

Electronic Companion
to
**“How To Tell a (News) Story? Quantifying the Impact of News Format and
Storytelling on Engagement”**

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EC.A. Conceptual Model, Positioning, and Theory

Figure A1.1: Conceptual Framework of Effects of Storytelling Design Features on Engagement

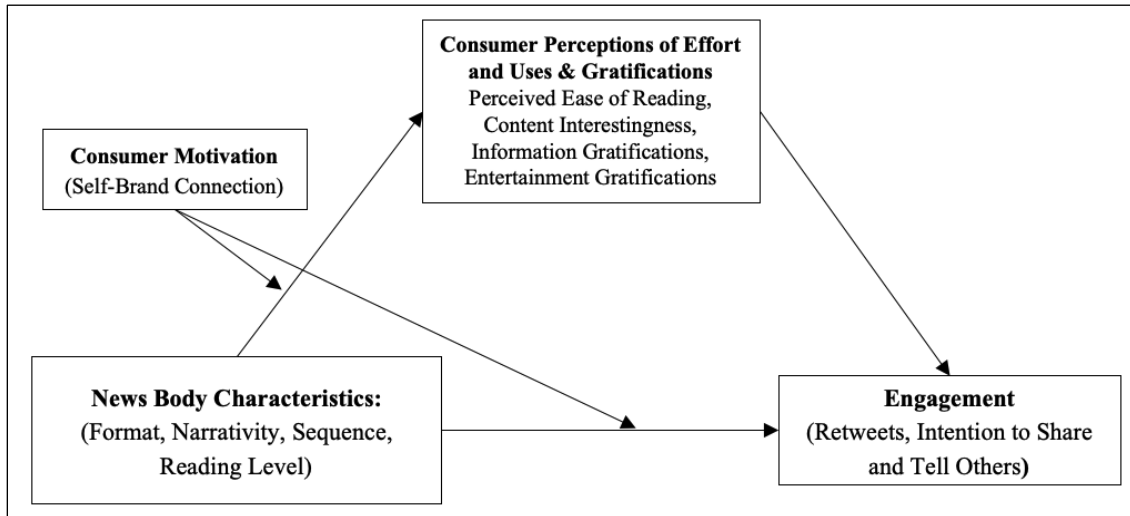


Figure A1.2: Study 1 – Model Tested

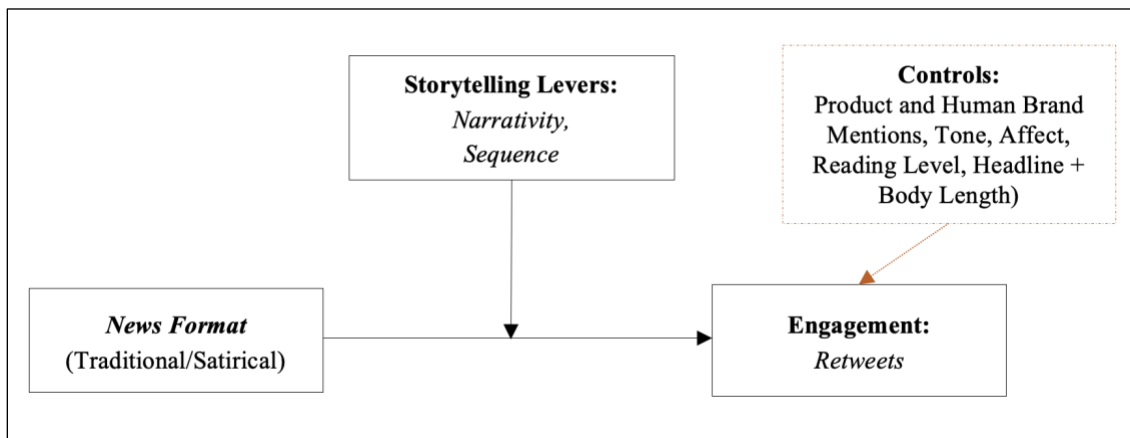


Figure A1.3: Studies 2 and 3 – Model Tested

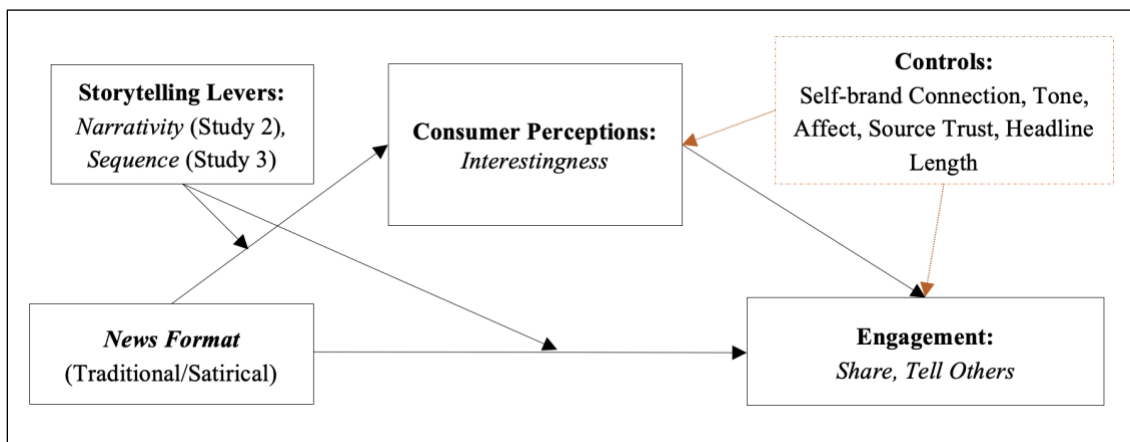


Figure A1.4: Study 4 – Model Tested

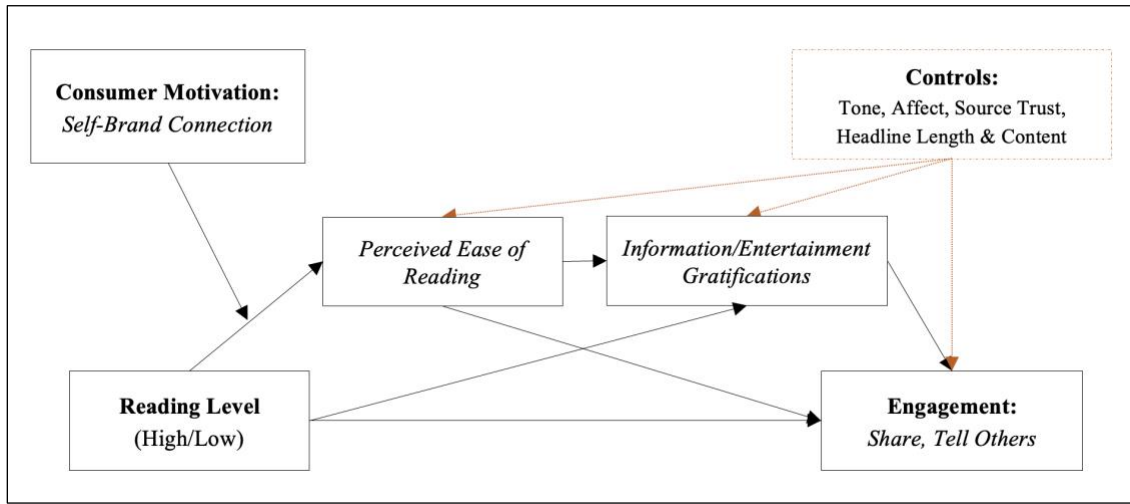


Figure A2: Positioning of Current Research Relative to Prior Literature

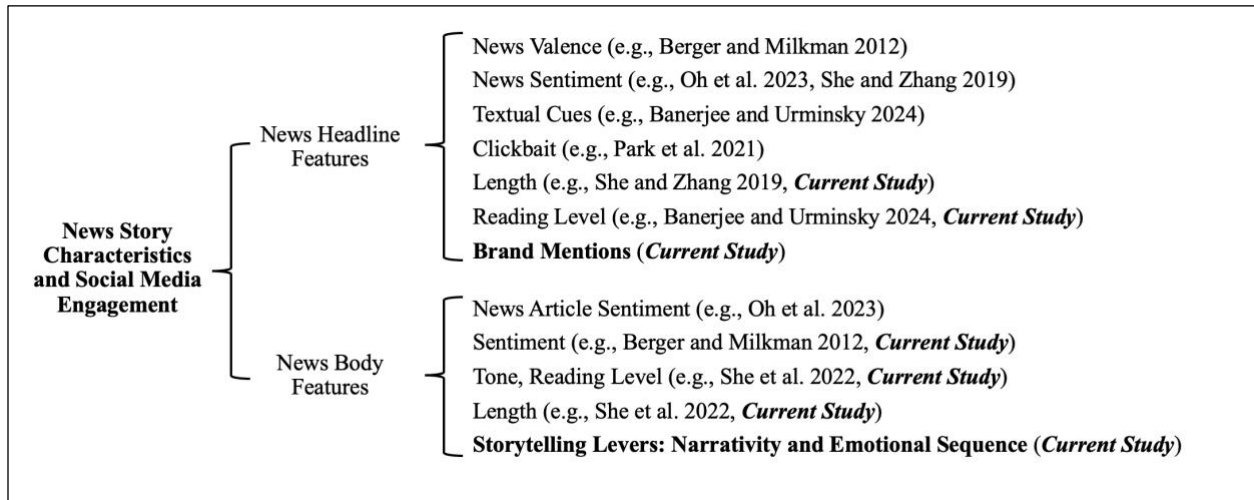
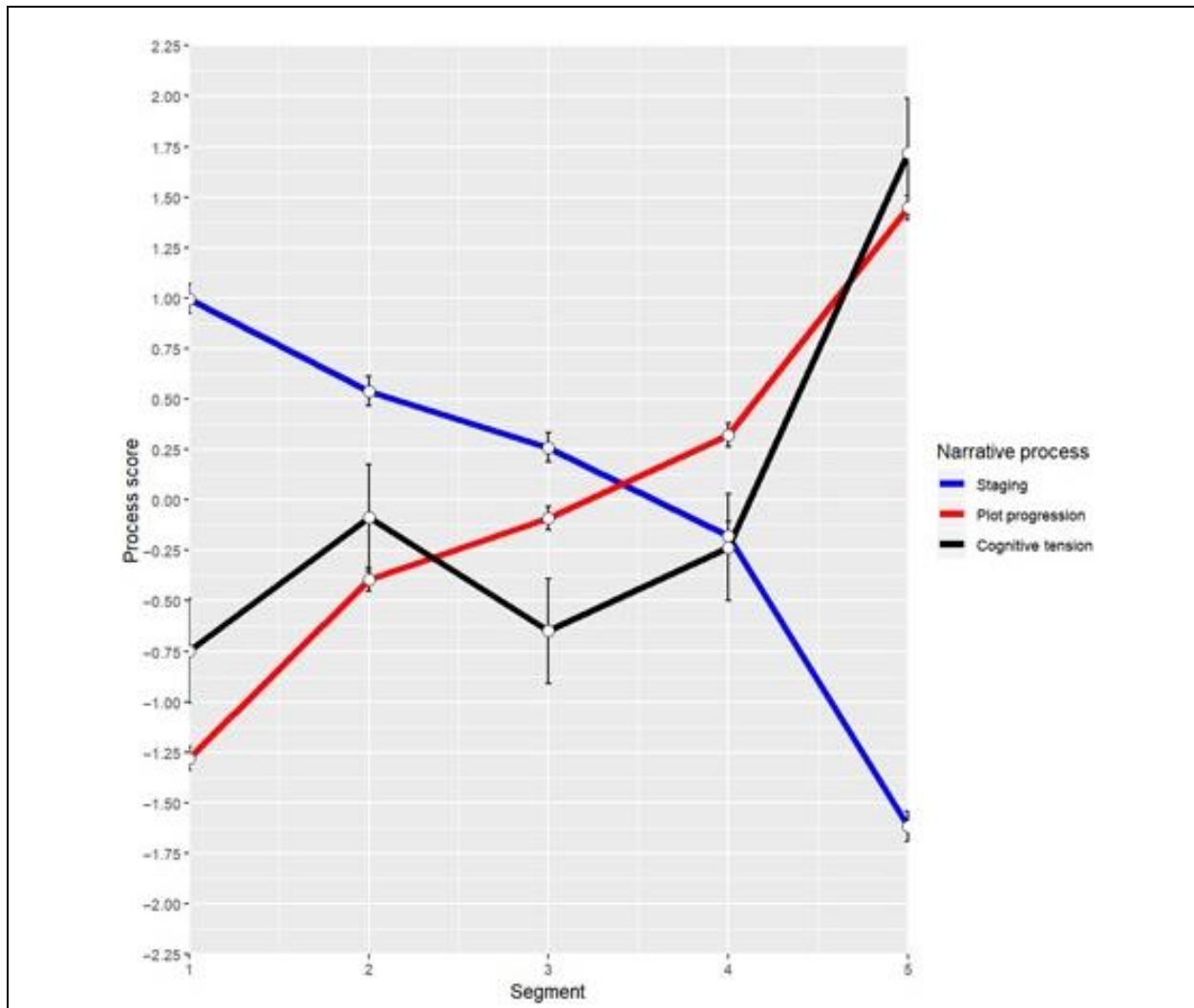
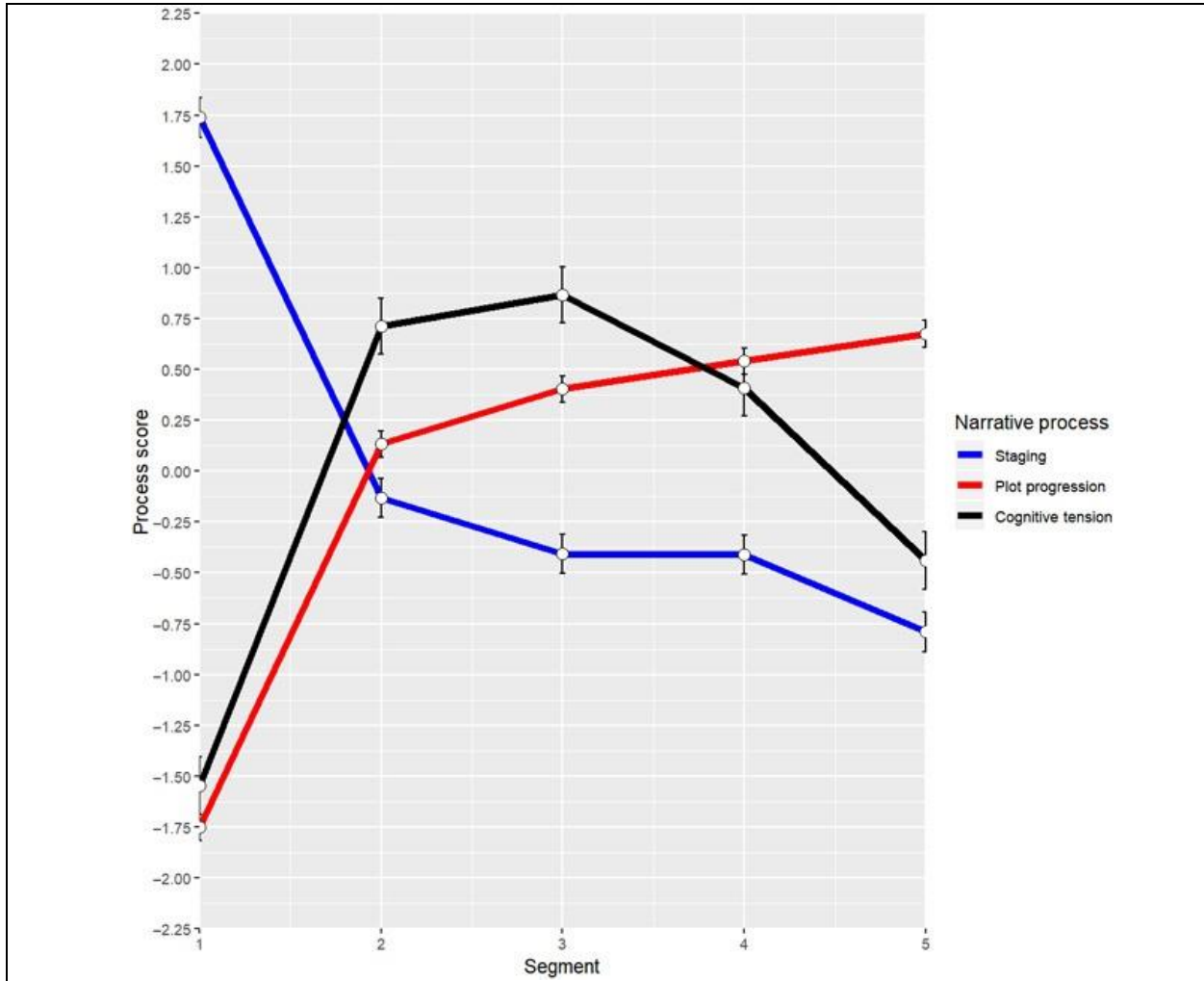


