 5. See Table C1 online for a full list of estimated means.

A similar pattern is observed for the high-effort engagement outcome, although the interaction terms are not statistically significant. Among respondents who were purposefully exposed, the gap between the low- and high-attraction groups is 0.87, and the difference between the low-attraction group and its nearest neighbor is 0.35. By contrast, the comparable differences among respondents reporting incidental exposure are 2.04 and 1.28, respectively, which are substantially greater. These patterns are visualized in Figure 6.

Taken together, these results provide evidence that incidental exposure widens (H3b) rather than closes (H3a) engagement gaps, although the evidence is relatively stronger for the overall engagement outcome, which includes low-effort behaviors, than for the high-effort outcome, which does not.1

**Discussion**

We started with the premise that our expectations about baseline levels of political news exposure and engagement should be based not solely on demand-side factors such as political interest but rather on a range of both demand- and supply-side factors relevant to changes in information flows brought about by the widespread adoption and use of major digital media platforms. Applying this logic, we developed Thorson’s (2020) ‘news attraction’ metaphor as an analytic concept that is characterized by a multivariate approach, with the assumption that interrelated dimensions of news attractiveness are manifest from a latent construct that can be measured and employed in statistical analysis. Doing so has provided added utility both in terms of empirical observation and theoretical insight.

In order to demonstrate the added value of the latent-class approach to operationalizing news attractiveness, we re-ran all regression analyses using only self-reported interest as a primary predictor, as this variable has received the most attention both theoretically and empirically from prior literature (e.g., Barnidge, 2021; Thorson et al., 2021). Results are both less robust and less rich in terms of their descriptive capacity. Whereas our analysis of the grouping variable revealed important and theoretically fruitful group differences in incidental exposure, self-reported interest is unrelated to the trait-like measure and only weakly related to the state-like measure (β = 0.12, *SE* = 0.05, *p* = .022). Thus, by accounting for latent classes defined by a range of behaviors, rather than just self-reported interest, we are able to not only improve our capacity to predict incidental exposure but also reveal non-linear patterns of group difference that cannot be observed by analyzing interest alone.

The endeavor has also proven to be theoretically fruitful, as analyzing the latent construct has revealed multifaceted conclusions regarding information gaps related to incidental news exposure. Gaps based not only on interest, but also on networks, curation, and algorithms. Difference between exposure and engagement. Not necessarily linear. Exposure, we find equalization the groups in middle. Engagement, gaps everywhere, but smaller for groups in middle. Zaller-esque sweet spot – not totally oblivious, but not so saturated that incidental encounters don’t make a difference. This is where digital platforms have the biggest effects. So who are they? Supplemental analyses.

On other hand, there is definitely a sizable low-attraction group that is major cause for concern. Substantial number of people not just ‘checked out’ – they are never getting this stuff despite being connected via social media. What is happening here? Social media news deserts. Supplemental analyses.

What picture does this paint? Initial takes were overly optimistic. Limited equalization. Won’t solve our problems. Serious informational inequalities will remain. Social media in particular can’t fill information void left by local media, lack of robust public media. Need investment in those areas to reduce inequalities, inform public, promote social cohesiveness and normative belief in democratic practice.

Limitations. Cross sectional. Imperfect stimulus. Can’t measure everything so went with most popular. Typical measurement issues – self report. One unique – what does purposeful really mean? Could be differences in interpretation rather than phenomenological difference. Analyses – unrealistic to expect total equalization? Perhaps, but we don’t observe any among low group. Even taking analysis on more realistic terms, limited evidence for equalization. Latent class analysis – only as good as the variables we give it. Different thresholds for determining number of groups.

Conclusions: Still a great study, so publish us please.

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List of Tables and Figures

|  |  |  |
| --- | --- | --- |
| Table 1  *Differences in Non-Social Media News Exposure among the News Attraction Groups* | | |
|  | Non-Social Media News Use | |
| **Fixed Effects** | β | *SE* |
| Intercept (*M* Low News Attraction) | 1.86\*\*\* | 0.04 |
| News Attraction (Δ versus Low) |  |  |
| Medium—Unmotivated | 0.57\*\*\* | 0.04 |
| Medium—Motivated | 1.46\*\*\* | 0.05 |
| High | 1.98\*\*\* | 0.07 |
| Age | -0.01 | 0.01 |
| Gender (1 = Female) | -0.20\*\*\* | 0.04 |
| Race (1 = Person of Color) | 0.07\* | 0.04 |
| Education | 0.06\*\*\* | 0.01 |
| Income | 0.05\*\*\* | 0.01 |
| Ideology (+ Conservative) | 0.00 | 0.01 |
| Party Identity (+ Republican) | 0.00 | 0.01 |
| **Random Effects** | *Var.* | *SD* |
| Intercept | 0.01 | 0.11 |
| **Fit Statistics** |  |  |
| ICC | .02 | |
| LL | -2,535.29 | |
| Pseudo-*R*2 | .52 | |
| *Note*: Cell entries are parameter estimates from linear multilevel model with random intercepts. Data are weighted by education and income. *N* = 2,008. Groups = 17. | | |

