**Abstract**

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*Keywords*: Incidental exposure, news exposure, digital inequalities social media, digital media, platforms

**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 has been that prominent platforms such as Facebook and Google tend to exacerbate 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 overemphasized the role of interest in explaining information gaps, and underemphasized how changes in ‘supply-side’ dynamics brought about by digital media platforms and the ways they shape information flows online.

Based on this observation, Thorson (2020) introduced the metaphor of ‘attracting the news’ in order to describe the confluence of supply- and demand-side 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. Doing so clarifies debates surrounding the equalizing or stratifying effects of digital media on news exposure and engagement. Deriving predictions about equalization or stratification based our explication of the ‘news attraction’ concept, we 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 largely parallel similar questions regarding broad stratificational effects of the internet (i.e., the ‘digital divide’), and it grew out of normative assumptions about the role of news and ‘the press’ in informing democratic electorates (e.g., Prior, 2007). In addition, the functionalist tradition in the study of mass communication asserts that mass media serve the important social function of informing the public (Wright, 1960), and 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.

Theoretically, widespread access to news and public affairs information should decrease informational and political inequalities among groups that are otherwise split along lines of socioeconomic status or other social inequalities, 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 (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 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). Research has documented inequalities in news exposure and engagement online (Kalogeropoulos & Nielsen, 2018; Merten et al., 2022), and although there is evidence that they are not reliably producing knowledge gaps across democratic contexts, there are strong indications of such 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, for that reason, 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).

Inspired by this debate, 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; Weeks et al., 2017), the conditions under which people engage with the news they encounter incidentally (Oledorf-Hirsch, 2018; Karnowski et al., 2017), and the effects of incidental exposure on knowledge and participation (Lee & Xenos, 2022; Lee et al., 2022; Nanz & Matthes, 2020; 2022; Valeriani & Vaccari, 2016).

But empirical findings are generally mixed when it comes to the question of whether incidental exposure has ‘equalizing’ or ‘stratifying’ effects on access to and engagement with news. 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 that incidental exposure is positively related to political learning and participation (Heiss & Matthes, 2019; Weeks et al., 2022). Importantly, a meta-analysis of incidental exposure research found that these positive effects tend to be small and contextual (Nanz & Matthes, 2022).

While studies cited above offer evidence of 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 news content they come across (Kümpel, 2020). These engagement 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). This suggests that 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, 2020; Thorson & Wells, 2016). As Kümpel (2020) argues, 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 (Thorson, 2020; Weeks & Lane, 2020).

To address this challenge, we turn to Thorson's (2020) concept of ‘news attraction.’ Thorson introduced the concept 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 the 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 (Thorson et al., 2021). Therefore, while news may be encountered in the course of doing something else, these encounters may not be entirely non-elective in that people previously have made choices that lead to them. Thus, on social media platforms, the object and 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 previously discussed, most models testing the equalizing or stratifying effects of incidental exposure focus solely on ‘demand-side’ factors such as self-reported interest, and generally consider incidental exposure (or its subsequent outcomes) among individuals with low interest to be evidence of equalizing effects (Barnidge, 2021; Fletcher & Nielsen, 2018). Yet, ‘news attraction’ helps integrate the ‘supply-side’ of news exposure by focusing attention on factors such as ego-centric social networks (Barnidge & Xenos, 2021) and algorithmic classification of users based on prior news-related activity (Thorson et al., 2021), and integrating these factors can further clarify whether incidental exposure closes or widens information gaps.

**Dimensions of News Attraction**

Prior literature has identified at least five dimensions of influence on processes of news exposure: (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. First, 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. But 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, research shows that characteristics of 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 news exposure, in large part because content is not only selected by news algorithms, it is also curated by social contacts (Thorson & Wells, 2016). Finally, while direct observations of algorithmic curation is somewhat rare, prior research has provided some evidence that is algorithms play a large role in shaping incidental exposure (e.g., Thorson et al., 2021). Therefore, we can conceptually define *news attraction* as follows: the force that results from the confluence of user attributes and interactions with social media platforms, which in turn affects the likelihood of encountering news or political information on those platforms.

Theoretically, news attraction should have a reciprocal relationship with both news exposure and news engagement, which are distinct but closely related concepts (Karnowski et al., 2017). 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, 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 and assess the extent to which incidental exposure occurs among individuals with varying levels of news attraction. This logic can be used to derive two sets of competing predictions about equalizing or stratifying effects.

First, if incidental exposure closes exposure gaps by drawing in potential news audience members who would not otherwise encounter news, we would expect to see (a) comparatively high 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:

H1a: Incidental news exposure will close exposure gaps between people who are low in news attraction and people who are high and news attraction.

