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Replication Study

How Social Media Metrics Shape News Production: A Replication Study

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Abstract

Audience engagement signals on social media platforms have shaped how media outlets produce news. Mukerjee et al. examined this phenomenon empirically by estimating the extent to which media outlets respond to audience engagement signals on Facebook in deciding what news to publish on the platform. However, the extent to which their findings can be generalized to other social media platforms remains unknown. We replicate their study on Twitter using the same methodological pipeline ($N \approx 4.55$ million posts, twenty-eight media outlets, between 2015 and 2019). Our results indicate that media responsiveness to audience engagement on Twitter aligns with the core patterns identified in the Facebook study. Specifically, topics receiving higher audience engagement generally experience significantly increased coverage shortly thereafter, and the responsiveness is not conditioned on the nature of topics. However, we observe three differences in dynamics on Twitter compared to Facebook: first, the maximum response window on Twitter is shorter; second, conservative outlets on Twitter are not more likely to respond to engagement signals; third, platform-specific metrics (e.g., retweets) show different patterns of responsiveness. Our replication thus highlights the generalizability of the original study while underscoring the importance of platform-specific characteristics in shaping media production on social media.

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social media, response, news production, metric, audience engagement

Introduction

Social media platforms have become pivotal intermediaries in shaping the public's engagement with news and information (Auxier and Anderson 2021). Meanwhile, media outlets leverage metrics on these platforms to gauge the preferences and opinions of their audience. This phenomenon has shaped journalism in a variety of ways, allowing media outlets to more closely track and incentivize journalistic labor. Previous studies, encompassing both newsroom observations (Christin 2020; Tandoc and Vos 2016) and quantitative analysis (Mukerjee et al. 2023), have illustrated the transformative impact of such metrics on journalistic practices. This digital transformation has given newsrooms the capability of real-time and constant monitoring over audiences' reactions on social media (i.e., re-posts, likes, etc.), thus allowing them to acquire a more granular understanding of audience preferences that can, in turn, better inform their news production strategies.

This transformation has also engendered a theoretical debate in the literature that relates to two competing models of journalism practice. On the one hand, many outlets incorporate these metrics into their news production processes, tailoring content to meet audience demands (Tandoc and Vos 2016). Conversely, adherence to journalistic professionalism appears to temper the lure of these metrics (Nelson and Tandoc Jr. 2019; Welbers et al. 2016). A recent empirical investigation of news production on Facebook suggests that the manner in which outlets respond to audience engagement signals is nuanced: certain media outlets exhibit greater responsiveness compared to others, and this responsiveness is influenced by the outlet's political slants and the nature of the news content being disseminated (Mukerjee et al. 2023).

These dynamics, however, were only examined on Facebook, and it is unclear whether similar patterns can be observed on other social media platforms such as Twitter.[1] The particular characteristics of each social media platform necessitate careful consideration when assessing the generalizability of findings derived from studying a single platform to other platforms. A growing body of research demonstrates that platform-specific affordances (Gibson 1977; Norman 1988) such as content constraints (e.g., word limits, auto-deletion), identifiability (e.g., anonymity, location traceability), and social signaling mechanisms (e.g., reactions, likes, upvotes, visibility)—vary across platforms like Facebook, Twitter, TikTok, Snapchat, Weibo, and purpose-built virtual environments used for research. These differences shape user behavior, influencing incivility, self-disclosure, content production (e.g., posting, commenting, replying), engagement patterns (e.g., shares, likes), and the overall quality of online discussions (e.g., Guo et al. 2023; Jaidka et al. 2021; Muchnik et al. 2013; Tenenboim 2022; Wang and Greenwood 2025; Wilkerson et al. 2021; Xu et al. 2016; Zannettou et al. 2024). Differences in affordances, thus, also influence audience engagement by limiting or enabling specific types of user expressions, thereby

shaping or constraining the ability of media outlets to observe and respond. This perspective suggests that patterns of responsiveness may vary across different platforms.

Another key difference lies in the unique communicative context or community culture each platform cultivates. Compared with other platforms, Twitter has different user demographics, particularly with regard to their political inclinations, and general consumption habits (Auxier and Anderson 2021; Dang-Xuan et al. 2017; Gottfried 2014; Mitchell et al. 2014; Mukerjee et al. 2022; Osborne and Dredze 2014; Shearer and Mitchell 2021; Soedarsono et al. 2020; Wong 2018). These differences shape the platform's community norms and expectations, creating a distinct context for news production that may influence how media outlets respond to audience engagement. While Twitter has changed considerably since its acquisition by Elon Musk, the platform characteristics discussed above—and the data analyzed in this study—reflect its functioning during the 2015–2019 period.