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| Table 2  *Differences in Social Media News Exposure Among the News Attraction* *Groups* | | | | | | | | | | | | | |
|  | Incidental Exposure | | | | | | Total Exposure | | | Story Exposure | | |
|  | Trait-Like Variable | | | State-Like Variable | | | Trait-Like Variable | | | State-Like Variable | | |
| **Fixed Effects** | β | | *SE* | β | | *SE* | β | | *SE* | β | | *SE* |
| Intercept (*M* Low News Attraction) | 1.15\*\*\* | | 0.05 | -2.07\*\*\* | | 0.13 | 1.12\*\*\* | | 0.06 | -1.73\*\*\* | | 0.11 |
| News Attraction (Δ versus Low) |  | |  |  | |  |  | |  |  | |  |
| Medium—Unmotivated | 0.62\*\*\* | | 0.06 | 0.68\*\*\* | | 0.13 | 0.79\*\*\* | | 0.05 | 0.75\*\*\* | | 0.12 |
| Medium—Motivated | 0.36\*\*\* | | 0.08 | 0.78\*\*\* | | 0.16 | 1.22\*\*\* | | 0.07 | 1.18\*\*\* | | 0.13 |
| High | -0.16 | | 0.11 | 0.40 | | 0.24 | 1.59\*\*\* | | 0.10 | 1.17\*\*\* | | 0.16 |
| Age | 0.08\*\*\* | | 0.02 | 0.12\*\*\* | | 0.04 | 0.06\*\*\* | | 0.02 | 0.01 | | 0.03 |
| Gender (1 = Female) | 0.06 | | 0.05 | -0.15 | | 0.10 | -0.06 | | 0.05 | -0.24\*\* | | 0.08 |
| Race (1 = Person of Color) | -0.17\*\*\* | | 0.05 | -0.12 | | 0.10 | -0.22\*\*\* | | 0.05 | 0.00 | | 0.08 |
| Education | 0.06\*\*\* | | 0.02 | 0.01 | | 0.03 | 0.06\*\*\* | | 0.02 | 0.02 | | 0.02 |
| Income | 0.00 | | 0.01 | -0.04 | | 0.03 | 0.00 | | 0.01 | -0.02 | | 0.02 |
| Ideology (+ Conservative) | -0.03\*\*\* | | 0.01 | -0.03 | | 0.02 | -0.03\*\* | | 0.01 | 0.01 | | 0.01 |
| Party Identity (+ Republican) | 0.05\*\*\* | | 0.01 | 0.03 | | 0.03 | 0.04\*\* | | 0.01 | 0.00 | | 0.02 |
| Frequency of Social Media Use | 0.07\*\*\* | | 0.01 | 0.09\*\* | | 0.03 | 0.06\*\*\* | | 0.01 | 0.00 | | 0.02 |
| Network Size | -0.03 | | 0.07 | -0.14 | | 0.15 | 0.40\*\*\* | | 0.07 | 0.23\* | | 0.10 |
| Network Diversity | 0.26\* | | 0.11 | -0.02 | | 0.22 | 0.30\*\* | | 0.10 | 0.32\* | | 0.15 |
| Group Activity | 0.25\* | | 0.11 | 0.13 | | 0.10 | 0.29\*\*\* | | 0.04 | 0.11 | | 0.07 |
| **Random Effects** | *Var.* | | *SD* | *Var.* | | *SD* | *Var.* | | *SD* | *Var.* | | *SD* |
| InterceptFrame | 0.01 | | 0.10 | 0.04 | | 0.19 | 0.03 | | 0.17 | 0.03 | | 0.18 |
| **Fit Statistics** |  |  | |  |  | |  |  | |  |  | |
| ICC | .01 | | | .02 | | | .03 | | | .02 | | |
| LL | -3,137.86 | | | -1,051.30 | | | -3,088.25 | | | -1,339.30 | | |
| Pseudo-*R*2 | .17 | | | .11 | | | .44 | | | .11 | | |
| *Note*: Cell entries are parameter estimates from multilevel models with random intercepts. Linear models are used for trait-like variables, and quasi-binomial models are used for state-like variables. Data are weighted by education and income. *N* = 2,008. Groups = 17. | | | | | | | | | | | | | |