H1b: 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 gaps in engagement with news, we 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. This prediction is based on the assumption that incidental exposure is providing users with opportunities to engage regardless of how fundamentally ‘attractive’ they are to news content (Karnowski et al., 2017). 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:

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

H2b: 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 rolling cross-sectional survey of adult social media users in the United States. The survey was administered online in 17 sampling frames of 3-4 days each (with Saturday/Sunday counted as one day), and survey responses were linked with social media content collected via Brandwatch (formerly Crimson Hexagon) and then validated by cross-checking content lists with CrowdTangle. In each sampling frame, we embedded a screenshot of (one of) the most popular news articles over the previous three days with source cues edited out of the image. Because most of the stories came from a single news organization (Fox News), we also included the most popular story from any other news organization and randomized which story a respondent saw. Respondents were told the story had been “recently circulating on Facebook”—a true statement. We developed several cued recall measures based on this method.

**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 a sample size of *N* = 2,008 with at least *n* = 100 in 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). The sample is composed of approximately 40% persons of color and 51% females. 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-quota 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 multiple imputation technique.

**Measures**

***Exposure and Engagement***

Prior literature suggests that news exposure has both ‘trait-like’ and ‘state-like’ properties (Weeks & Lane, 2020), and our study design allows us to include both. 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, 2022). 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 were 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*. Respondents who reported story exposure were asked additional follow-up questions, including those for the ‘state-like’ measures of *incidental exposure* (“When you say the story, were you purposefully seeking information on this topic? 1 = *Purposeful* and 0 = *Incidental*; 54% of subset and 23% of full sample said ‘purposeful’) and *engagement* (“When you saw the story, did you engage in any of the following activities?: 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; 1 = *Yes* and 0 = *No*; responses were summed for each respondent; Cronbach’s alpha = .79; *Min*. = 0 and *Max*. = 7, *M* = 3.5, *SD* = 2.2). 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).

***News Attraction***

The study includes five 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, we measured the extent to 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). Fourth, social news curation 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; *M* = 2.9, *SD* = 1.1). Finally, we measured *algorithmic categorization* using a technique pioneered by Thorson and colleagues (2021). 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, and a little more than half (59%) as uninterested.

***Covariates***

Prior research shows that it is important to include indicators of social network structures as covariates in the analysis (Barnidge & Xenos, 2021), 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). A structural measure of *network diversity* uses a standardized list of 22 occupations and asks respondents whether they are connected to 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). *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 index was then 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). Respondents were also asked about their party identity (*Democrat*/ *Republican*/ *Other*/ *None*). Those who selected *Democrat* or *Republican* were asked about the strength of that identity (*Strong*/ *Not that strong*). Those who selected *Other* or *None* were asked about party lean (*Closer to Democrat*/ *Closer to Republican*). These items were 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 by 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 Plan**

In the first stage of the analysis, a Latent Class Analysis (LCA) is conducted with the five indicators of news attraction. LCA detects unobserved groups based on patterns of association among a set of observed criteria variables. To establish the model with the optimal number of latent classes, we compare the fit statistics for models ranging from 2 to 5 classes, choosing the model with the lowest Bayesian Information Criterion (BIC). In the second stage of the analysis, we test the hypotheses using multi-level modeling (MLM). This approach allows us to estimate differences between the attraction groups while controlling for measurement invariance across the 17 sampling frames. The analysis accounts for this data structure by including random intercepts for each frame. Linear models are used for the trait-like variables, while quasibinomial models are used for the state-like variables to account for data weighting. Covariates in these model are group-mean centered by frame to ease interpretation of the intercepts.

**Results**

**Latent Class Analysis**

The correlations among the five criteria variables range between .34 and .72 (*p* < .001 for all; see Table B1 online for a full matrix), indicating that they may be empirical manifestations of a common underlying construct—that is, they arise from latent ‘news attraction’ groups. The model with the lowest BIC has 4 latest classes (see Table B2 online).

There are important qualitative differences among the four groups, which we labelled *low-attraction, moderate—unmotivated group, moderate—motivated group,* and *high-attraction*, and which can be described according to differing response probabilities on the five criteria variables in the analysis. These probabilities are visualized in Figure 1. 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 *high-attraction* *group* is the final group, and it 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 (.10 predicted probability).