Figure A3: Traditional News Narrativity



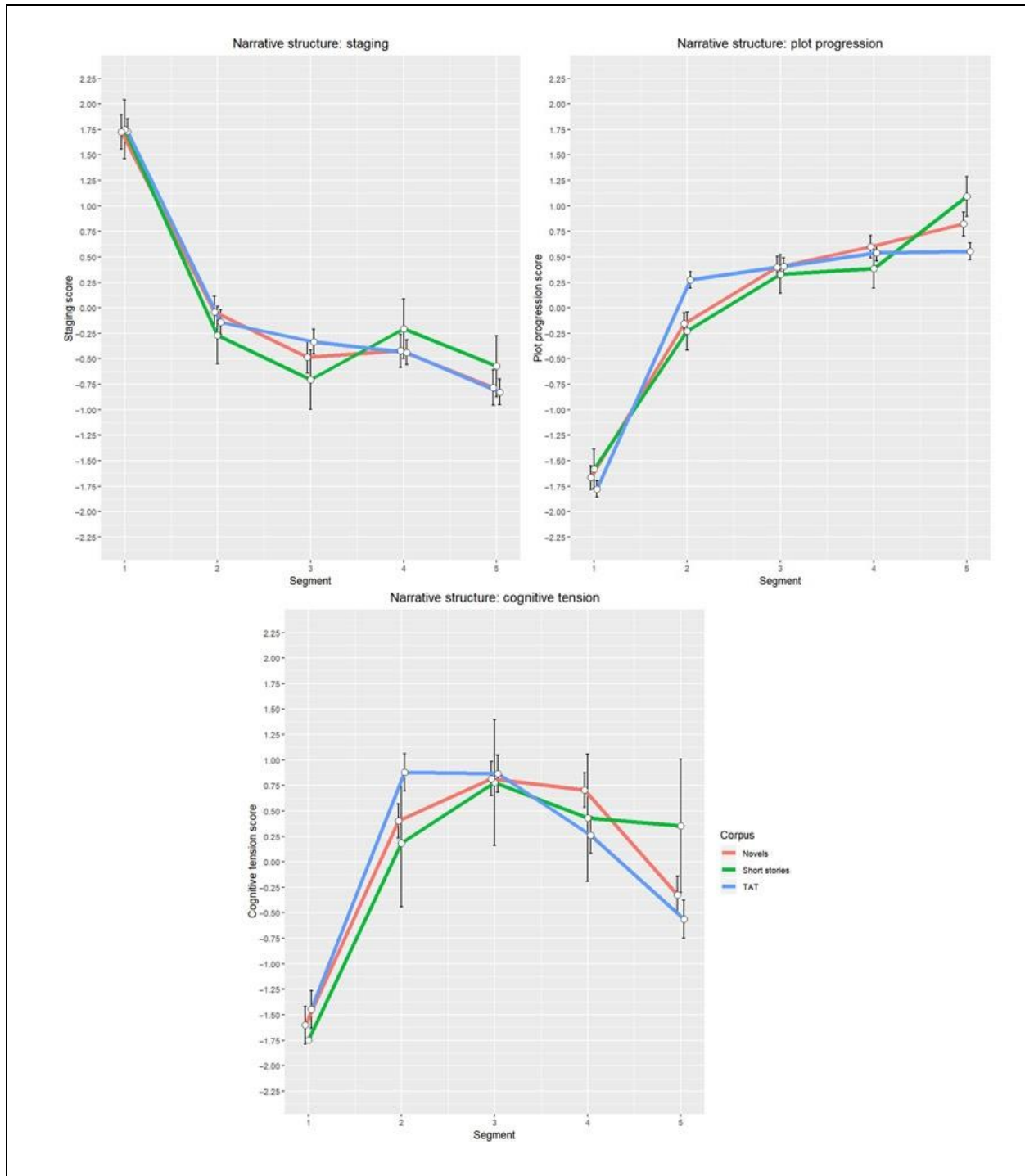
Illustrative purposes only. Figure A3 shows the three narrative processes across five segments for New York Times news stories. Traditional news stories are built around one or more essential questions that are eventually resolved. Essential facts are provided in the first few sentences (setting the stage), followed by supporting information (plot progression), and concluded with relevant questions (cognitive tension) or possible implications for the future. Cognitive tension tends to build towards the end of a traditional news story, as shown (Boyd et al. 2020).

Figure A4: Fictional Story Narrativity



Illustrative purposes only. Figure A4 shows that, like fictional stories (novels, short stories, TATs, romance novels, and movie dialogue), in satirical news stories, cognitive tension eases as the story progresses. The structure of staging and plot progression is similar to traditional news (Boyd et al. 2020).

Figure A5: Standard Structures for Each Component of Narrativity



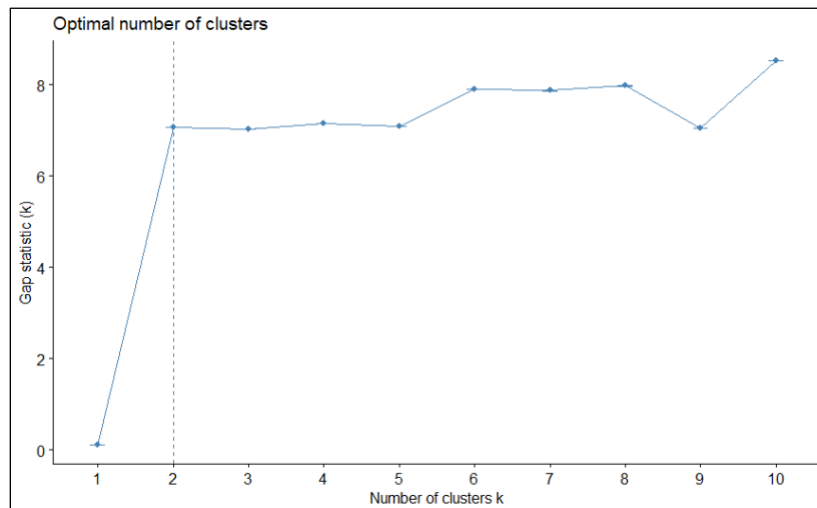
Illustrative purposes only. The traditional stories included 2,523 fiction novels from the Gutenberg corpus, 2,092 short stories from various online sources, and 14,419 brief stories written by internet users in response to a standardized thematic apperception test (TAT; Boyd et al. 2020)

EC.B. Details on Study 1 – Preliminary Investigation

Figure B1: Study 1 – Twitter and Web Pages of Firstpost and Faking News



Figure B2: Study 1 – Optimal Number of Clusters of *Sequence*



EC.B1. Study 1 – Data Collection Method

We developed our dataset of traditional and satirical news stories posted to Twitter (currently rebranded to X) through a multi-step process:

1. **Collection of Satirical News:** We identified and downloaded all satirical news stories published on the satirical website *fakingnews.com* since 2013, when the news organization Firstpost acquired the satirical website (N= 5,064). We then tracked these satirical headlines on the satirical news account *@fakingnews* to collect an objective sharing statistic, the number of retweets. This constitutes the portion of our dataset categorized as *satirical* news. This process ensures that we collect only those traditional and satirical news stories published from the same newsroom.
2. **Identification of Related Traditional News:** We aim to identify the traditional news stories on which these satirical stories may have been based via the following steps:
 - 2.1. **Keyword Extraction:** For each satirical news story i , we use natural language processing methods to extract two dimensions that potentially inform the subject and context of the traditional news:
 - 2.1.1. **Brands Mentioned in Headline** (i.e., the subject of the news): Following the literature (Bauman and Tuzhilin 2022), we employ named entity recognition to identify the people and companies mentioned in the satirical headline.
 - 2.1.2. **Summary of the News Story** (i.e., the context of the news): We use an unsupervised graph-based lexical centrality approach (Erkan et al. 2004) to determine the “most important” sentence in the news story, which intuitively also captures its essence (i.e., the context). Using search terms for subject and context, we collect traditional news stories posted to the traditional news account *@firstpost*. Lexrank may underestimate the importance of sentences with unique information if they are not highly similar to others, potentially impacting the identification of context keywords for a small subset of satirical news stories where the most vital facts may appear less frequently.
 - 2.2. **Traditional News Search:** Satirical news temporally follows traditional news. Hence, we search for traditional news published before the satirical news. Specifically, we constrain our search to the period ending at the time the satirical news was published and beginning one month before the publication of the satirical news story i . This allows us to capture traditional news published soon before the satirical news while ensuring that the traditional news remains relevant to the satirical news. Since a satirical news story may be based on multiple real-life news events, we collect up to ten tweets from a Twitter search for each satirical news i (N = 55,197) within one month. For a hypothetical satirical story published on Jan 1, 2023, at 5 p.m., we restrict our traditional news search to Dec 1, 2022, 5 p.m. – Jan 1, 2023, 5 p.m., and collect the ten most relevant stories (as reported by Twitter). Each matched set is assigned a unique ID (called *FKID*).
3. **Dataset Refinement:** We further refined this matched dataset of *@firstpost* tweets by retaining only the tweets that contained a URL linked to a news story (not simply video or media) on the parent website *firstpost.com*. Finally, we filter out satirical and traditional stories that contain less than 250 words. Importantly, if the URL and word length filtering removed a satirical (traditional) story, we did not remove its matching traditional (satirical) stories(s) to reduce the impact of LexRank on data collection. Retaining unmatched pairs introduces variability, which can reduce potential systematic influences of LexRank.
4. **Final Dataset:** Thus, our final sample of 5,064 satirical stories and 35,019 traditional news stories consisted of both matched and unmatched news stories (Total N = 40,813). To restrict LexRank’s

potential influences, we analyze this sample. In this sample, 4,512 satirical and 29,902 traditional news stories are matched.

We note that this data collection procedure cannot capture satirical/traditional versions of a news event if (i) the traditional news was released after the satirical news or (ii) the traditional news was released more than one month before the satirical news. Following our discussion in Section 2, we conceptualize sharing as a function of the news format, narrativity, and storytelling (see Figure A1, EC.A). Table B1, EC.B provides summary statistics for our sample: satirical news has a higher number of retweets than traditional news ($M_{Satirical} = 27$, $M_{Traditional} = 8$); however, both news formats have similar ranges and standard deviations of *Narrativity* and have similar mean values of reading levels of headline and body, lengths of headline and body, *Affect*, and *Tone*.

Table B1: Study 1 – Summary Statistics

	Traditional News					Satirical News					Overall Sample				
	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max	N
Dependent:															
<i>Retweets</i>	8.0	22.3	0.0	1689	35019	27.0	34.8	0.0	778	5064	10.4	25.0	0.0	1689	40083
Independent:															
<i>Narrativity</i>	15.2	31.8	-95.7	96.2	35019	26.4	29.9	-90.3	93.1	5064	16.6	31.8	-95.7	96.2	40083
<i>Sequence (= 1)</i>					17802					2627					20429
Controls:															
<i>HumanBrand (= 1)</i>					19535					2320					21855
<i>ProductBrand (= 1)</i>					4320					1123					5443
<i>Affect</i>	3.8	1.6	0.0	13.4	35019	4.4	1.7	0.3	15.5	5064	3.9	1.6	0.0	15.5	40083
<i>Tone</i>	29.9	22.4	1.0	99.0	35019	34.6	22.6	1.0	99.0	5064	30.5	22.5	1.0	99.0	40083
<i>FOG_Head</i>	11.46	4.71	0.4	37.10	35019	12.58	3.87	1.6	33.2	5064	11.6	4.6	0.4	37.1	40083
<i>FOG_Body</i>	15.58	2.67	5.90	49.11	35019	13.41	2.35	5.89	44.08	5064	15.3	2.7	5.89	49.1	40083
<i>Headline_Length</i>	13.52	3.06	4	28	35019	14.61	3.57	4	28	5064	13.7	3.2	4	28	40083
<i>Body_Length</i>	743.1	795.4	250	9607	35019	376.5	96.36	250	1463	5064	696.8	754.2	250	9607	40083

Note: As shown in this table, satirical news has a higher number of retweets than traditional news ($M_{Satirical} = 27$, $M_{Traditional} = 8$); however, both news formats have similar ranges and standard deviations of *Narrativity* and have similar mean values of reading levels of headline and body, lengths of headline and body, *Affect*, and *Tone*.