Considering the variability in user interactions and the content norms, coupled with the substantial differences in their user demographics, we hypothesize that the relationship between media outlets and audience engagement manifests in different ways across various social media platforms. Thus, the manner in which media outlets respond to audience engagement signals on platforms other than Facebook remains an empirically open question.

In the present study, we conceptually replicate Mukerjee et al. (2023)'s Facebook study on Twitter to assess how media outlets respond to audience engagement signals—on a platform other than Facebook. To this end, we analyze a five-year longitudinal archive encompassing 4.55 million tweets from twenty-eight of the twenty-nine media outlets in the original study.[2] We then use topic modeling and panel data analysis techniques, replicating the same pipeline in the original study, to measure the degree to which media outlets on Twitter respond to audience engagement signals in their subsequent news coverage. We define Audience engagement signal, following the formulation provided in the Supplemental Appendix of the original study (Mukerjee et al. 2023), as the weighted average of all engagement signals toward the news coverage around a topic posted from a media outlet relative to the average engagement received by all posts from that media outlet during the same time period. By employing the methodological pipeline used in the original study, our study both replicates their core findings and highlights platform-specific differences in how news outlets respond to audience signals.

Literature Review

Responsiveness in News Production: The Market Model Versus Trustee Model

The production of news has been shaped by interactions between news producers and consumers in both legacy and modern news ecosystems (Brosius and Weimann 1996; Galtung and Ruge 1965; Harcup and O'Neill 2001, 2017; Lewin 1943; Ragas et al. 2014; Schudson 2003; Shoemaker and Vos 2009; Usher 2018; Welbers et al. 2016;

Wells et al. 2020; White 1950). To better understand these dynamics, scholars have developed a range of theoretical frameworks that explain how news is selected, structured, and circulated. Theories of news values propose criteria that cater to the informational and affective needs of both producers and consumers—such as the power elite, celebrity, entertainment, surprise, negativity, positivity, magnitude, relevance, continuity, and editorial agenda (e.g., in Galtung and Ruge 1965; Harcup and O'Neill 2001, 2017). Theories of gate-keeping and agenda setting emphasize the dominant role played by journalists and editors in culling and crafting information for the public (Cohen 1963; Lewin 1943; McCombs and Shaw 1972; Shoemaker and Vos 2009; White 1950). Reverse-agenda setting, on the other hand, highlights the role played by news consumers' preferences on the coverage of news topics (Brosius and Weimann 1996; Ragas et al. 2014; Wells et al. 2020). In the context of digital social media, scholars have increasingly applied Schudson (2003)'s framework (e.g., Usher 2018; Welbers et al. 2016) to discuss these two competing orientations in journalistic practice.

Editorial decisions to publish certain news over others have highlighted a tension between two competing models of journalism: the Market Model and the Trustee Model (Schudson 2003). The market model posits that digital metrics have substantially shaped news production practices (Lee et al. 2017; Vu 2014) by making media outlets more attuned to audience preferences: media outlets use real-time metrics such as social media "likes" to gauge audience interest and publish more news on topics that get traction versus those that don't. Such decisions are primarily profit-driven, with some outlets being more responsive to these indicators than others (Lee et al. 2017; Tsuriel et al. 2021; Welbers et al. 2016). As a result of this shift toward the market model, scholars observed a trend toward soft news on Facebook (Lamot 2022). In contrast, the trustee model maintains that journalistic norms and professionalism continue to hold sway in newsrooms, despite the lure of audience engagement signals (Nelson and Tandoc Jr. 2019).

The study that we are replicating focused on one social media platform, viz. Facebook, where the original evidence suggests that the lure of engagement signals is particularly visible (Mukerjee et al. 2023), albeit with substantial heterogeneity across outlets: conservative outlets are significantly more likely to respond to audience engagement signals than liberal outlets, particularly in the context of partisan topics. Our replication focuses on Twitter, and since most newsrooms publish news on both these platforms (Tandoc and Vos 2016), one may expect similar adaptations to metric-driven news production to be found on Twitter as well.

Yet, the manner in which newsrooms respond to engagement signals may vary across platforms. Outlets adopt distinct tactics to boost engagement with their news articles, and the effectiveness of these strategies differs across platforms (Hase et al. 2023; Lamot and Paulussen 2024). Indeed, Mukerjee et al. (2023) raised concerns about whether their findings on Facebook may be replicated on Twitter as well.