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| --- | --- | --- | --- | --- | --- | --- |
| Table 3  *Conditional Effects of News Attraction on Story Engagement* | | | |  |  | |
|  | Engagement | | High-Effort Engagement | | | | |
| **Fixed Effects** | β | *SE* | β | | | *SE* | |
| Intercept (*M* Low News Attraction) | 4.11\*\*\* | 0.44 | 1.77\*\*\* | | | 0.29 | |
| News Attraction (Δ versus Low) |  |  |  | | |  | |
| Medium—Unmotivated | -.40 | 0.48 | -0.09 | | | 0.31 | |
| Medium—Motivated | 0.11 | 0.47 | 0.18 | | | 0.31 | |
| High | 0.87 | 0.49 | 0.67 | | | 0.32 | |
| Incidental Exposure (State-Like) | -2.67\*\*\* | 0.47 | -1.38\*\*\* | | | 0.31 | |
| Incidental Exposure (Trait-Like) | -0.12\* | 0.06 | -0.09\* | | | 0.04 | |
| Age | 0.00 | 0.05 | -0.03 | | | 0.03 | |
| Gender (1 = Female) | -0.29\* | 0.12 | -0.20\* | | | 0.08 | |
| Race (1 = Person of Color) | 0.25 | 0.13 | 0.06 | | | 0.08 | |
| Education | -0.03 | 0.04 | -0.03 | | | 0.03 | |
| Income | 0.02 | 0.03 | 0.01 | | | 0.02 | |
| Ideology (+ Conservative) | 0.02 | 0.02 | 0.03\* | | | 0.01 | |
| Party Identity (+ Republican) | -0.05 | 0.03 | -0.04\* | | | 0.02 | |
| Frequency of Social Media Use | 0.02 | 0.04 | 0.02 | | | 0.03 | |
| Network Size | 0.27 | 0.17 | 0.31\*\* | | | 0.11 | |
| Network Diversity | 0.74\*\* | 0.24 | 0.42\*\* | | | 0.16 | |
| Group Activity | 0.27\* | 0.11 | 0.21\*\* | | | 0.07 | |
| **Interactions** |  |  |  | | |  | |
| News Attraction (Mod—Unmot) x Incidental Exposure (State-Like) | 1.17\* | 0.52 | 0.44 | | | 0.34 | |
| News Attraction (Mod—Mot) x Incidental Exposure (State-Like) | 1.23\* | 0.51 | 0.41 | | | 0.33 | |
| News Attraction (High) x  Incidental Exposure (State-Like) | 0.95 | 0.57 | 0.20 | | | 0.37 | |
| **Random Effects** | *Var*. | *SD* | *Var*. | | | *SD* | |
| Intercept | 0.02 | 0.16 | 0.02 | | | 0.13 | |
| **Fit Statistics** |  |  |  | | |  | |
| ICC | .01 | | .02 | | | | |
| LL | -1,634.20 | | -1,285.53 | | | | |
| Pseudo-*R*2 | .45 | | 0.46 | | | | |
| *Note*: Cell entries are parameter estimates from a multilevel model with random intercepts. Data are weighted by education and income. Analysis uses subset of respondents who report exposure to story. *N* = 842. Groups = 17. Mod: Moderate. Unmot: Unmotivated. Mot: Motivated. | | | | | | |

Figure 1

*Theoretical Relationships Among News Attraction, News Exposure, and News Engagement*



Figure 2

*Predicted Probabilities for Criterion Variables in Latent Class Analysis*



Figure 3

*Differences Among News Attraction Groups in Non-Social Media News Use*



Figure 4

*Differences Among Attraction Groups in News Exposure*

**

Figure 5

*Differences in News Engagement Between Attraction Groups by Exposure Type (Purp. = Purposeful & Inc. = Incidental)*



Figure 6

*Differences in High-Effort News Engagement Between Attraction Groups by Exposure Type (Purp. = Purposeful & Inc. = Incidental)*