EC.B2. Study 1 – Details on Independent Variable (*Narrativity*)

Narrativity has received little attention in IS research owing to the difficulty of quantifying narratives narrativity objectively using automation (Toubia et al. 2021). We overcome this challenge by exploiting the “Arc of Narrative” feature newly introduced in the text analysis software Linguistic Inquiry and Word-Count (LIWC-22). Although the literature extensively uses previous iterations of LIWC (e.g., Kumar et al. 2022, Mallipeddi et al. 2021a), limited research utilizes the narrativity tools of LIWC-22.

The narrativity score is an average of 3 components of the narrative process: staging, plot progression, and cognitive tension (Boyd et al. 2022). LIWC-22 splits a news story into five segments and quantifies each narrative process within each segment. The assigned score reflects how closely the text resembles the standard structures in a corpus of fictional stories (see Figure A4, EC.A). Min-max normalization standardizes the score for each narrative process within each segment. To exemplify, if a news story starts with a high degree of staging that slowly falls off, with the least amount of staging occurring towards the end, LIWC-22 assigns a “staging” score of 100 to the first segment and a score of 0 to the last segment.

The scores of segments 2, 3, and 4 reflect their relative standing to the high and low staging points of segments 1 and 5, respectively.

Calculating the percentage of function and cognitive words used in each segment allows quantifying staging, plot progression, and cognitive tension. Articles and prepositions quantify staging; pronouns, auxiliary verbs, negations, conjunctions, and nonreferential adverbs quantify plot progression; cognitive tension words quantify cognitive tension. Dividing the sum of each function word category for each text by the total number of words in the text yields the percentage of words belonging to each narrativity subprocess (Boyd et al. 2020). Comparing these scores with established norms allows the derivation of overall similarity scores (*Narrativity*). The total score for *Narrativity* indicates the similarity of a news story i with the norms shown in Figure A4, EC.A. The norms suggest that staging occurs at its highest at the beginning of a story, followed by a rise in plot progression, paired with a rise and fall in cognitive tension around the middle-to-late parts of a story. A score of 100 indicates the complete similarity of news story i with the norm of fictional stories, while a score of -100 indicates the complete dissimilarity.

Figure B3: Study 1 – Sequence



EC.B3. Study 1 – Details on Control Variables

B3.1. Brand Mentions in News Headlines

Brand mentions can signify the relevance of the news to the user, thereby encouraging sharing (Duffy and Ling 2020, Karlsson and Strömbäck 2010). In our research context, a brand mention happens when a brand name appears in a news headline. A brand mention in this context is not a direct link to the brand, and one cannot click on it and navigate to the brand page. Instead, a brand mention informs readers about the brand without providing a direct hyperlink (Panda and Ofitserov 2012).

Names contain cognitive cues (Jiang et al. 2021), and a brand mention carries weight for its intended audience based on its relevance to them (Hagar et al. 2022). Users’ motivation to access news on social media is based on their perceptions of the people and organizations mentioned (Mendoza et al. 2020), and brand mentions in headlines can appeal to users’ interests and affect social media engagement (Baraniak and Sydow 2021, Lee et al. 2018). Since brand mentions can draw attention (Surber and Schroeder 2007) and impact news attractiveness (Reis et al. 2015), they could confound the effects of our focal variables (*NewsFormat*, *Narrativity*, and *Sequence*) on sharing. Consequently, we seek to empirically control the effect of brand mentions on sharing.

Following the literature in IS and marketing, we define brands as organizations, products, services, or persons subject to marketing communication efforts (Mallipeddi et al. 2021a, Saboo et al. 2016, Thomson 2006). This definition suggests that brands can be of two types: product or human (e.g., McShane et al. 2021), and we seek to control for the effects of these two types of brands mentioned in news headlines.

Each type of brand mention could have a distinct effect on signifying the relevance of the news to the user. For instance, since most mass media features product brands (e.g., Apple), product brands are likely top of mind (Berger and Schwartz 2011, pg. 870), and could signify news relevance to some users when mentioned in news headlines. However, for some users, product brand mentions could activate negative associations with advertisements (van den Broeck et al. 2018), leading to avoidance and a reduced interest in the news. In contrast, human brands can exert more substantial social influence than product brands and make consumers feel appreciated, empowered, and autonomous, forming emotionally significant relationships such as idolatry and fandom (Thomson 2006). Since brand mentions carry weight based on their relevance to news audiences (Hagar et al. 2022), we need to include both types of brand mentions and create two dummy variables *ProductBrand* and *HumanBrand*.

To compute *ProductBrand* and *HumanBrand*, we curate a dictionary of 3,210 unique product and human brands from an analysis of 9,197 hashtags supplied with the news stories. We remove brand names analogous to common English words (e.g., gap, surf, tide). We assign actors, musicians, athletes, politicians, CEOs, political parties, and music groups as human brands. In contrast, we assign durable/non-durable goods, TV channels, sports teams, online services, private colleges/universities, companies, and movies/songs as product brands. We developed an algorithm to identify whether human and product brands were mentioned in news headlines. When a certain brand type was mentioned, we captured its presence in binary format. For instance, for the headline “Tesla CEO, Elon Musk to Buy Twitter for \$44 Billion,” *ProductBrand* = 1 and *HumanBrand* = 1, whereas for the hypothetical headline “Twitter sold for \$44 Billion,” *ProductBrand* = 1 and *HumanBrand* = 0. The algorithm also captures variations of certain brand names (e.g., Narendra Modi, PM Modi, Modi, Prime Minister of India).

B3.2 Affect

Affect refers to subjective aspects of discrete emotions. The affect expressed in news articles can influence engagement (Berger and Milkman 2012, Deng and Chau 2021, Horner et al. 2021) and may confound the effects of our focal variables. To control for affect, we utilize LIWC-22 to compute *Affect*, a variable that captures the proportions of words representing positive emotions as well as the specific emotions of anger, anxiety, and sadness (2,999 words) and swear words (462 words) within the body of the news story. It should be noted that affect refers to specific emotions and is distinct from tone, the overall degree of positivity or negativity of the news story.

B3.3 Tone

Tone reflects the overall degree of positivity or negativity of online content (Boyd et al. 2022). Research suggests that both negative and positive tones can influence engagement. For instance, Bellovary et al. (2021) and Aggarwal et al. (2011) find that users are generally more interested in sharing negatively toned news and reading negative blogs, respectively. In contrast, other research finds that users tend to avoid sharing negative content (Barasch and Berger 2014) and instead prefer to share upbeat stories (Berger and Milkman 2012) that shape the sharer’s reputation among peers (Qiu and Kumar 2017). In our context, while sharing positive news content may reflect positively on the sender, sharing negative content that is interesting and entertaining may also be helpful. Specifically, as satirical news tends to deliver social commentary via irony and parody, although it could be negative in tone, it may be appreciated by others in

the user’s network. Considering the mixed findings reported in past research, it is important to control for the effects of tone on engagement.

We utilize LIWC-22 to quantify tone. *Tone* is a standardized composite variable transformed to a scale from 1 to 100, which analyzes 1,020 positive emotion and 1,530 negative emotion words (Boyd et al. 2022). *Tone* measures the overall degree of positive or negative emotion in the news, putting the negative and positive dimensions into a single summary variable such that the higher the value, the more positive the emotion. Values below 50 suggest a more negative emotion.

B3.4 Length of Story

The length of posts or tweets can also influence engagement (Li and Xie 2020, Mudambi and Schuff 2010, Oh et al. 2022), with some evidence that longer tweets achieve higher engagement (e.g., Sprout Social 2021). To control for the effect of length, we measure the length of headlines and bodies separately and add them to our empirical specification.

EC.B4. Study 1 – Empirical Model Specification and Identification Strategies

To identify the effects of news format, we examine the change in the number of retweets due to news format, holding constant the narrativity and emotional sequence of news story i . As shown in Table B4.1, EC.B4, *NewsFormat*, *Narrativity*, and *Sequence* are only weakly associated with each other and controls (all $r < 0.4$), supporting their estimation in an OLS setting. Thus, we specify Model 1 as:

$$\log(\text{Retweets}_i) = \beta_0 + \beta_{01}\text{NewsFormat}_i + \beta_{02}\text{Narrativity}_i + \beta_{03}\text{Sequence}_i + \gamma\text{Controls}_i + \varepsilon_i \quad (1)$$

To answer RQ1 and test H1a and H1b regarding the role of narrativity in satirical and traditional news, respectively, we examine the interaction of news format with narrativity (Model 2a) as follows:

$$\begin{aligned} \log(\text{Retweets}_i) = & \beta_0 + \beta_{01}\text{NewsFormat}_i + \beta_{02}\text{Narrativity}_i + \beta_{03}\text{Sequence}_i \\ & + \beta_{04}\text{NewsFormat}_i \times \text{Narrativity}_i + \gamma\text{Controls}_i + \varepsilon_i \end{aligned} \quad (2a)$$

Next, to further answer RQ1 and test H2a and H2b regarding the role of emotional sequence in satirical and traditional news, respectively, we examine the interaction of news format with emotional sequence (Model 2b) as follows:

$$\begin{aligned} \log(\text{Retweets}_i) = & \beta_0 + \beta_{01}\text{NewsFormat}_i + \beta_{02}\text{Narrativity}_i + \beta_{03}\text{Sequence}_i \\ & + \beta_{04}\text{NewsFormat}_i \times \text{Sequence}_i + \gamma\text{Controls}_i + \varepsilon_i \end{aligned} \quad (2b)$$

The number of retweets indicates social media engagement (Mallipeddi et al. 2021a, 2021b) in that the higher the number of retweets, the higher the sharing. *NewsFormat* is a dummy variable indicating whether the news story i is traditional (=0) or satirical (=1). *Narrativity* is a continuous variable ranging theoretically from -100 to +100. *Sequence* is a dummy variable indicating the emotional variation through the story’s narrative. *Sequence* = 0 (1) for news that begins on a strongly positive (negative) note and ends on a strongly negative (positive) note. The interaction terms *NewsFormat* X *Narrativity* and *NewsFormat* X *Sequence* capture the moderating effect of the two storytelling components on the effect of news format on sharing.

The vector *Controls* includes the variables *HumanBrand*, *ProductBrand*, *Affect*, *Tone*, *FOG_Head*, *FOG_Body*, *WC_Head*, and *WC_Body*. *HumanBrand* and *ProductBrand* are dummy variables indicating whether the headline of news story *i* mentions a human or product brand (*HumanBrand/ProductBrand* = 1 if a human/product brand is mentioned; otherwise, 0). *HumanBrand* and *ProductBrand* control for the effect of news relevance by capturing the main effects of brand mentions in headlines on the number of retweets received by news story *i*. *Affect* is a continuous variable representing the proportion of emotion-laden words used in the body of news story *i*, expressed as a percentage, and can theoretically range from 0 to 100. *Tone* is a continuous variable that captures the positivity and negativity of expression in the body of news story *i*, expressed as a percentage, and can theoretically range from 0 (extremely negative) to 100 (extremely positive). *FOG_Head* and *FOG_Body* are continuous variables that capture the reading level of the story *i*'s headline and body, respectively, with higher values indicating that the text is more difficult for the average reader to understand. *WC_Head* and *WC_Body* are continuous variables that measure the length of the story *i*'s headline and body, respectively.

Table B4: Study 1 – Measures of Association

	<i>Retweets</i>	<i>NewsFormat</i>	<i>Narrativity</i>	<i>Sequence</i>	<i>ProductBrand</i>	<i>HumanBrand</i>	<i>Tone</i>	<i>Affect</i>	<i>FOG_Head</i>	<i>FOG_Body</i>	<i>Headline_Length</i>	<i>Body_Length</i>
<i>Retweets</i>	1.000											
<i>NewsFormat</i>	0.253	1.000										
<i>Narrativity</i>	0.029	0.117	1.000									
<i>Sequence</i>	0.005	0.005	0.029	1.000								
<i>ProductBrand</i>	0.030	0.095	0.009	0.006	1.000							
<i>HumanBrand</i>	0.046	0.067	-0.022	0.038	-0.059	1.000						
<i>Tone</i>	0.009	0.071	-0.029	0.096	0.071	0.076	1.000					
<i>Affect</i>	0.055	0.128	0.037	0.035	0.004	0.060	0.148	1.000				
<i>FOG_Head</i>	0.019	0.081	0.013	0.005	-0.015	-0.052	-0.001	0.005	1.000			
<i>FOG_Body</i>	-0.084	0.263	-0.059	0.010	-0.067	0.002	-0.079	-0.184	0.135	1.000		
<i>Headline_Length</i>	0.046	0.115	0.022	0.011	0.008	0.045	0.007	-0.041	0.061	-0.026	1.000	
<i>Body_Length</i>	-0.048	0.161	-0.085	0.014	-0.031	0.068	-0.022	0.041	-0.054	-0.005	-0.056	1.000

Note: As shown in the table, *NewsFormat*, *Narrativity*, and *Sequence* are only weakly associated with each other and controls (all $r < 0.15$), supporting their estimation in an OLS setting.

B4.1: Interaction of NewsFormat with Controls

In this section, we dig deeper into the potential roles of the control variables (included in the vector *Controls*) in moderating the effect of the news format on retweets. The results reported here in Table B4.1 and the interaction plots in Figure B4.1 reveal that the interaction coefficient of *NewsFormat* is always positive even though all the control variables impact the magnitude of the effect. This suggests that while these control variables can help increase retweets for satirical news, they do not always help for traditional

news formats. For instance, as Column 1 shows, although *ProductBrand* has a significant negative coefficient ($\beta = -0.1287$), its interaction with *NewsFormat* is positive and significant ($\beta = 1.265$). This suggests that the overall effect of *NewsFormat* on *Retweets* is positive for satirical news ($= -0.1287 + 1.265$). However, for traditional news, the overall effect is negative ($= -0.1287$). This may suggest that traditional news about product brands may be less engaging than counterpart satirical news. Similarly, for *HumanBrand*, as Column 2 shows, the main ($\beta = -.036$) and interaction effects with *NewsFormat* ($\beta = 1.413$) are positive and significant, suggesting that the satirical news format increases retweets by a higher amount when human brands are mentioned in headlines. However, for traditional news, the overall effect of *HumanBrand* is negative ($= -0.036$), suggesting that traditional news about human brands is less engaging than counterpart satirical news. We observe similar effects on satirical news (relative to traditional news) for our other control variables. Panels a through h in Figure B4.1, EC.B, show these relationships graphically. Together, these results suggest that the overall effect of *NewsFormat* = 1 (satirical news) on retweets is always positive, despite being moderated by *Controls*.