Twitter differs from Facebook in at least two aspects. First, because Twitter does not provide metrics that capture emotional reactions in the way Facebook does, media outlets may face constraints in monitoring and responding to these dimensions of audience engagement. This limitation persists despite Twitter's reputation as the platform

of choice for breaking news (Osborne and Dredze 2014). Second, Twitter's user base and typical usage patterns differ significantly from Facebook: Facebook's larger and older audience provides engagement data that may be more reflective of the larger population, making it a valuable resource for media outlets seeking to understand broad audience preferences. In contrast, Twitter has a smaller, younger user base (Auxier and Anderson 2021). User behavior on Twitter is also relatively more political compared to that on Facebook. For example, elites and key opinion leaders use it as a de facto communication channel (Shearer and Mitchell 2021) and users who are more interested in politics report higher exposure to political content on Twitter, compared to Facebook (Gottfried 2014; Mitchell et al. 2014). Given that conservative outlets are more responsive to engagement signals on Facebook, as per the original study (Mukerjee et al. 2023), a relatively more politicized environment and different user demographics on Twitter may further shape how media outlets respond to the engagement signals they receive on the platform.

Thus, while the structural and functional differences between Twitter and Facebook render it an open empirical question whether the patterns of media responsiveness identified on Facebook generalize to Twitter, we retain the original hypotheses in the spirit of a conceptual replication. Consistent with the prior study, we therefore propose the following H1.

H1: *Engagement signals on social media affect news content production. News topics that attract greater engagement are increasingly covered in subsequent time periods on Twitter.*

Responsiveness to Engagement with Different Kinds of Topics

Given that users with stronger political interests are more likely to encounter political content on Twitter than on Facebook, outlets on Twitter may exhibit distinct patterns shaped by differences in user behavior and preferences across the platforms. This can potentially challenge the generalizability of the engagement-signals-driven dynamics observed on Facebook to Twitter, especially in the context of partisan news. On Twitter, users may engage with political content differently, influencing how outlets respond to engagement signals to partisan political topics vis-a-vis other topics.

That said, the potential mechanisms driving topic-relevant differences may be similar on Twitter. This is because professional values, operational costs, and practical flexibility that may lead to topic-relevant differences are not likely to be constrained to a single platform. Moreover, Twitter is not as dominated by politics as previously assumed (Mukerjee et al. 2022)—and non-partisan content such as entertainment and sports still remains more popular than politics or hard news. Thus, we expect outlets to respond strongly to engagement signals for both partisan and entertainment-oriented topics. Given these contrasting considerations, we propose our next hypothesis, in line with the original study:

H2: *Media outlets are more likely to respond to audience engagement with partisan politics topics (H2a) and entertainment-oriented topics (H2b) compared to other topics.*

Responsiveness Across Different Kinds of Outlets

The original study found a significant association between an outlet's political slant and its responsiveness to engagement signals on Facebook. Specifically, right-leaning outlets were more likely to respond to audience engagement signals compared to left-leaning outlets. While this finding could potentially generalize to other platforms like Twitter, such generalization is not guaranteed.

On the one hand, news production across platforms may share important commonalities. When right-leaning outlets are motivated to carve out a niche for themselves, the digital environment can amplify such tendencies -manifesting, for instance, in the adoption of distinct journalistic norms on Facebook. Similar motivations and practices may also be present on Twitter.

On the other hand, the ideological leaning of media outlets may exert stronger effects on Twitter, given the higher levels of political news circulation on the platform and the liberal skew in its user base (Mitchell et al. 2014; Wojcik and Hughes 2019). These dynamics, in turn, may prompt outlets with different ideological orientations to respond in different ways to audience engagement signals.

Whether this results in similar or divergent patterns of responsiveness compared to what was observed on Facebook remains uncertain. In the absence of further evidence, we extend the same hypotheses regarding the association between responsiveness and ideology that were tested in the Facebook study:

H3: *Responsiveness of outlets to topics will be associated with their ideological slants: right-wing outlets are more likely to respond to audience engagement signals than left-wing outlets*.

H4: *Responsiveness of outlets to audience engagement with partisan topics will be associated with their ideological slants: right-wing outlets are more likely to respond to audience engagement signals received by partisan news posts than left-wing outlets.*

Finally, given the lack of any significant correlation between responsiveness to entertainment-oriented topics and media slant in the original study, we propose RQ1 to mirror the same question on Twitter.