**Regression Analyses: Exposure**

Before testing the hypotheses, we tested the predictive validity of the news attraction grouping variable. Reasoning that the dimensions of news attraction reflect generalized news consumption habits, and therefore that news attraction should be positively correlated with news use *via any medium or platform*, we tested the relationship between news attraction and non-social media news use. Results show that each successive news-attraction group has a higher mean than the next, validating the measure. See Appendix C online for full results.

The first model in Table 1 tests differences in the trait-like incidental exposure variable. Because 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 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 (see Figure 2 upper-left).

The second model in the table tests differences in the state-like incidental exposure variable. Because this model is quasibinomial (Poisson), the interpretation of the coefficients differs slightly from the linear model reported above. In this model, the exponentiated intercept can be interpreted as the weighted proportion of respondents in the reference group reporting incidental exposure, and the exponentiated coefficients as the percent increase or decrease from this reference in 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%). Figure 2 plots these estimates as a log-transformed linear function, and thus predicted values range from approximately -3.5 to 1.25.

The third model tests differences in the trait-like overall exposure variable. 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 (see Figure 2 lower-left).

The last model in the table tests differences in the state-like overall exposure variable. The model estimates the 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 (see Figure 2 lower-right for the log-transformed effects).

Putting these results together, respondents in the low-attraction group 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 (H1a). That said, the high- and low-groups report roughly the same amount of incidental exposure, and therefore we have no evidence that incidental exposure widens gaps in news exposure (H1b). On the other hand, the two moderate-attraction 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 close to the high-attraction group. Therefore, we have evidence that incidental exposure closes (H1a) rather than widens (H1b) exposure gaps for the ‘motivated’ group and, to a lesser extent, the ‘unmotivated’ group.

**Regression Analyses: Engagement**

For news engagement (Table 2), 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 use the state-like (binary) measure of incidental exposure to 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 (see Figure 3 top row). A full list of estimated means is reported online in Table D1.

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 (see Figure 3 bottom row).

Taken together, these results provide evidence that incidental exposure appears to *widen* (H2b) rather than closes (H2a) engagement gaps, although the evidence is relatively stronger for the overall engagement outcome than for the high-effort outcome.

**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 both demand- and supply-side factors relevant to changes in digital news environments. 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 some novel theoretical insights: The news-related preferences and habits of the news attraction groups are qualitatively different from one another; the equalizing effects on exposure may be non-linear; and there are major differences between exposure and engagement from a news inequality perspective.

To elaborate on the first point, the attraction groups are different from one another not just in terms of self-reported interest, but also along a range of other factors. In fact, if one were to characterize the groups solely based on interest, the differences between the low-attraction group and the next group is not stark. Yet, the latter reports substantially more incidental news exposure than the former, because differences along the other variables in the latent model—as captured by our measures of algorithmic filtering, curation activities, news interest, and reasons for using social media in the first place—are more pronounced. Meanwhile, the two moderate-attraction groups appear relatively similar in terms of algorithmic categorization and environmental perceptions, but the motivated group reports higher frequencies of following accounts for news and higher levels of active social curation of political news within their networks. These differences among the groups are not trivial, nor are they merely artifacts of the latent-class analysis. In fact, they track with long-standing offline social inequalities in socioeconomic status, race, and gender. Supplemental analyses (see Appendix E online) show that each successive attraction group has higher levels of both education and income. Further, people of color and women are less likely to be in the high-attraction group than they are in the low-attraction group. The fact that the latent groups reflect these demographic differences raises important concerns not only about digital inequalities in political news—their online environments may be described as what some have called ‘social media news deserts (Barnidge & Xenos, 2021; Thorson, 2019)—but also digital *inequities* that may arise from fundamentally unfair social structures, which could potentially discourage political engagement among underserved communities and limit the inclusiveness of democratic processes.

To the second point, the distribution of incidental exposure among the latent-class groups is non-linear, which presents another key difference with using self-reported interest as the sole predictor, which is are both less consistent and less rich in terms of its descriptive capacity (see Appendix F online). 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 differences that cannot be observed by analyzing interest alone. These observations provide a novel theoretical insight. Our findings reveal that there may be a ‘sweet spot’ of news attraction when it comes to exposure. While we find no evidence of equalization among the low-attraction group, we do find substantial evidence of equalization in the two groups in the middle. The two groups in the middle do not exist in online information environments that are so devoid of news and political information that they report no exposure, but neither are their environments so saturated that incidentality has little impact on their overall exposure. To the contrary, these groups have optimum levels of news attraction for facilitating the contributions of incidental exposure, and therefore the proportion of their overall exposure attributable to incidentality is higher than in the low- or high-attraction groups. Thus, we can conclude that digital media platforms may have the biggest impact on the information diets of the two groups in the middle, which tend to be middle-of-the-road in terms of both socioeconomic status and their political leanings.