Tests of equality of the two coefficients reported in Columns 1 and 2 of Table B4.1, EC.B, using the method described in Paternoster et al. (1998) reveal that they are significantly different from each other since the value of $Z > 1.96$, where $Z = (\beta_1 - \beta_2) / \sqrt{(SE \beta_1)^2 + (SE \beta_2)^2}$. Specifically, the Z for the difference in coefficients of *NewsFormat* X *ProductBrand* and *NewsFormat* X *HumanBrand* reported in Columns 1 and 2 in Table EC8A, respectively, is 2.95 (where $Z = (1.265 - 1.1413) / (\sqrt{(.0347)^2 + (.0234)^2})$). Further, the coefficient of *NewsFormat* X *ProductBrand* (Column 1, Table B4.1, EC.B) is not different from the coefficient of *NewsFormat* estimated in Model 1 (reported in Column 4, Table 2) since $Z = (1.265 - 1.323) / (\sqrt{(.0347)^2 + (.0129)^2}) = 1.56$; however, the coefficient of *NewsFormat* X *HumanBrand* (Column 2, Table B4.1, EC.B) is different as $Z = (1.413 - 1.323) / (\sqrt{(.0234)^2 + (.0129)^2}) = 3.37$.

Table B4.1: Study 1 – Model 1 (Effect of Interactions of *NewsFormat* with *Controls* on $\log(\text{Retweets})$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Control: <i>Product Brand</i>	Control: <i>Human Brand</i>	Control: <i>Tone</i>	Control: <i>Affect</i>	Control: <i>FOG Headline</i>	Control: <i>FOG Body</i>	Control: <i>Headline Length</i>	Control: <i>Body Length</i>
<i>Narrativity</i>	0.0009*** (0.0002)	0.0005*** (0.0002)	0.0003 (0.0002)	-1.41e-5 (0.0002)	2.58e-5 (0.0002)	-0.0001 (0.0002)	-6.75e-5 (0.0002)	-1.24e-5 (0.0002)
<i>Sequence</i>	0.0196* (0.0107)	0.0203* (0.0104)	0.0194* (0.0102)	0.0236** (0.0100)	0.0250** (0.0100)	0.0217** (0.0099)	0.0213** (0.0100)	0.0242** (0.0100)
<i>NewsFormat X Control</i>	1.265*** (0.0347)	1.413*** (0.0234)	0.0263*** (0.0004)	0.2603*** (0.0037)	0.0948*** (0.0013)	0.0961*** (0.0012)	0.0857*** (0.0011)	0.0031*** (4.93e-5)
<i>ProductBrand</i>	-0.1287*** (0.0174)	0.0736*** (0.0164)	0.0498*** (0.0160)	0.0188 (0.0157)	0.0307** (0.0155)	0.0140 (0.0154)	0.0292* (0.0155)	0.0281* (0.0156)
<i>HumanBrand</i>	0.1074*** (0.0111)	-0.0360*** (0.0109)	0.1444*** (0.0106)	0.1498*** (0.0105)	0.1511*** (0.0104)	0.1534*** (0.0103)	0.1589*** (0.0104)	0.1563*** (0.0105)
<i>Tone</i>	-0.0008*** (0.0003)	-0.0011*** (0.0002)	-0.0046*** (0.0003)	-0.0016*** (0.0002)	-0.0016*** (0.0002)	-0.0016*** (0.0002)	-0.0016*** (0.0002)	-0.0015*** (0.0002)
<i>Affect</i>	0.0161*** (0.0035)	0.0098*** (0.0033)	0.0043 (0.0033)	-0.0316*** (0.0033)	0.0030 (0.0032)	-0.0019 (0.0032)	0.0036 (0.0032)	0.0037 (0.0032)
<i>FOG_Head</i>	0.0139*** (0.0012)	0.0099*** (0.0011)	0.0081*** (0.0011)	0.0063*** (0.0011)	-0.0025** (0.0011)	0.0042*** (0.0011)	0.0047*** (0.0011)	0.0045*** (0.0011)
<i>FOG_Body</i>	-0.0429*** (0.0021)	-0.0318*** (0.0020)	-0.0221*** (0.0020)	-0.0178*** (0.0020)	-0.0122*** (0.0020)	-0.0176*** (0.0020)	-0.0103*** (0.0020)	-0.0123*** (0.0020)
<i>Headline_Length</i>	0.0486*** (0.0023)	0.0378*** (0.0022)	0.0326*** (0.0022)	0.0275*** (0.0021)	0.0263*** (0.0021)	0.0223*** (0.0021)	0.0079*** (0.0022)	0.0249*** (0.0021)
<i>Body_Length</i>	-0.0001*** (8.88e-6)	-6.56e-5*** (8.13e-6)	-5.37e-5*** (8.18e-6)	-2.59e-5*** (7.9e-6)	-2.85e-5*** (7.88e-6)	-0.0000153** (0.00000775)	-0.0000196** (0.00000788)	-3.31e-5*** (7.87e-6)
Fixed-Effects:								
<i>FKID</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year Mon</i>	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	40,083	40,083	40,083	40,083	40,083	40,083	40,083	40,083
R ²	0.33194	0.37672	0.39138	0.41415	0.4177	0.43122	0.42152	0.41421
Within R ²	0.09222	0.15307	0.17298	0.20392	0.20875	0.22712	0.21394	0.20401
AIC	114,011.00	111,230.00	110,276.10	108,747.80	108,504.20	107,562.40	108,240.50	108,743.50

Note: Robust standard errors are reported in parenthesis, “*” = $p < 0.10$, “**” = $p < 0.05$, “***” = $p < 0.01$.

The results reported in Table B4.1, EC.B and the interaction plots in Figure B4.1, EC.B reveal the overall effect of *NewsFormat* = 1 (satirical news) on retweets is always positive, despite being moderated by *Controls*.

Figure B4.1: Study 1 – The Effect of *NewsFormat* on $\log(\text{Retweets})$ is moderated by *Controls* but is always positive

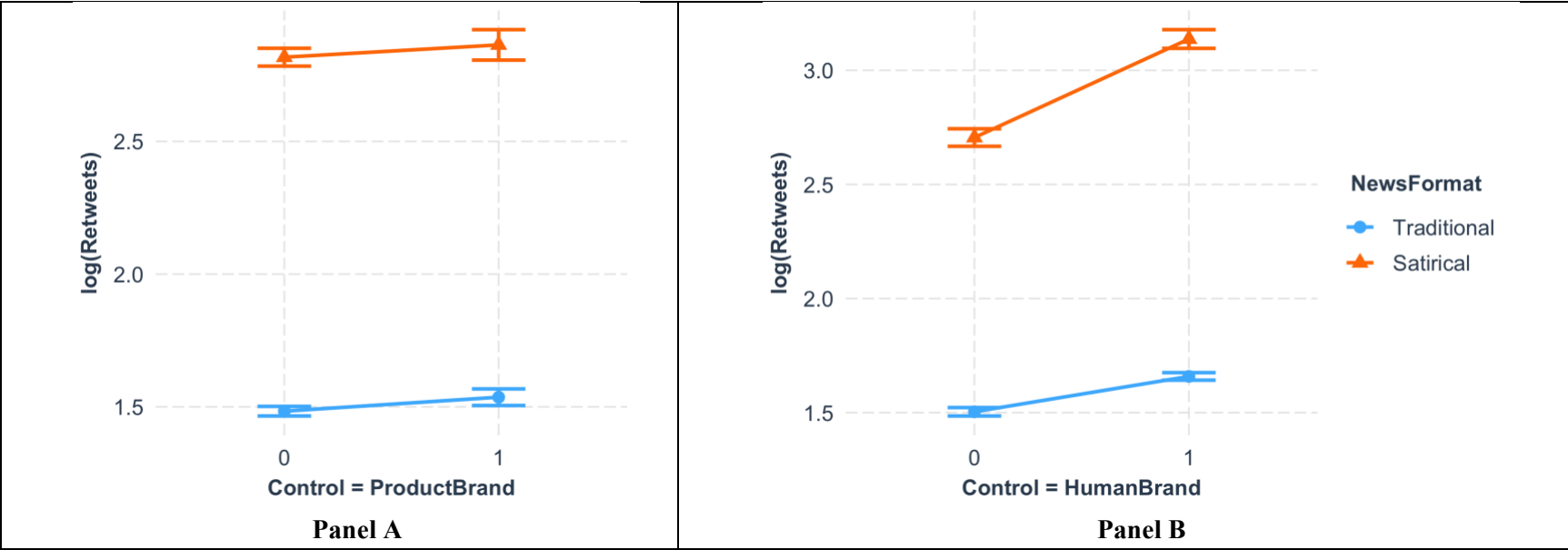
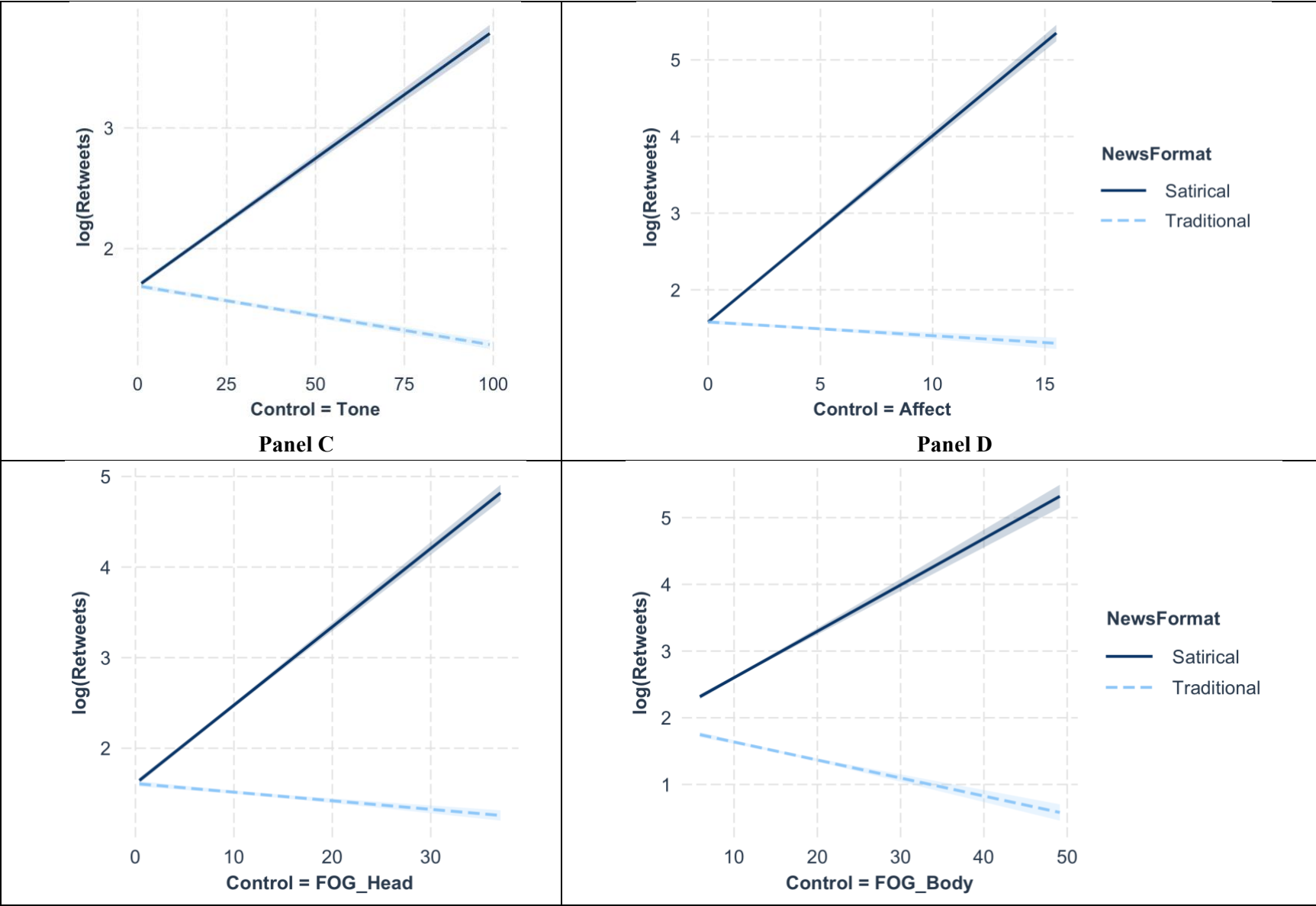
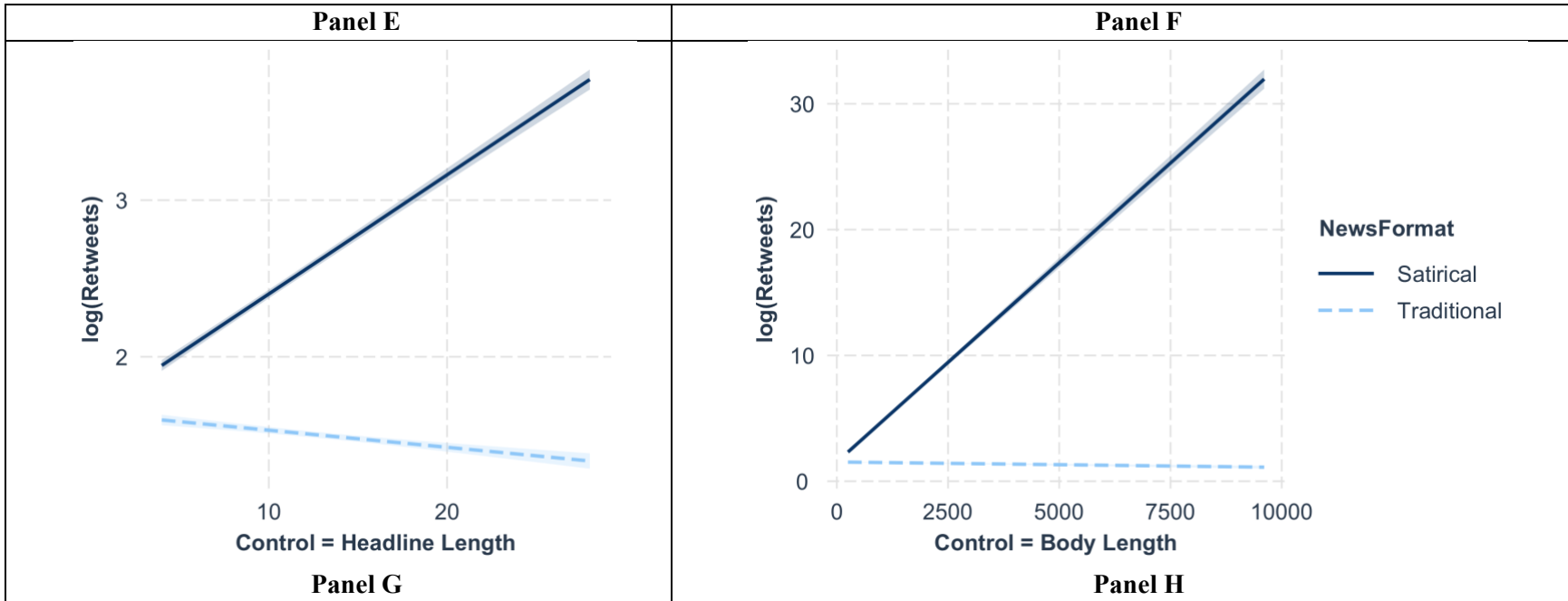