RQ1: *How is the responsiveness of an outlet to audience engagement with entertainment-oriented topics related to its ideological slant?*

Method

Data

To replicate the findings of the original study on Twitter, we focused on the same twenty-nine outlets examined in the original. These outlets, identified using the American Trends Panel Survey by the Pew Research Center (Pew Research Center 2019), represent an ideologically diverse set of the most widely used media sources in the USA. However, one of these outlets (Rush Limbaugh, a conservative political commentator) did not have a presence on Twitter. Consequently, our replication included twenty-eight outlets, encompassing approximately 4.55 million tweets posted by these outlets between January 1, 2015, and December 31, 2019, aligning with the timeframe of the Facebook study. All the data were obtained using the Academic Twitter API from May to June 2023.[3]

To prevent platform-specific content on Twitter from distorting the operationalization of news stories, we removed posts that were either pure retweets or user-specific reminders.[4] For transparency, we also report a robustness test that retains these posts to assess the impact of this data cleaning procedure.

Topic Modeling

The first step involved the identification of news topics. Following the original study, we divided the timeframe into 60 one-month intervals to account for the evolving nature of news topics over time. Then, we employed the Non-Negative Matrix Factorization (Lee and Seung 1999, NMF) technique in conjunction with coherence analysis (Röder et al. 2015) to identify the number of topics for each season. At this stage, our data did not include content such as "Message," "Link Text," "Image Text," and "Description" (Mukerjee et al. 2023: 265)—all of which were used in the original study. We performed seasonal topic modeling using NMF, selecting the optimal number of topics for each season based on coherence analysis. This yielded 383 distinct topics across the five-year span, which we annotated and incorporated into subsequent regression analyses.

Measures

Responsiveness. In line with the original study, the key independent variable in our model was the log-transformed Engagement Signal, $ES_{i,m,t-1}$, received by the outlet m on the topic i at time $t-1$. We first calculate the total engagement for each post as a sum of all types of engagement on Twitter (i.e., retweet + reply + like + quote; a robustness check using only retweets is provided in the Supplemental Appendix). We then define Engagement Signal ($ES_{i,m,t-1}$) following the original study as the weighted average engagement received by posts of topic i, by outlet m, and at time $t-1$, relative to the average engagement received by all posts published by the outlet at the same time. The engagement signal is then log-transformed. A higher engagement signal for

a topic suggests that posts of this topic get more engagement metrics compared with other topics at time $t-1$. Conversely, a lower value suggests that this topic received less engagement metrics compared with other topics at time $t-1$.

News Salience. A key confounder that governs the provision of news is the salience of a topic, or how important that topic is for coverage. This is because news salience can influence both the extent of news coverage and the level of audience engagement with the news coverage. Mirroring the previous study, we capture news salience by measuring the coverage of a topic i at time $t-1$ by the same outlet ($\text{Freq}_{i,m,t-1}$) as well as by all outlets. ($\text{Freq}_{i,t-1}$) at $t-1$ of a topic i, and the overall engagement signal at $t-1$ to all media ($ES_{i,t-1}$). While this operationalization of news salience is neither definitive nor without theoretical contention, it offers a pragmatic proxy for assessing the relative importance of a topic within the news landscape. More importantly, this operationalization mirrors that of the original study, acting as a valid control variable for the regression analyses we aim to replicate.

Future Coverage. The dependent variable was $Freq_{i,m,t}$, that is, the future coverage of the topic i by outlet m at time t.

Fixed Effects. Additionally, in our time-series model, we controlled for fixed effects for topic (ζ_i), time in days (λ_t), and media outlets (ξ_m). Formally, the model used was a fixed-effects model with a lagged dependent variable, as shown in equation (1). We estimated the models using OLS with robust standard errors clustered at the outlet and day levels, consistent with the original study (Mukerjee et al. 2023).

$$\begin{aligned}\text{Freq}_{i,m,t} = \beta_0 + \beta_1 \log\left(ES_{i,m,t-1}\right) + \beta_2 \text{Freq}_{i,m,t-1} + \beta_3 \text{Freq}_{i,t-1} \\ + \beta_4 \log\left(ES_{i,t-1}\right) + \zeta_i + \lambda_t + \xi_m + \epsilon\end{aligned} \tag{1}$$

Classifying Topics. In line with the previous study, we also examine differences in responsiveness across topic categories by including two separate binary variables, $T^{(Pol.)}$, and $T^{(Ent.)}$, which indicate whether a topic is about partisan politics, entertainment-oriented, or neither. As per the original study, we define partisan topics as discussions about two political parties in the United States (i.e., Democratic and Republican), politicians, highly polarized issues (e.g., the Mueller report), and elections. Entertainment topics are defined as non-politician celebrities, life hacks and tips, and activities related to recreation and culture (e.g., sports, music, movies, etc.). All other topics that cannot be put in either category are classified as "other." To increase the transparency of topic modeling, we provide the detailed codebook and the results of an intrusion test (for topic validation) in the Supplemental Appendix.