While we find some evidence of equalization in terms of exposure, we find evidence of stratification in terms of engagement. The gap between low- and high-attraction groups is much higher where incidental exposure is reported than where purposeful exposure is reported. Certainly, this pattern is partially explainable by the perception of respondents. That is, individuals who are high in news attraction are more likely to say they intended to be exposed because they set up their social media feeds in order to get news on a regular basis, while individuals in the low-attraction group are much less likely to express such intention. That said, we have seen that the relationship between news attraction and incidental exposure is non-linear. Additionally, it is not immediately clear that a lack of intentionality should reduce engagement, per se. Therefore, to interpret this result, we must turn to the political incidental news exposure (PINE) model forwarded by Matthes and colleagues (2020). The model proposes a two-stage process of incidental exposure and engagement, in which information processing (Stage 2) follows from incidental exposure (Stage 1) only if content is evaluated as relevant and new processing motivations are formed. In the absence of these psychological conditions, individuals will not attend to the information they encounter online, and thus will be less likely to incorporate it into their mental schemas for understanding and engaging with politics. Assuming that the behavioral forms of news engagement we measured in this study are associated with cognitive information processing, our findings support this idea that while incidentality does seem to narrow the gap in news exposure, it does not necessarily lead to a deeper engagement with that content. But our findings push this argument a step further: Incidental exposure may not only be unassociated engagement, it may even *reduce* the likelihood of engagement. Therefore, while digital media platforms may be successful in terms of getting content in front of people, they may nevertheless be disengaged from that content, rendering its beneficial effects on learning and political participation to be minimal, at best (Nanz & Matthes, 2022).

Before discussing the broader implication of these findings, it is important to acknowledge the ways in which they are limited. The study is based on cross-sectional data, and which cannot be used to make causal inferences. Our goal was to observe patterns of information exposure and engagement across groups, and we leave it to future research to assess causal effects over time. Another design limitation is its strategy for exposing respondents to the ‘popular story’ stimulus is imperfect. It is not possible to present respondents with all of the popular stories, and even showing them more than one story would add ‘noise’ to our measures. We therefore opted to show them a single story and let that story serve as a proxy for all popular content circulating at the time. This is a practical compromise that leaves substantial room for measurement error. However, we believe the law of averages cancels out these errors, leaving us with an imperfect-but-functional measure that is also high in external validity. Beyond this issue, our survey is limited by self-reported measures of key variables. However, this issue is not unique to our study but rather endemic to survey research. Additionally, prior work shows that people generally underestimate their news exposure on surveys, which means the true differences between exposure and engagement are probably even more pronounced than those we observed. The study’s analysis is also limited. There are different thresholds for determining the optimal number of groups in a latent class analysis, and the number of groups estimated is sensitive to model specification. While there is a strong argument for using the BIC as the primary criterion, there is also a case to be made for using the AIC instead. Future research should fit similar models across multiple datasets in order to validate the analysis presented here.

With these caveats in mind, our findings do point to a larger conclusion: They generally do not support an optimistic view of social media platforms when it comes to informational inequalities. Rather, they suggest that initial prognostications about information equalization were perhaps overly sanguine, because equalization in exposure is not accompanied by a similar dynamic in engagement. Therefore, if we as a society are counting on social media platforms to fill informational voids left by the erosion of local media and/or the lack of robust public media, we may be disappointed to find that their ability to facilitate equalization is limited. Thus, we may need investments of both money and public attention to other areas to reduce inequalities, inform the electorate, and promote social cohesion and belief in democratic practice.

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| Table 1  *Differences in Social Media News Exposure Among the News Attraction* *Groups* | | | | | | | | | | | | | |
|  | Incidental Exposure | | | | | | Total Exposure | | | Story Exposure | | |
|  | Trait | | | State | | | Trait | | | State | | |
| **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 2  *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) | -2.67\*\*\* | 0.47 | -1.38\*\*\* | | | 0.31 | |
| Incidental Exposure (Trait) | -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) | 1.17\* | 0.52 | 0.44 | | | 0.34 | |
| News Attraction (Mod—Mot) x Incidental Exposure (State) | 1.23\* | 0.51 | 0.41 | | | 0.33 | |
| News Attraction (High) x  Incidental Exposure (State) | 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

*Predicted Probabilities for Criterion Variables in Latent Class Analysis*



Figure 2

*Differences Among Attraction Groups in News Exposure*

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Figure 3

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