Figure B4.1 (continued): Study 1 – The Effect of *NewsFormat* on $\log(\text{Retweets})$ is moderated by *Controls* but is always positive





In Panels C through F above, for traditional news (the dotted line), $NewsFormat = 0$ in the interaction term $NewsFormat \times Control$ variable. So, we need to interpret the main effects of the control variables on $\log(Retweets)$ when the news format is traditional news. As shown in Table B4.1, all the main effects of control variables are significant (for traditional news), suggesting how the retweets decrease with an increase in the value of the control variable, despite the slope of the control variable looking relatively flat in some figures.

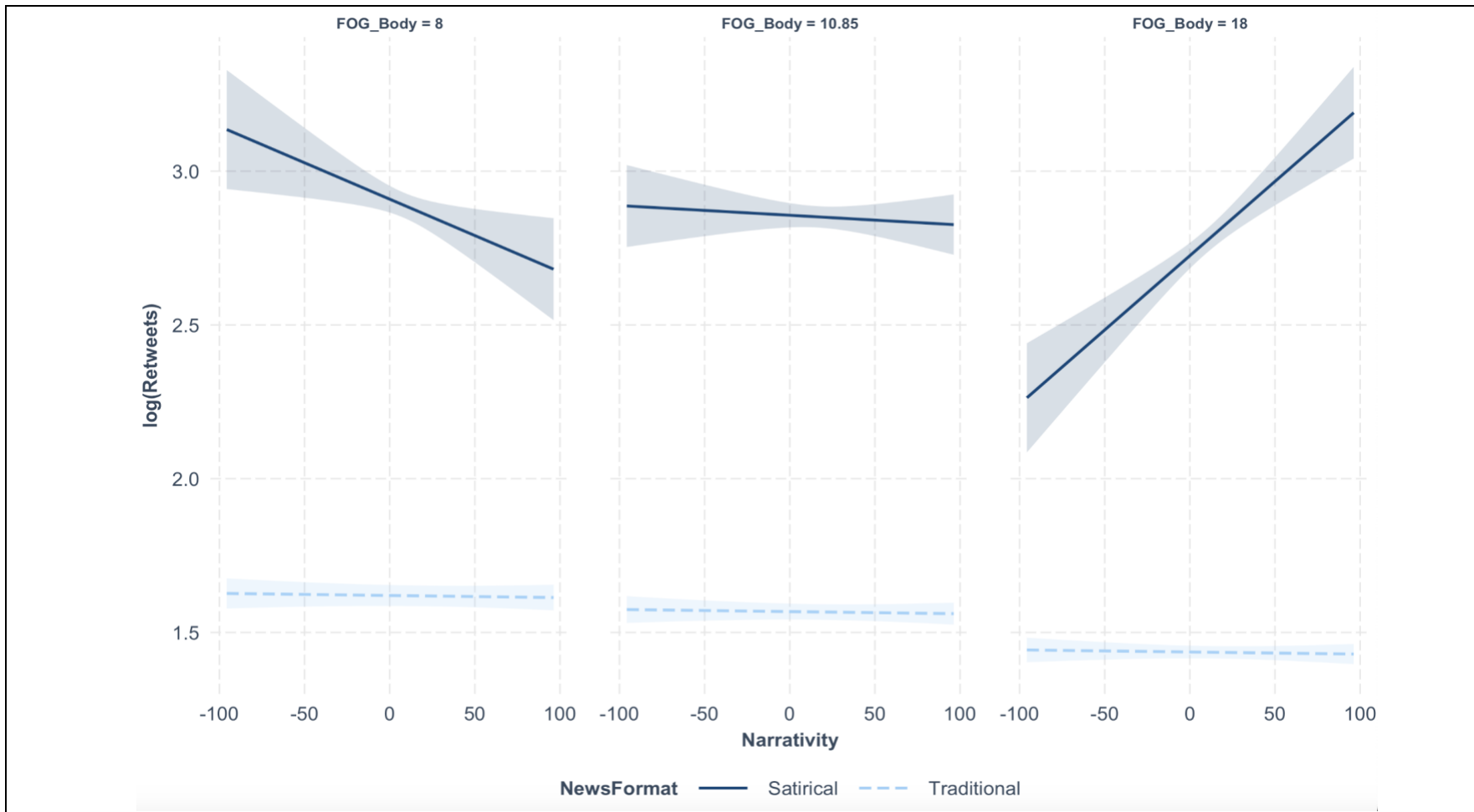
Table B4.2: Study 1 Model 2a – Effect of Interactions of *NewsFormat* X *Narrativity* with *Controls* on $\log(\text{Retweets})$

	(1) Control: <i>ProductBrand</i>	(2) Control: <i>HumanBrand</i>	(3) Control: <i>Tone</i>	(4) Control: <i>Affect</i>	(5) Control: <i>FOG Head</i>	(6) Control: <i>FOG Body</i>	(7) Control: <i>Headline Length</i>	(8) Control: <i>Body Length</i>
<i>NewsFormat</i>	1.296*** (0.0517)	1.294*** (0.0517)	1.296*** (0.0517)	1.296*** (0.0517)	1.296*** (0.0517)	1.293*** (0.0512)	1.294*** (0.0518)	1.296*** (0.0518)
<i>Narrativity</i>	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
<i>Sequence</i>	0.0235* (0.0121)	0.0233* (0.0121)	0.0234* (0.0121)	0.0235* (0.0121)	0.0235* (0.0121)	0.0231* (0.0121)	0.0236* (0.0120)	0.0234* (0.0122)
<i>NewsFormat X Narrativity</i>	0.0010* (0.0005)	-0.0007 (0.0007)	0.0017* (0.0009)	0.0022* (0.0012)	0.0019 (0.0013)	-0.0076*** (0.0026)	0.0066*** (0.0023)	0.0105*** (0.0019)
<i>NewsFormat X Narrativity X Control</i>	0.0003 (0.0010)	0.0041*** (0.0010)	-1.76e-5 (2.03e-5)	-0.0002 (0.0002)	-6.98e-5 (0.0001)	0.0007*** (0.0002)	-0.0004** (0.0002)	-2.51e-5*** (5.21e-6)
<i>ProductBrand</i>	0.0163 (0.0290)	0.0178 (0.0267)	0.0175 (0.0266)	0.0178 (0.0267)	0.0175 (0.0266)	0.0172 (0.0267)	0.0176 (0.0267)	0.0170 (0.0268)
<i>HumanBrand</i>	0.1591*** (0.0149)	0.1466*** (0.0152)	0.1590*** (0.0149)	0.1592*** (0.0149)	0.1591*** (0.0149)	0.1586*** (0.0148)	0.1587*** (0.0149)	0.1581*** (0.0149)
<i>Tone</i>	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0015*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)
<i>Affect</i>	-0.0003 (0.0047)	-0.0005 (0.0047)	-0.0002 (0.0047)	0.0006 (0.0047)	-0.0003 (0.0047)	-0.0008 (0.0047)	-0.0005 (0.0047)	-0.0006 (0.0047)
<i>FOG_Head</i>	0.0042*** (0.0013)	0.0043*** (0.0013)	0.0042*** (0.0013)	0.0042*** (0.0013)	0.0043*** (0.0013)	0.0042*** (0.0013)	0.0042*** (0.0013)	0.0044*** (0.0013)
<i>FOG_Body</i>	-0.0078*** (0.0024)	-0.0080*** (0.0024)	-0.0078*** (0.0024)	-0.0077*** (0.0024)	-0.0078*** (0.0024)	-0.0094*** (0.0026)	-0.0078*** (0.0024)	-0.0078*** (0.0024)
<i>Headline_Length</i>	0.0230*** (0.0033)	0.0229*** (0.0033)	0.0230*** (0.0033)	0.0230*** (0.0033)	0.0230*** (0.0033)	0.0228*** (0.0033)	0.0249*** (0.0037)	0.0236*** (0.0033)
<i>Body_Length</i>	-1.33e-5 (8.79e-6)	-1.26e-5 (8.77e-6)	-1.33e-5 (8.81e-6)	-1.34e-5 (8.79e-6)	-1.33e-5 (8.8e-6)	-1.34e-5 (8.8e-6)	-1.35e-5 (8.77e-6)	-1.21e-5 (8.83e-6)
Fixed-Effects:								
FKID	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Mon	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,083	40,083	40,083	40,083	40,083	40,083	40,083	40,083
R2	0.4312	0.43173	0.43122	0.43122	0.43121	0.43148	0.43142	0.43196
Within R2	0.22709	0.22782	0.22712	0.22712	0.2271	0.22747	0.22739	0.22813
AIC	107,568.00	107,530.10	107,566.60	107,566.40	107,567.50	107,548.40	107,552.60	107,514.30

Note: Robust standard errors are reported in parenthesis, “*” = $p < 0.10$, “**” = $p < 0.05$, “***” = $p < 0.01$.

The significance and coefficient of the *NewsFormat* X *Narrativity* interaction effect on *Retweets* depends on *FOG_Body*, the reading level of the body of the story. As shown in Column 6 of Table B4.2, EC.B, the coefficients of *NewsFormat* X *Narrativity* ($\beta = -0.0076$) and *NewsFormat* X *Narrativity* X *FOG_Body* ($\beta = 0.0007$) are significant, suggesting that *NewsFormat* X *Narrativity* has a negative coefficient when *FOG_Body* < 10.85 ($-0.0076 + 0.0007 \text{ FOG_Body} < 0$ when *FOG_Body* < 10.85) but has a positive coefficient when *FOG_Body* > 10.85.

Figure B4.2: Study 1 Model 2a – The effect of *Narrativity* via *NewsFormat* on $\log(\text{Retweets})$ depends on the reading level (*FOG_Body*)



Note: We plot the interaction of *NewsFormat* X *Narrativity* at different values of *FOG_Body* (the reading level of the story body). A FOG score of less than 14 generally means that the content is easy to read (Wylie 2018), while higher scores suggest that the content is difficult to read. As the plots reveal, for satirical news, the effect of high *Narrativity* (scores > 0) on $\log(\text{Retweets})$ is negative for easy-to-read content (*FOG_body* = 8) and gradually becomes positive as the content becomes more difficult to read (*FOG_Body* = 18).

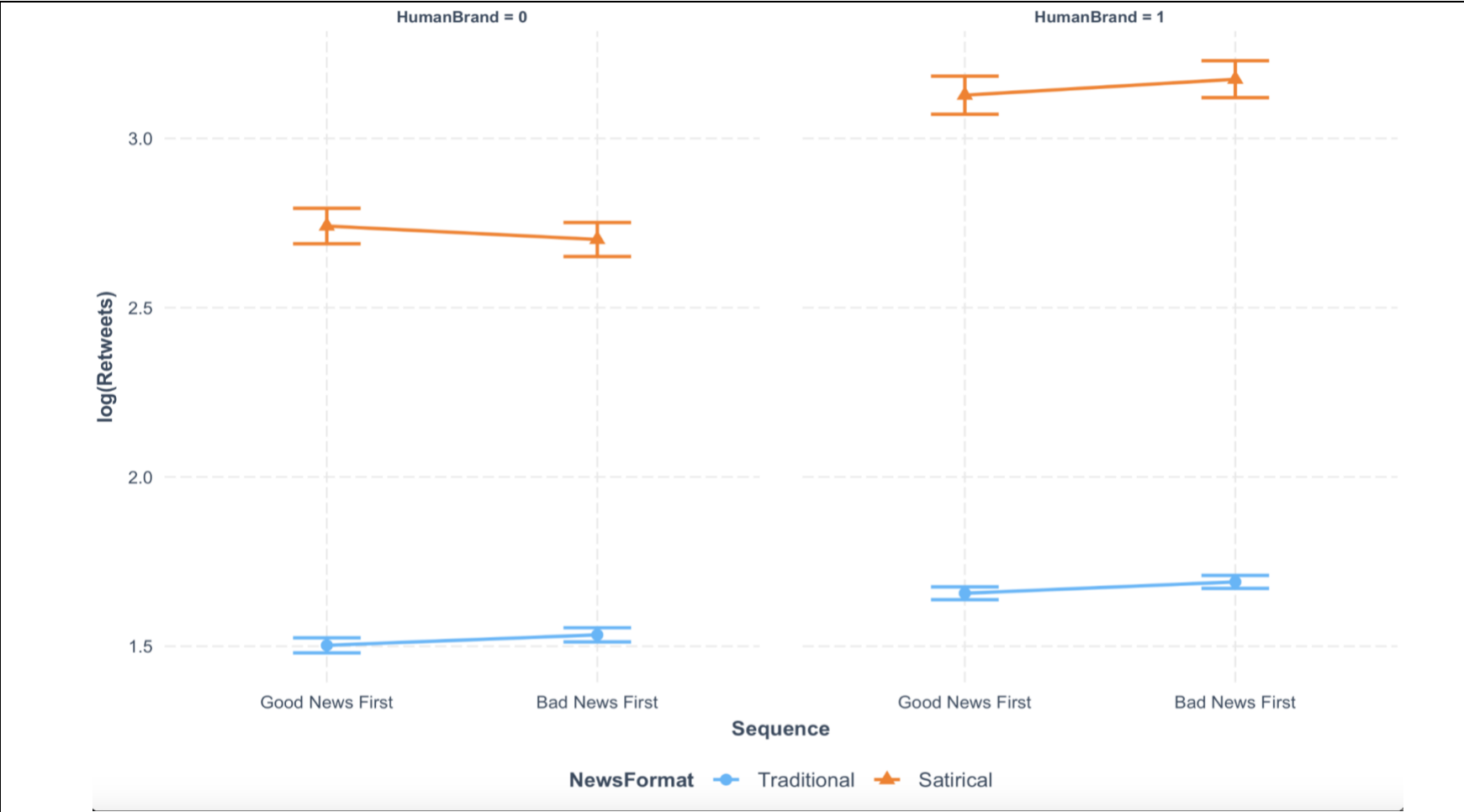
Table B4.3: Study 1 Model 2b – Effect of Interactions of *NewsFormat X Sequence* with *Controls* on $\log(\text{Retweets})$