Classification of topic categories was based on top words and top documents identified during the topic modeling exercise. Following the method of the original study, two independent coders undertook two manual coding tasks to classify each topic into whether it was partisan-political or not, and whether it was entertainment-oriented or

not. The same codebook as the one in the original study was used to guide the coding. Results of the annotation demonstrated good face validity and inter-coder reliability (Krippendorff's $\alpha = .95$). Subsequently, to test moderation effects, two interaction variables were added to the model. These variables captured the interaction between the engagement signal and two dummy variables representing the nature of the topic (entertainment-oriented versus non-entertainment oriented, and partisan-political versus not-partisan-political; see equation (2)), respectively.

$$\begin{aligned}\text{Freq}_{i,m,t} = {} & \beta_0 + \beta_1 \log\left(ES_{i,m,t-1}\right) + \beta_2 \text{Freq}_{i,m,t-1} + \beta_3 \text{Freq}_{i,t-1} \\ & + \beta_4 \log\left(ES_{i,t-1}\right) + \beta_5 \log\left(ES_{i,m,t-1}\right) \times T_i^{(Pol.)} \\ & + \beta_6 \log\left(ES_{i,m,t-1}\right) \times T_i^{(Ent.)} + \zeta_i + \lambda_t + \xi_m + \epsilon\end{aligned} \tag{2}$$

Partisan Slant of Media Outlets. We leverage the same partisan slant scores used in the original study to analyze the correlation between ideology and responsiveness. These scores include two independent sources of media bias: the first is an audience-centric measure of outlet bias, obtained from Pew Research Center based on self-reported survey responses (Pew Research Center 2019, $N = 12,043$) and the second is a content-based measure of media bias, obtained from Ad Fontes (Ad Fontes Media n.d.). These two sets of media bias measures, obtained from two independent sources indicate a high correlation $r = .907, p < .001$, thereby demonstrating high reliability.

In sum, to enable a direct comparison between the patterns observed on Twitter and those on Facebook, all methodological steps described for the current study—from the selection of outlets, variable definitions and operationalizations, to steps used for data transformation, optimization procedures, human annotation protocols, model specifications, and robustness tests—are identical to those in the original study.

Results

Findings that Replicate

Responsiveness (H1). We find that past engagement with topics significantly affects subsequent coverage of the same topic ($\beta = .008, p = .001$; after controlling for news salience and topic category), thus lending support to H1. In other words, on any day, media outlets on average, increase the coverage of topics that receive higher audience engagement the day before. This echoes patterns found on Facebook ($\beta = .002, p < .001$; Mukerjee et al. 2023) demonstrating that outlets are, in general, responsive to audience engagement signals on Twitter as they are on Facebook (see Model 3 in Table 1).

Further analysis of the temporal dynamics of the responsiveness in H1 reveals that the maximum response window is shorter for Twitter (two days) compared to the four days found for Facebook in the original study (see Figure 1). In other words, media outlets on Twitter appear to stop responding to engagement signals received more than two days ago, differing from Facebook, where media outlets monitor engagement signals, on average, for up to four days. Thus, while the effects on Twitter diminish over

Table 1. OLS regressions on frequency of topic at time t in media m.

Variable	Model 1	Model 2	Model 3	Model 4
ES[a] with topic for media m at $t-1$	.009***[b]	.008***	.008**	.009**
	(.002)[c]	(.002)	(.002)	(.003)
Covariates				
Frequency of topic at $t-1$ in media m	.433***	.432***	.423***	.423***
	(.049)	(.049)	(.055)	(.055)
Average ES with topic for all outlets		.030*	.021	.021
		(.011)	(.011)	(.011)
Frequency of topic across all outlets at $t-1$			.084	.084
			(.057)	(.057)
Fixed effects for media	Yes	Yes	Yes	Yes
Fixed effects for time	Yes	Yes	Yes	Yes
Fixed effects for topic	Yes	Yes	Yes	Yes
Interactions				
ES with topic for media m at $t-1 \times$ partisan topic		−.002		(.003)
ES with topic for media m at $t-1 \times$ entertainment topic		−.001		(.002)
N	280,259	280,259	280,259	280,259
R^2	.689	.689	.689	.689
$R^2_{adj.}$	.688	.688	.688	.688

[a]Engagement Signal (log-transformed) as defined in the text.
[b]*$p < .05$. **$p < .01$. ***$p < .001$.
[c]Robust standard errors (clustered at the outlet and time levels) are in parentheses.