**Appendix A:**

**Sample Demographics and Weighting Scheme**

|  |  |  |
| --- | --- | --- |
| Table A1  *Demographic Profile of Survey Sample and Target Population* | | |
|  | Current Survey | U.S. Census Bureau:  2016 American Community Survey | |
|  | (%) | (%) | |
| Gender |  |  | |
| Male | 49.0 | 49.2 | |
| Female | 51.0 | 50.8 | |
| Age (median) | 35-44 | 37.7 | |
| Ethnicity/race |  |  | |
| White | 59.6 | 62.0 | |
| Black or African American Native | 15.9 | 12.3 | |
| American Indian and Alaska Native | 1.5 | 0.7 | |
| Asian | 12.9 | 5.2 | |
| Native Hawaiian and other Pacific Islander | 0.2 | 0.2 | |
| Hispanic | 7.6 | 17.3 | |
| Household income (median) | US $60,000–75,000 | US $57,617 | |
| Education |  |  | |
| Less than high school graduate | 2.1 | 13.0 | |
| High school diploma or equivalent | 15.7 | 27.5 | |
| Some college or associate degree | 26.2 | 29.2 | |
| Bachelor’s degree or higher | 56.1 | 30.3 | |
| *Note*: The US Census Bureau 2016 American Community Survey is available online at http://factfinder.census.gov/ | | |

|  |  |
| --- | --- |
| Table A2  *Survey Weights* | |
| Income | |
| Category | Weight |
| Less than $15k | 1.02 |
| $15k to 30k | 1.00 |
| $30k to $45k | 1.00 |
| $45k to 60k | 1.00 |
| $60k to $75k | 1.00 |
| $75k to $100k | 0.86 |
| $100k to $150k | 0.95 |
| More than $150k | 0.95 |
| Education | |
| Category | Weight |
| None, or grades 1-8 | 5.75 |
| High school incomplete (grades 9-11) | 1.77 |
| High school graduate (grade 12 or GED certificate) | 1.33 |
| Some college, no 4-year degree (includes Associate’s Degree) | 0.89 |
| Technical, trade, or vocational school after high school | 0.65 |
| College graduate (Bachelor’s Degree) | 0.42 |
| Post-graduate training/professional school after college | 0.42 |
| *Note*. Income measured as annual household income. Education measured in terms of highest level completed. Final survey weights created by multiplying weights for income and education. | |

**Appendix B:**

**Full Results from Latent Class Analysis**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table B1  *Correlations Among Variables Used in Latent Class Analysis* | | | | | |
| Variable | 1. | 2. | 3. | 4. | 5. |
| 1. SM as News Source | 1.00 |  |  |  |  |
| 2. Self-Reported Interest | .34 | 1.00 |  |  |  |
| 3. Follow Accounts for News | .52 | .50 | 1.00 |  |  |
| 4. Algorithmic Categorization | .35 | .34 | .46 | 1.00 |  |
| 5. Social Curation | .40 | .41 | .72 | .41 | 1.00 |
| *Note*: Cell entries are Pearson’s correlation coefficients (*r*). *N* = 2,008. SM: Social Media. | | | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table B2  *Model Fit Statistics for Models with Varying Number of Latent Classes* | | | | |
| Model | AIC | BIC | *G*2 | χ2 |
| 2 Classes | 21,236.67 | 21,399.22 | 1,340.29 | 1,805.39 |
| 3 Classes | 20,613.65 | 20,860.26 | 687.27 | 902.79 |
| **4 Classes** | 20,428.18 | **20,758.87** | 471.80 | 720.57 |
| 5 Classes | 20,403.53 | 20,818.29 | 417.15 | 558.00 |
| *Note*: BIC was the primary criterion for model selection. *N* = 2,008. | | | | |

|  |  |  |
| --- | --- | --- |
| Table B3  *Predicted and Observed Latent Class Membership* | | |
| Latent Class | Predicted | Observed |
| 1: Low Attraction (*n* = 594) | .40 | .38 |
| 2: Medium Attraction—Unmotivated (*n* = 805) | .30 | .31 |
| 3: Medium Attraction—Motivated (*n* = 416) | .21 | .21 |
| 4: High Attraction (*n* = 193) | .10 | .10 |
| *Note*: Cell entries are predicted probabilities and observed proportions obtained from a latent class analysis (LCA) model. Column totals may not equal 1 due to rounding. *N* = 2,008. | | |

**Appendix C:**

**Additional Results from Regression Analysis**

|  |  |  |
| --- | --- | --- |
| Table C1  *Estimated Adjusted Means of News Engagement Among the News Attraction Groups by Exposure Type* | | |
| **Engagement** |  |  |
| Group | Purposeful | Incidental |
| Low | 4.11 | 1.44 |
| Moderate—Unmotivated | 4.88 | 3.71 |
| Moderate—Motivated | 5.45 | 4.22 |
| High | 5.93 | 4.98 |
| **High-Effort Engagement** |  |  |
| Group | Purposeful | Incidental |
| Low | 1.77 | 0.40 |
| Moderate—Unmotivated | 2.12 | 1.68 |
| Moderate—Motivated | 2.36 | 1.95 |
| High | 2.64 | 2.44 |
| *Note*: Cell entries are adjusted means estimated from multilevel models reported in Table 3. | | |