	(1) Control: <i>ProductBrand</i>	(2) Control: <i>HumanBrand</i>	(3) Control: <i>Tone</i>	(4) Control: <i>Affect</i>	(5) Control: <i>FOG Head</i>	(6) Control: <i>FOG Body</i>	(7) Control: <i>Headline Length</i>	(8) Control: <i>Body Length</i>
<i>NewsFormat</i>	1.332*** (0.0548)	1.330*** (0.0547)	1.332*** (0.0547)	1.333*** (0.0548)	1.332*** (0.0548)	1.327*** (0.0546)	1.331*** (0.0549)	1.332*** (0.0547)
<i>Narrativity</i>	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)	-0.0001 (0.0002)
<i>Sequence</i>	0.0255* (0.0129)	0.0251* (0.0129)	0.0256* (0.0129)	0.0256* (0.0129)	0.0255* (0.0129)	0.0253* (0.0129)	0.0255* (0.0129)	0.0255* (0.0129)
<i>NewsFormat X Sequence</i>	-0.0216 (0.0432)	-0.1368*** (0.0438)	-0.0073 (0.0559)	-0.0925 (0.0729)	0.0123 (0.0834)	-0.7177*** (0.1576)	0.0656 (0.1295)	0.5897*** (0.1232)
<i>NewsFormat X Sequence X Control</i>	0.0174 (0.0627)	0.2643*** (0.0495)	-0.0003 (0.0012)	0.0166 (0.0127)	-0.0024 (0.0056)	0.0521*** (0.0112)	-0.0056 (0.0082)	-0.0016*** (0.0003)
<i>ProductBrand</i>	0.0160 (0.0289)	0.0192 (0.0266)	0.0177 (0.0266)	0.0173 (0.0266)	0.0176 (0.0266)	0.0168 (0.0268)	0.0175 (0.0267)	0.0172 (0.0268)
<i>HumanBrand</i>	0.1591*** (0.0150)	0.1435*** (0.0157)	0.1591*** (0.0150)	0.1591*** (0.0150)	0.1592*** (0.0150)	0.1577*** (0.0149)	0.1591*** (0.0149)	0.1581*** (0.0150)
<i>Tone</i>	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)	-0.0016*** (0.0004)
<i>Affect</i>	-0.0003 (0.0047)	-0.0004 (0.0047)	-0.0003 (0.0047)	-0.0014 (0.0048)	-0.0003 (0.0047)	-0.0008 (0.0047)	-0.0003 (0.0047)	-0.0006 (0.0047)
<i>FOG Head</i>	0.0042*** (0.0013)	0.0042*** (0.0013)	0.0042*** (0.0013)	0.0042*** (0.0013)	0.0043*** (0.0013)	0.0041*** (0.0013)	0.0042*** (0.0013)	0.0045*** (0.0013)
<i>FOG Body</i>	-0.0077*** (0.0024)	-0.0081*** (0.0024)	-0.0077*** (0.0024)	-0.0079*** (0.0024)	-0.0077*** (0.0024)	-0.0103*** (0.0026)	-0.0077*** (0.0024)	-0.0077*** (0.0024)
<i>Headline Length</i>	0.0231*** (0.0033)	0.0229*** (0.0033)	0.0231*** (0.0033)	0.0231*** (0.0033)	0.0231*** (0.0033)	0.0227*** (0.0033)	0.0237*** (0.0036)	0.0235*** (0.0033)
<i>Body Length</i>	-1.32e-5 (8.78e-6)	-1.23e-5 (8.82e-6)	-1.31e-5 (8.8e-6)	-1.3e-5 (8.77e-6)	-1.31e-5 (8.79e-6)	-1.32e-5 (8.82e-6)	-1.32e-5 (8.79e-6)	-1.12e-5 (8.75e-6)
Fixed-Effects:								
FKID	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Mon	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,083	40,083	40,083	40,083	40,083	40,083	40,083	40,083
R2	0.43113	0.43185	0.43113	0.43116	0.43113	0.43173	0.43114	0.43225
Within R2	0.22699	0.22798	0.22699	0.22704	0.227	0.22782	0.22701	0.22851
AIC	107,573.00	107,521.80	107,573.00	107,570.80	107,572.90	107,530.30	107,572.00	107,494.10

Note: Robust standard errors are reported in parenthesis, “*” = $p < 0.10$, “**” = $p < 0.05$, “***” = $p < 0.01$.

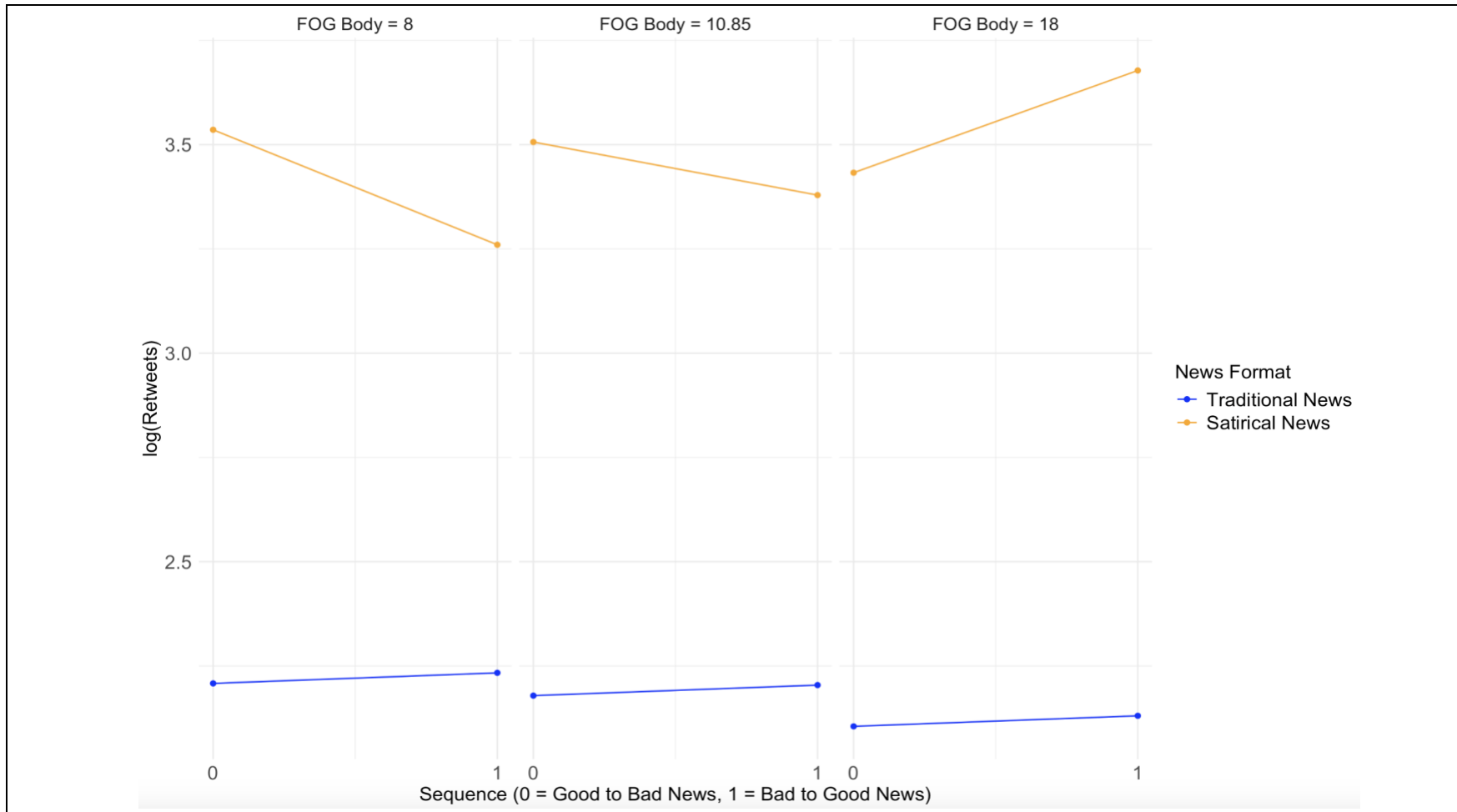
As shown in Column 2 of Table B4.3, EC.B, the coefficients of *NewsFormat X Sequence* ($\beta = -0.1368$) and *NewsFormat X Sequence X HumanBrand* ($\beta = 0.2463$) are significant, suggesting that when a human brand is mentioned (i.e., *HumanBrand* = 1), the coefficient of *NewsFormat X Sequence* is positive ($-0.1368 + .2463 = 0.1095$); however, when a human brand is not mentioned, the coefficient is negative ($= -0.1368$). Further, as shown in Column 6 of Table B4.3, EC.B the coefficients of *NewsFormat X Sequence* ($\beta = -0.7177$) and *NewsFormat X Sequence X FOG Body* ($\beta = 0.0521$) are significant, suggesting that the coefficient of *NewsFormat X Sequence* is positive when *FOG Body* > 14.35 ($-0.7177 + 0.0521 \text{ FOG Body} > 0$ when *FOG Body* > $0.7177/0.0521$) but is negative when *FOG Body* < 14.35

Figure B4.3a: Study 1 Model 2b – The Effect of *Sequence* on $\log(\text{Retweets})$ varies across *NewsFormat* and is moderated by *HumanBrand*



Note: We plot the effect of *Sequence* on $\log(\text{Retweets})$ for each *NewsFormat* at different levels of *HumanBrand*. The plots suggest that when satirical news mentions a human brand (*HumanBrand* = 1), revealing the bad news first increases retweets relative to revealing the good news first; however, if a human brand is not mentioned, revealing the good news first is better for garnering retweets.

Figure B4.3b: Study 1 Model 2b – The Effect of *Sequence* on $\log(\text{Retweets})$ varies across *NewsFormat* and is moderated by the reading level (*FOG_Body*)



Note: We plot the effect of *Sequence* on $\log(\text{Retweets})$ for each *NewsFormat* at different levels of *FOG_body*. The plots suggest that when satirical news is easy to read (e.g., when *FOG_Body* = 8), *Sequence* = 1 (Bad to Good news) can hurt engagement. In contrast, when satirical news has difficult reading levels (e.g., when *FOG_Body* = 18), *Sequence* = 1 can help engagement.

EC.B5. Study 1 - Robustness Tests

The results of Study 1 answer our research questions on the moderating effects of narrativity and emotional sequence (RQ1). In this section, we address several issues that could potentially impact our results.

We first check for multicollinearity in Section B5.1. Next, we address a potential endogeneity concern that publishers *self-select* to develop satirical or traditional versions of a news event (and similarly self-select into adopting a storytelling style). In other words, the decision regarding the news format and storytelling may not be random: The news events that get covered in satirical news formats or linear narrativity or a certain emotional sequence may be systematically different from the events covered in traditional news and other storytelling styles. If the selection process is observable, we resort to the coarsened exact matching approach in Section B5.2 (To address the unobservable selection process, we investigate the effects of decisions regarding news format, narrativity, and sequence in a controlled lab setting in Studies 2 and 3 in Sections 5 and 6, respectively). In Section B5.3, we acknowledge that retweet data tends to contain excessive zero counts and address the issue of overdispersion, utilizing alternate model specifications such as negative binomial and Poisson.

B5.1 Multicollinearity

We test our models for multicollinearity with the variance inflation factor (VIF) approach. Most prior studies rely on informal rules of thumb applied to the VIF (Burtch et al. 2013, Petryk et al. 2022). If the values of VIF are greater than 10, then it signals that the data have collinearity problems (Chatterjee and Hadi 2012; p. 250). Results in Table B5.1 (EC.B) demonstrate that the VIF associated with each variable is well below the accepted conventional threshold ($VIF < 10$), indicating that multicollinearity is not an issue in our model and does not significantly impact our findings.

Table B5.1: Study 1 – VIF Coefficients

	Model 1 (1)	Model 2a (2)	Model 2b (3)	Joint Model (4)
<i>NewsFormat</i>	1.163	1.869	2.246	2.921
<i>Narrativity</i>	1.023	1.154	1.023	1.154
<i>Sequence</i>	1.014	1.014	1.160	1.160
<i>ProductBrand</i>	1.020	1.020	1.020	1.020
<i>HumanBrand</i>	1.028	1.028	1.028	1.028
<i>Tone</i>	1.050	1.050	1.051	1.051
<i>Affect</i>	1.076	1.076	1.076	1.076
<i>FOG_Head</i>	1.041	1.041	1.041	1.041
<i>FOG_Body</i>	1.138	1.138	1.138	1.138
<i>Headline_Length</i>	1.025	1.025	1.025	1.025
<i>Body_Length</i>	1.044	1.045	1.044	1.045

Note: VIF associated with each variable is well below the accepted conventional threshold ($VIF < 10$) (Chatterjee and Hadi 2012; p. 250).

B5.2 Matching

This section addresses the possibility that some observable background variables could drive the decision to write satirical news. For instance, editors may require news writers to develop a story following a specific narrativity style, tone, and word complexity. These restrictions could influence the decision to develop satirical stories about a news event. To mitigate hidden selection bias, we aim to create a “proper” control group (traditional news) for treated news stories (satirical news) by using a matching procedure (e.g., Goh et al. 2013). When control and treated groups are similar, we can attribute any differences in outcomes within these pairs to the treatment rather than background covariates. Further, matching reduces the dependence of the effect estimate on the correct specification of the outcome model (Ho et al. 2011).