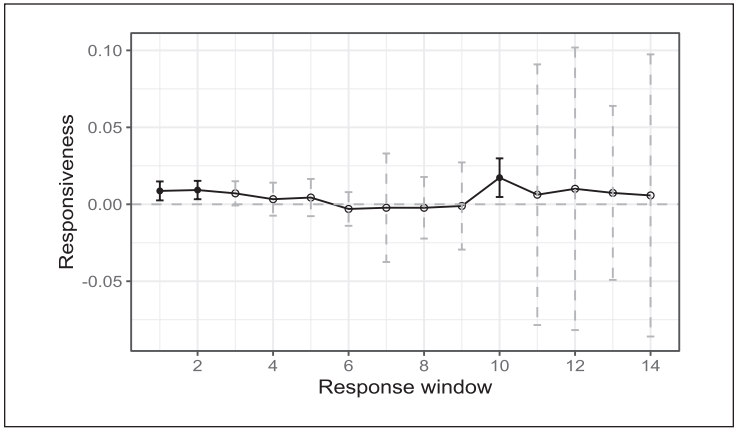


Figure 1. Point estimates for responsiveness scores (and 95% CIs) for response windows ranging from one day to fourteen days.

time—much like the findings from the Facebook study—they fade even more quickly on Twitter. While these differences are not discussed in the original hypotheses, they are worth noting in a cross-platform conceptual replication.

Responsiveness is not Contingent on the Nature of Topics (H2). Consistent with the original study, we find that media responsiveness on Twitter exhibits no significant interaction effects with either partisan or entertainment topics (see Table 1). That is, media outlets' responsiveness to engagement signals remains relatively stable regardless of two topic categories. The replicated pattern thus corroborates the robustness of the previous finding.

Findings That Did Not Replicate

Outlet-Level Responsiveness: All Topics (H3), Partisan (H4), and Entertainment Topics (RQ1). Overall, conservative outlets are not more likely to respond more to audience engagement signals ($r = -.284$, $p = .151$) compared to the liberal outlets (see Figure 2). This is qualitatively different from the Facebook study where the conservative outlets are significantly more responsive ($r = .412$, $p = .026$; Mukerjee et al. 2023). We next reran the model on two subsamples of both topic categories and then estimated the correlations between their ideological slants and responsive scores.

For partisan topics (H4), as shown in Figure 3a, the correlation is statistically non-significant ($r = .277$, $p = .171$). Thus, even within the domain of partisan politics, conservative outlets are not more likely than liberal outlets to respond to audience engagement signals. Similarly, for entertainment topics (RQ1), conservative outlets are not significantly more responsive ($r = -.087$, $p = .672$) to audience engagement signals than liberal outlets (see Figure 3b). However, if the engagement signal is measured using only retweets, conservative outlets are significantly less responsive to audience engagement of entertainment-oriented topics ($r = -.456$, $p = .019$).

Robustness

Differences Related to Affordances. Responsiveness on Twitter varies across different types of afforded interactions between the audience and media outlets. If we account for platform-specific behaviors on Twitter in Model 4, Table 1, by including non-original news posts (see Footnote 4), responsiveness on Twitter exhibits a markedly different pattern. Specifically, responsiveness for partisan topics becomes statistically non-significant ($\beta = .006$, $p = .120$), whereas it remains significant for the other two topic categories, entertainment and others. This means that the affordances of retweeting and direct interactions with users on platform Twitter have led to media outlets adopting distinct response patterns to such posts compared to Facebook, highlighting the importance of different affordances in social media news production. Additional robustness tests are detailed in the Supplemental Appendix, including analyses with ten periods instead of sixty, an alternative media slant measure, a quadratic model term, moderation analysis using ideology, and after controlling for the number of posts.