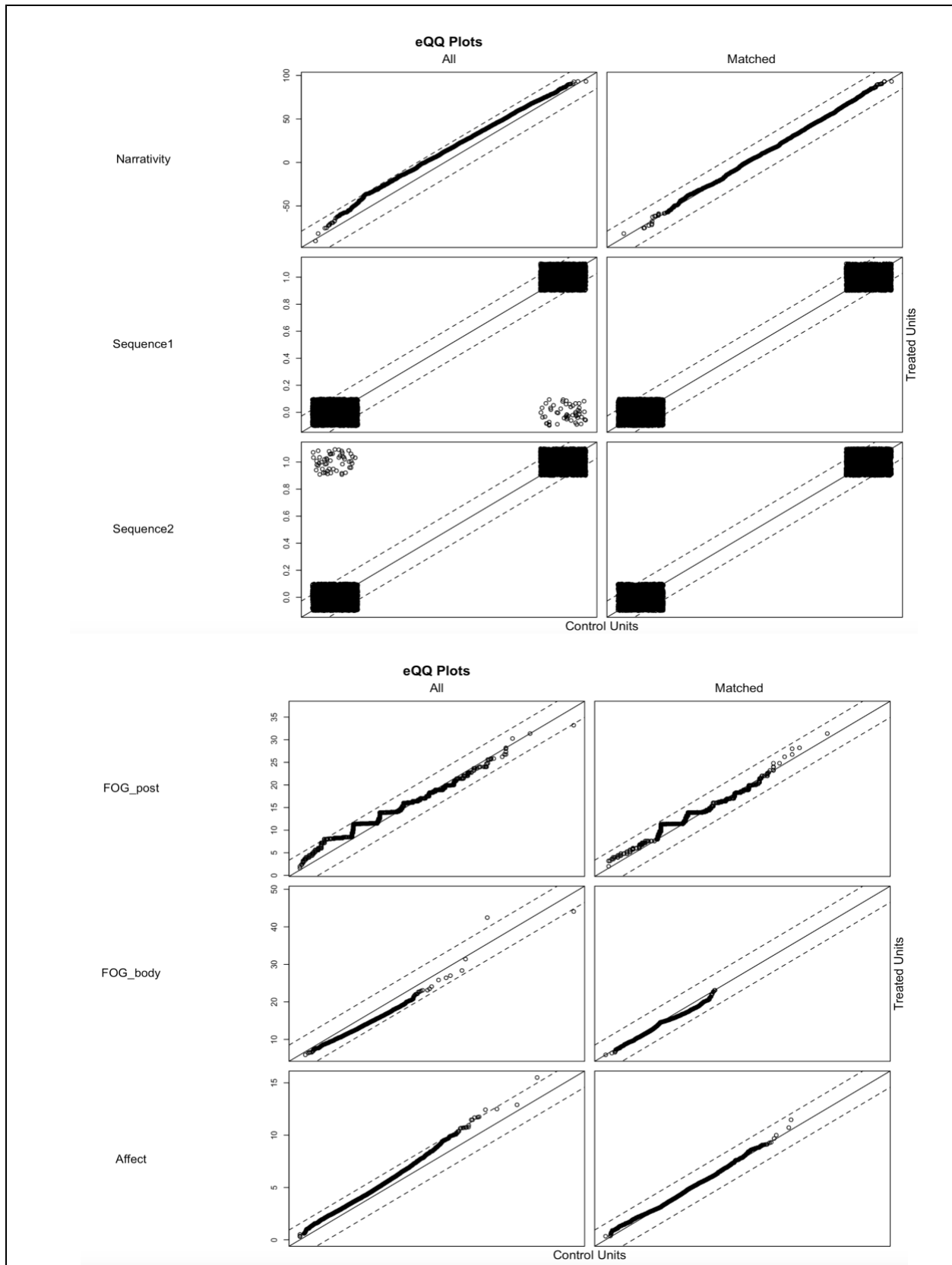
Following the literature (Nian et al. 2021), we perform coarsened exact matching (CEM) in R (Ho et al. 2011). We define treatment as the development of a satirical news story. There are 35,019 control units and 5,064 treatment units before matching. We aim to match control and treatment units that are similar in terms of the following observable background covariates: (1) *Narrativity*, (2) *Sequence*, (3) reading level of the body (*FOG_Body*), (4) reading level of the headline (*FOG_Headline*), (5) *Affect*, (6) *Tone*, (7) the relative length of headline (*WC_head_scaled*), (8) the relative length of body (*WC_body_scaled*), (9) whether brands are mentioned in the headlines (*ProductBrand* and *HumanBrand*), and (10) the relative appeal of the traditional news that preceded the satirical news (*Like_scaled*). An exact matching algorithm on coarsened covariate data determines matches and prunes unmatched units. We coarsen each covariate by recoding them into bins so that substantively indistinguishable values are grouped and assigned the same numerical value. Specifically, we recode *Tone*, *Affect*, *Like_scaled*, and *Narrativity* into five bins each, *FOG_Head* and *FOG_Body* into 2 bins each, and *WC_head_scaled* and *WC_body_scaled* into 3 bins each. *ProductBrand*, *HumanBrand*, and *Sequence*, being binary variables, are used as originally coded (i.e., not coarsened). We use a complete cross of the coarsened covariates to form subclasses defined by each combination of the coarsened covariate levels. We discard any subclass that does not contain treated and control units, leaving only subclasses containing treatment and control units that are equal on the coarsened covariates. Each subclass is assigned a weight calculated based on the proportion of treated units. After matching, we discard the coarsened data and retain the original (uncoarsened) values of the matched data (Iacus et al. 2012). This way, we match 31,334 control and 4,834 treated units; 3,685 control units and 230 treatment units are left unmatched. To assess the matching quality, we report the variance ratios in Table B5.2a and empirical quantile-quantile plots in Figure B5.2. Our variance ratios after matching are in the acceptable range of .92 and 1.08 (Austin 2009), suggesting that matching was successful. Figure B5.2 shows the decrease in imbalance after matching.

Next, we re-estimate our log-linear fixed effects models (Models 1, 2a, and 2b) using the sample weights created by CEM to estimate the marginal effect of news format, narrativity, and emotional sequence on retweets. Results with robust errors presented in Table B5.2b show that the effects of brand mentions are generally consistent with our fixed effects models reported in Section 5.

Table B5.2a: Study 1 – Assessment of Coarsened Exact Matching

Summary of Balance for All Data:							
	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max	
<i>Narrativity</i>	26.3904	15.175	0.3757	0.8821	0.0876	0.1463	
<i>Sequence=0</i>	0.4812	0.4916	-0.0208	.	0.0104	0.0104	
<i>Sequence=1</i>	0.5188	0.5084	0.0208	.	0.0104	0.0104	
<i>FOG_Head</i>	12.5813	11.4588	0.2902	0.674	0.0565	0.1888	
<i>FOG_Body</i>	13.4184	15.5793	-0.9194	0.7731	0.2379	0.3723	
<i>Affect</i>	4.4421	3.8069	0.374	1.0905	0.0643	0.1471	
<i>Tone</i>	34.6339	29.8589	0.2111	1.0212	0.0578	0.1057	
<i>Body_length_scaled</i>	0	0	0	1	0.0612	0.261	
<i>Head_length_scaled</i>	0	0	0	1	0.0207	0.1128	
<i>Prod.dummy</i>	0.2218	0.1234	0.2369	.	0.0984	0.0984	
<i>Hum dummy</i>	0.4581	0.5578	-0.2001	.	0.0997	0.0997	
<i>Like_scaled</i>	0	0	0	1	0.0455	0.4552	
Summary of Balance for Matched Data:							
	Means Treated	Means Control	Std. Mean Diff.	Var. Ratio	eCDF Mean	eCDF Max	Std. Pair Dist.
<i>Narrativity</i>	26.3052	25.0095	0.0434	0.99	0.01	0.0247	0.4072
<i>Sequence=0</i>	0.4797	0.4797	0	.	0	0	0
<i>Sequence=1</i>	0.5203	0.5203	0	.	0	0	0
<i>FOG_Head</i>	12.4745	11.293	0.3055	0.6914	0.0567	0.1926	1.0734
<i>FOG_Body</i>	13.4051	15.3081	-0.8097	0.7107	0.2107	0.3308	1.3566
<i>Affect</i>	4.3571	4.2151	0.0836	0.9492	0.0145	0.0414	0.525
<i>Tone</i>	34.2428	33.5602	0.0302	0.9019	0.0152	0.0555	0.2923
<i>Body_length_scaled</i>	-0.0482	-0.0776	0.0294	1.914	0.0637	0.2644	0.7117
<i>Head_length_scaled</i>	0.0168	-0.0473	0.0641	1.0601	0.0217	0.1165	0.7103
<i>Prod.dummy</i>	0.2089	0.2089	0	.	0	0	0
<i>Hum dummy</i>	0.4582	0.4582	0	.	0	0	0
<i>Like_scaled</i>	-0.0032	-0.0046	0.0014	1.8675	0.0439	0.4516	0.6831
Sample Sizes							
	Control	Treated					
All	35019	5064					
Matched (ESS)	15685.64	4834					
Matched	31334	4834					
Unmatched	3685	230					
Discarded	0	0					

Figure B5.2: Study 1 – eQQ Plots



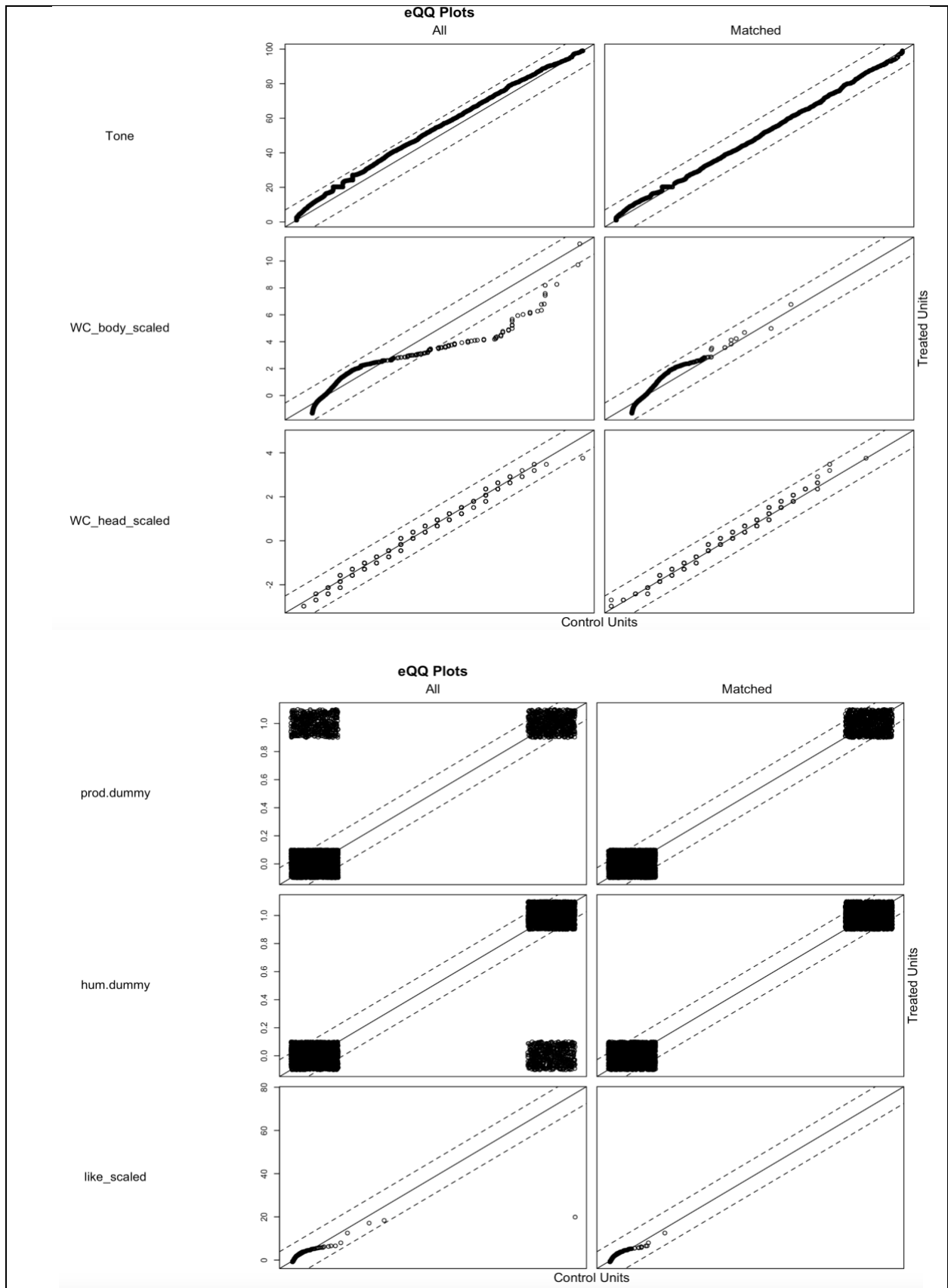


Table B5.2b: Study 1 – Estimation of OLS Fixed Effects After Coarsened Exact Matching

	Model 1 (1)	Model 2a (2)	Model 2b (3)
<i>NewsFormat</i>	1.357*** (0.0164)	1.327*** (0.0217)	1.377*** (0.0234)
<i>Narrativity</i>	-0.0002 (0.0002)	-0.0003 (0.0002)	-0.0002 (0.0002)
<i>Sequence</i>	0.0333*** (0.0117)	0.0334*** (0.0117)	0.0383*** (0.0126)
<i>NewsFormat X Narrativity</i>		0.0011** (0.0006)	
<i>NewsFormat X Sequence</i>			-0.0380 (0.0326)
Controls	Yes	Yes	Yes
Fixed Effects for <i>FKID</i> and <i>Year_Mon</i>	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes
Observations	36,168	36,168	36,168
R ²	0.50511	0.50519	0.50513
Within R ²	0.25508	0.25521	0.25512

Notes: * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$. Robust standard errors in parentheses. The results after utilizing coarsened exact matching are similar in direction and significance to those reported in Table 2 of Study 1.