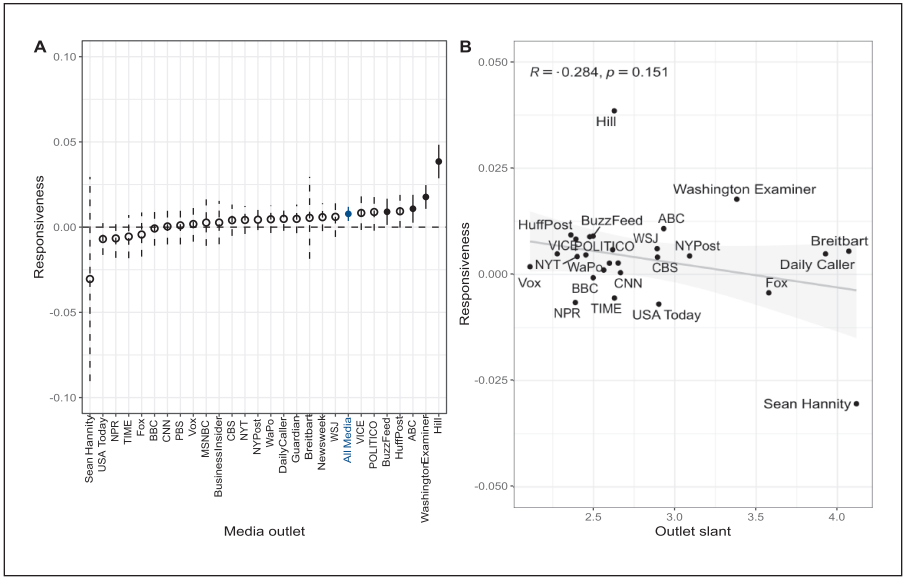


Figure 2. Responsiveness scores for individual outlets (a) and a scatter plot showing correlation between responsiveness and ideological slant scores (b). Conservative outlets are not significantly more likely to respond to audience engagement signals than liberal outlets when accounting for all engagement signals.

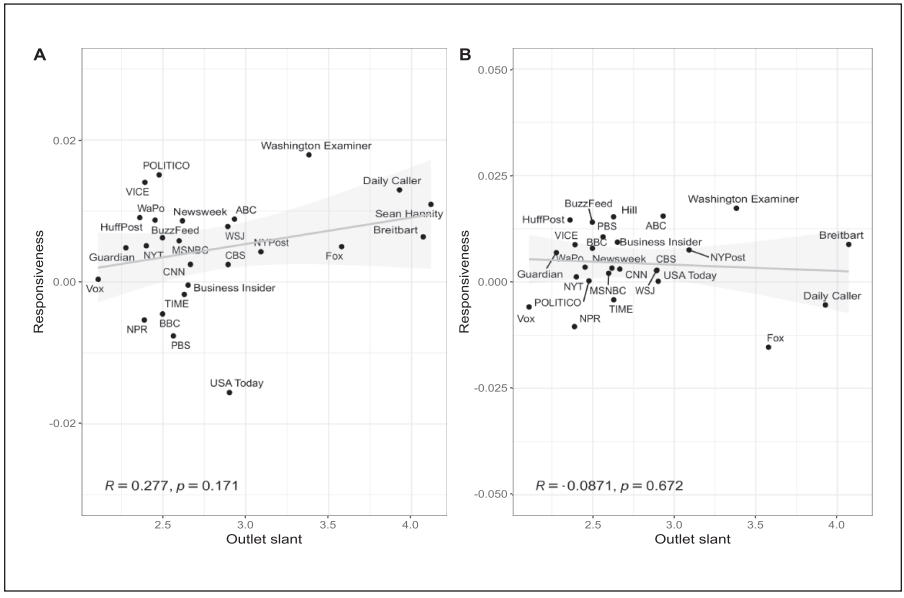


Figure 3. Correlation between ideological slant scores and responsiveness values to partisan topics (a) and entertainment-oriented topics (b).

Discussion and Conclusion

Our findings demonstrate that media outlets on Twitter adjust their news production tactics based on audience engagement signals on Twitter, and responsiveness to such signals does not vary by news content category. Therefore, the core findings qualitatively align with those of the original study we set out to replicate (Mukerjee et al. 2023). These two results suggest that social media engagement signals are shaping journalists' and editors' choices regarding subsequent topic selection, at least among the twenty-eight major and highly influential media outlets in the USA. Our findings thus lend credence to the overall applicability of the original study's conclusions to Twitter.

Yet, the specific dynamics on Twitter differ in nuanced ways from those documented in the original study. First, media outlets exhibit a shorter maximum response window on Twitter than they do on Facebook, perhaps reflecting the fact that Twitter is perceived to be a more real-time platform than Facebook. This finding is in line with the fact that Twitter's recommendation system prioritizes real-time content, reducing the likelihood of older posts appearing on users' timelines (Twitter 2023). Second, while responsiveness does not vary significantly across ideologically diverse outlets, differences emerge at the topic level. In the Facebook study, ideological differences in responsiveness appear exclusively within partisan topics; in contrast, the replication on Twitter does not identify such differences in the main model specification. This difference could indicate a preference for producing softer news on Twitter or a greater consumption of non-political content. Both mechanisms align with the responsiveness pattern identified in the original study but require further validation. Third, non-original posts and direct interactions with specific users on Twitter (see Footnote 4) uniquely influence responsiveness to partisan topics, presenting a marked deviation from the findings on Facebook. This observation aligns with an emerging line of research on how the affordances of microblog social media affects the behaviors of users—including institutional ones (e.g., Freelon 2015; Guo et al. 2023; Jaidka et al. 2021; Oz et al. 2018; Wang and Greenwood 2025; Zhou 2021). These three differences suggest that the same media outlets indeed exhibit varying preferences for audience engagement signals across platforms. Given that the replication study focused on the same set of outlets as the original study—thereby capturing similar institutional and editorial characteristics—the observed cross-platform differences may be attributed to the differences in the two platforms, specifically their different affordances and user bases. This highlights the necessity for conducting cross-platform replications in the future.

One possible explanation for the ideological patterns not replicating on Twitter is that Facebook offers a more conducive environment for conservative outlets to track audience engagement signals. First, Facebook's user base is larger and more representative of the general population than Twitter's (Auxier and Anderson 2021; Shearer and Mitchell 2021; Vogels et al. 2021; Walker and Matsa 2021). Second, Republicans are more likely to use Facebook (69%) than Twitter (17%) (Vogels et al. 2021), making it especially valuable for conservative media. Taken together, these factors - spanning user behavior, production practices, and platform affordances—make Facebook a more transparent and reliable site for assessing audience preferences. In other words,

conservative outlets may not be responding to audience engagement signals on Twitter more than liberal outlets simply because Twitter's user base does not reflect their core audience as accurately as Facebook's does. This suggests that conservative outlets may rely more on Facebook for monitoring engagement signals.

The current study, however, has several limitations that necessitate cautious interpretation. First, measurement error may exist in how we measure engagement signals. While audience engagement signals may seem similar across platforms, the underlying affordances and algorithmic factors that lead to engagement can vary significantly. For example, Twitter's recommendation algorithm weights retweets as twenty times more influential than replies, while favorites (which are not completely transparent) seem to be roughly 1.5 times more important than retweets (Twitter 2023). The selective emphasis and downweighting of certain interaction metrics may have broader implications for news production and social power dynamics, warranting further investigation in future research. Second, the consistency of our estimation of top topics across platforms may be biased due to different corpora even while using the same method. Specifically, since NMF uses a linear transformation of the original document, differences in corpora, differences in the hyper-parameters, or the presence of non-unique solutions may result in completely different decomposition matrices, even with an identical method. For example, the shorter length of tweets compared to Facebook posts could substantially alter the resulting topics. Third, the temporal external validity of this study is constrained by both platform drift and shifts in data availability. In particular, platform-level changes—such as temporal fluctuations and Musk's acquisition, changes in content moderation, user suspension, deletion, protection, and deactivation (Knöpfle and Schatto-Eckrodt 2024) introduce analytical complexities that are difficult to disentangle. However, in the case of mainstream media outlets, suspensions and protections are unlikely to meaningfully affect the results. Finally, the findings drawn from Facebook and Twitter in the USA—a context marked by high levels of polarization and politicization—are unlikely to be generalizable to other platforms or national settings that are organized around different fault lines, ideological or otherwise.

Our findings underscore that media outlets actively engage with their audiences on social media platforms, though the level of responsiveness varies across platforms. While our analysis indirectly speaks to how platform affordances may shape these dynamics, it also potentially exhibits the role played by user demographics, usage patterns, and platform design in shaping these interactions. This replication study advances the understanding of media-audience reciprocity by uncovering both overarching similarities and platform-specific nuances. We employ a rigorous comparative framework that enables direct cross-platform analysis. Given the ever-changing nature of social media platforms—illustrated by recent structural transformations on Twitter, as well as substantial changes in Facebook's curation of news—it is imperative that such replications are done frequently and regularly. This will investigate the dynamics over time and provide insights into how evolving platform features continue to reshape media-audience dynamics.

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Data Availability Statement

The data and codes for replication are available at https://osf.io/q9xuw/.

Supplemental Material

Supplemental material for this article is available online.

Notes

1. We clarify that, although Twitter has since been renamed X, our data collection and analysis pertain to the period prior to this change; therefore, we refer to the platform as Twitter throughout the manuscript.
2. One outlet, Rush Limbaugh, is missing because of its absence on Twitter at that time.
3. The Academic Twitter API has since been discontinued. We are no longer eligible to share the original data due to the platform's current ToS.
4. Twitter users can opt in to receive targeted reminders from accounts, prompting public tweets that mention each user individually. These tweets enter our dataset due to their public nature but are excluded from analysis to avoid artificially inflating topic coverage beyond organic levels.

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