B5.3 Poisson and Negative Binomial

We use a Poisson model in this subsection to estimate our count data model. Further, we use the likelihood ratio test to verify if the data are overdispersed and find evidence to confirm. Additionally, we acknowledge that in the presence of overdispersed data, the negative binomial model may be an appropriate estimator (Wooldridge 2010). Hence, we also present the results of the negative binomial model. We also show robust standard errors for Poisson and negative binomial models and account for fixed effects of *FKID* and *Year_Mon*. The estimation results reported in Table B5.3 indicate that the direction and statistical significance of the main and interaction effects are qualitatively similar to our main results.

Table B5.3: Study 1 – Negative Binomial and Poisson Fixed Effects Estimation

	Negative Binomial			Poisson		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>NewsFormat</i>	1.499*** (0.0178)	1.465*** (0.0229)	1.503*** (0.0249)	1.152*** (0.0342)	1.097*** (0.0421)	1.178*** (0.0498)
<i>Narrativity</i>	-0.0005** (0.0002)	-0.0006*** (0.0002)	-0.0005** (0.0002)	-0.0008 (0.0004)	-0.0013*** (0.0005)	-0.0008* (0.0004)
<i>Sequence</i>	0.0270** (0.0119)	0.0272** (0.0119)	0.0280** (0.0127)	0.0185 (0.0258)	0.0187 (0.0257)	0.0308 (0.0288)
<i>NewsFormat X Narrativity</i>		0.0014** (0.0006)			0.0023** (0.0010)	
<i>NewsFormat X Sequence</i>			-0.0073 (0.0338)			-0.0498 (0.0581)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects of <i>FKID</i> & <i>Year_Mon</i>	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,068	40,068	40,068	40,068	40,068	40,068
AIC	252,827.3	252,823.8	252,829.2			
BIC				595,099	594,838.9	595,074.1

Note: * = $p < 0.10$, ** = $p < 0.05$, *** = $p < 0.01$, **** = $p < .001$. Standard errors in parentheses. As shown in the panels for our Negative Binomial and Poisson models, the direction and significance of the effects of *NewsFormat*, *Narrativity*, and *Sequence* are similar to those reported in Table 2 of Study 1.

EC.C. Details on Study 2 – Differential Effects of *Narrativity* on Engagement

Table C1a: Study 2 – Summary Statistics

Ind Vars		Mediator (M)	Dep Vars (Y)		Descriptors of Stimuli Computed by Text Analysis						
<i>News Format (X)</i>	<i>Narrativity (W)</i>	<i>Interestingness</i>	<i>Share (%Yes)</i>	<i>TellOthers (%Yes)</i>	<i>Affect</i>	<i>Tone</i>	<i>FOG _Head</i>	<i>FOG _Body</i>	<i>Length _Head</i>	<i>Length _Body</i>	<i>Narrativity</i>
Trad	High	4.80	31.4%	58.8%	5.42	91.35	11.33	18.14	15	317	26.75
Trad	Low	4.22	18.0%	54.0%	1.55	43.23	11.33	22.77	15	179	-1.99
Sat	High	4.57	12.4%	51.5%	5.73	94.79	12.00	10.56	20	294	21.96
Sat	Low	4.85	17.5%	54.4%	3.75	72.45	12.00	15.54	20	220	-1.63
		Mean: 4.55 SD: 1.57									

Notes:

Share is a measure of the intention to share online (Yes/No) while *TellOthers* is a measure of the intention to discuss offline with others (Yes/No).

An analysis of narrativity using LIWC-22 reveals the following scores for the stimuli utilized: Traditional News High Narrativity = 26.75, Traditional News Low Narrativity = -1.99, Satirical News High Narrativity = 21.96, Satirical News Low Narrativity = -1.63.

Table C1b: Study 2 – Comparability Checks

	<i>NewsFormat:</i>	Satirical	Satirical	Traditional	Traditional
	<i>Narrativity:</i>	High	Low	High	Low
Age	18-24 Yrs	11	8	19	13
Age	25-34 Yrs	31	32	35	35
Age	35-44 Yrs	24	27	28	21
Age	45-54 Yrs	21	25	8	16
Age	55-64 Yrs	6	8	7	11
Age	65+ Yrs	4	3	5	4
Sample Size		97	103	102	100
Gender	Male	31	35	44	38
Gender	Female	63	65	52	59
Gender	Non-binary	3	3	3	0
Gender	Self-describe	0	0	1	0
Sample Size		97	103	102	100

Notes:

Age Distribution: $\chi^2(15) = 17.70, p = 0.2785$. The age group distributions are not significantly different across the conditions.
 Gender Distribution: $\chi^2(9) = 9.86, p = 0.3619$. The gender distributions are not significantly different across the conditions.

EC.C1. *NewsFormat* Manipulation Checks

We ran several tests to check whether our manipulation of *NewsFormat* was successful. Specifically, we checked whether our manipulation of *NewsFormat* affected participants’ perceptions of (1) whether the news story was trying to be funny, (2) whether the claims made in the news story were accurate, and (3) whether the story contained satirical content. We expected that successful manipulation of *NewsFormat* would result in the satirical news story being perceived as funnier, less accurate, and containing more satirical content than the traditional news story. We present the results of our manipulation checks in the following subsections, which support our successful news format manipulation.

CI.1. Funny

A one-way ANOVA on participants' ratings of how much the news story was trying to be funny revealed a significant effect of news format ($F(1, 400) = 468.06, p < .001, \eta_p^2 = .54$) such that the satirical news story ($M_{Satirical} = 4.75, CI_{Satirical} = [4.57, 4.93]$) was perceived to be more funny than the traditional news ($M_{Traditional} = 2.00, CI_{Traditional} = [1.82, 2.18]$).

CI.2. Information Accuracy

A one-way ANOVA on participants' ratings of the accuracy of the claims in the news story revealed a significant effect of news format ($F(1, 400) = 3.70, p = .055, \eta_p^2 = .01$) such that the claims in the satirical news story ($M_{Satirical} = 4.16, CI_{Satirical} = [3.99, 4.33]$) were perceived to be less accurate than the claims in the traditional news ($M_{Traditional} = 4.39, CI_{Traditional} = [4.22, 4.56]$).

CI.3. Satirical Content

A one-way ANOVA on participants' ratings of how much satire was contained in the news story revealed a significant effect of news format ($F(1, 400) = 135.99, p < .001, \eta_p^2 = .25$) such that the satirical news story ($M_{Satirical} = 3.89, CI_{Satirical} = [3.70, 4.08]$) was perceived to contain more satire than the traditional news ($M_{Traditional} = 2.27, CI_{Traditional} = [2.08, 2.47]$), suggesting that participants could distinguish between them.

EC.C2. Narrativity Manipulation Checks

An analysis of narrativity using LIWC-22 reveals the following scores for the stimuli utilized: Traditional News $_{High\ Narrativity} = 26.75$, Traditional News $_{Low\ Narrativity} = -1.99$, Satirical News $_{High\ Narrativity} = 21.96$, Satirical News $_{Low\ Narrativity} = -1.63$. Since we term positive values of narrativity as High Narrativity and negative values as Low Narrativity, these scores affirm that the stimuli were aligned with our expectations. Nonetheless, to ascertain the manipulation of narrativity in the experiment, we conducted ANOVAs of two measures: *Perceived_Straightforward* and *Perceived_Storytelling*. *Perceived_Straightforward* measured the extent to which participants perceived the content to be written in a straightforward manner (i.e., low narrativity), while *Perceived_Storytelling* measured the extent to which participants perceived the content to be written in a storytelling manner (i.e., high narrativity). A one-way ANOVA of *Perceived_Straightforward* revealed significant effects of *Narrativity* ($F(1, 400) = 30.405, p < .05, \eta_p^2 = .71$) such that low narrativity style was found to be written more straightforwardly than high narrativity ($M_{Low\ Narrativity} = 5.02, CI_{Low\ Narrativity} = [4.81, 5.22]$; $M_{High\ Narrativity} = 4.20, CI_{High\ Narrativity} = [3.99, 4.40]$). Further, a one-way ANOVA of *Perceived_Storytelling* revealed significant effects of *Narrativity* ($F(1, 400) = 102.17, p < .05, \eta_p^2 = .20$) such that low narrativity was perceived to contain lesser storytelling than high narrativity ($M_{Nonfiction} = 4.03, CI_{Nonfiction} = [3.83, 4.23]$; $M_{Fiction} = 5.50, CI_{Fiction} = [5.30, 5.71]$). These results strongly suggest that our manipulation of narrativity was successful; participants perceived high narrativity as written less straightforwardly and with more storytelling than low narrativity.

Table C2: Study 2 – Narrativity Moderated Mediation Results with Self-Brand Connection as Control

DV = <i>Interestingness</i>		β	SE	t	p	LLCI	ULCI
<i>Panel 1</i>	constant	2.4329	0.1901	12.7989	0	2.0592	2.8066
	<i>NewsFormat</i> (X)	0.7658	0.1869	4.098	0.0001	0.3984	1.1332
	<i>Narrativity</i> (W)	0.612	0.1879	3.2575	0.0012	0.2426	0.9813
	<i>NewsFormat</i> X <i>Narrativity</i>	-0.8165	0.2659	-3.0714	0.0023	-1.3392	-0.2939
	<i>SBC</i>	0.497	0.0425	11.6964	0	0.4135	0.5806
DV = <i>Sharing</i>		coeff	SE	Z	p	LLCI	ULCI
<i>Panel 2</i>	constant	-7.2873	0.8924	-8.166	0	-9.0364	-5.5383
	<i>NewsFormat</i> (X)	-0.7788	0.2971	-2.6217	0.0087	-1.3611	-0.1966
	<i>Interestingness</i> (M)	1.0251	0.1661	6.1718	0	0.6995	1.3506
	<i>SBC</i>	0.2621	0.1069	2.4513	0.0142	0.0525	0.4716
	Direct effect of <i>NewsFormat</i> on <i>Sharing</i>	Effect	SE	Z	p	LLCI	ULCI
		-0.7788	0.2971	-2.6217	0.0087	-1.3611	-0.1966
	Index of Moderated Mediation <i>Narrativity</i> (W)	Index	BootSE			BootLLCI	BootULCI
	-0.837	0.3319			-1.5654	-0.2747	
DV = <i>TellOthers</i>		coeff	SE	Z	p	LLCI	ULCI
<i>Panel 3</i>	constant	-6.7907	0.7541	-9.0052	0	-8.2687	-5.3127
	<i>NewsFormat</i> (X)	-0.5856	0.2803	-2.089	0.0367	-1.1349	-0.0362
	<i>Interestingness</i> (M)	1.3304	0.1547	8.6016	0	1.0273	1.6336
	<i>SBC</i>	0.3693	0.103	3.5865	0.0003	0.1675	0.5712
	Direct effect of <i>NewsFormat</i> on <i>TellOthers</i>	Effect	SE	Z	p	LLCI	ULCI
		-0.5856	0.2803	-2.089	0.0367	-1.1349	-0.0362
Index of Moderated Mediation <i>Narrativity</i> (W)	Index	BootSE			BootLLCI	BootULCI	
	-1.0863	0.378			-1.874	-0.3872	

Notes: Where indicated in parentheses, X = Independent variable, W = Moderator, M = Mediator, DV = Dependent variable. Boot = Bootstrapped, SE = Standard Errors, LLCI/ULCI = Lower/Upper limit of confidence interval.

These results with SBC as a covariate align with those reported in Study 2 (without SBC), indicating robustness.

EC.C3. Stimuli Generation

Step 1 – User Input: The user inputted a traditional and satirical headline. E.g., Traditional Headline = “NVIDIA’s New AI Assistants Are So Smart, They Can Now Help You in Interactive Games,” Satirical Headline = “NVIDIA’s New AI Assistants Are So Smart, They Can Now Help You in Interactive Games and Judge Your Life Choices.” The satirical version of the headline included a creative prompt (e.g., “and Judge Your Life Choices”) that the LLM could utilize to generate satirical content.

Step 2 – LLM Processes Keywords: The LLM conducted a web search using the keywords in the supplied traditional headline to identify facts reported in published news about the brand mentioned (e.g., NVIDIA). The LLM used these facts as the basis for the traditional and satirical news versions it wrote. The satirical news version included the facts from the traditional version as well as satirical content based on the user inputted prompt.

Step 3 – LLM Processes Narrativity Style: The LLM generated traditional and satirical news in the two storytelling styles specified in the instructions (see Section EC.C4). Specifically, Low Narrativity was described as concise and factual, with a focus on delivering essential information quickly and efficiently, while High Narrativity was described as more immersive and descriptive, with a focus on building up characters, settings, and dramatic tension.

Step 4 – LLM Output: The LLM displays four news stories (Traditional/Satirical news with High/Low Narrativity).

In summary, after the LLM was prompted with the instructions and the user inputted a pair of headlines, the LLM displayed the four news story versions. Steps 2-3 occurred in the background and did not involve user interaction. Apart from minor changes, the four stories were used as received from the LLM. Please see EC.C3 for details on the LLM prompts we utilize.

EC.C4. Study 2 – LLM Prompts to Manipulate *NewsFormat* and *Narrativity*

To prime the LLM, we supply the following set of instructions (Note: in the following prompts, “traditional news” refers to Low Narrativity while “fictional story” refers to High Narrativity).

1. **User Provides Two Headlines:**
 - One for the traditional news versions
 - One for the satirical news versions
2. **Find Real News Story:**
 - Search for an actual news story similar to the traditional headline.
 - Extract facts and key information from the real news story.
3. **Generate 4 News Stories:**
 - **2 Traditional News Stories:**
 - Based on the facts from the real news story.
 - One with traditional news narrativity.
 - One with fictional story narrativity.
 - **2 Satirical News Stories:**

- Take creative inspiration from the satirical headline to generate humorous/satirical elements.
- Some real facts will be taken from the traditional news versions.
- One with traditional news narrativity.
- One with fictional story narrativity.

4. **Narrativity Styles:**

- **Traditional News Narrativity:**
 - Concise and factual
 - Focuses on delivering essential information quickly and efficiently
- **Fictional Story Narrativity:**
 - More immersive and descriptive
 - Builds up characters, settings, and dramatic tension

5. **Consistency Across Versions:**

- **Traditional News Versions:** Real facts remain the same; only the narrativity style differs.
- **Satirical News Versions:** Both real and made-up facts remain the same; only the narrativity style differs. Ensure the real facts in the satirical versions come from the traditional news versions.

6. **Length and Reading Level:**

- Each story should be at least 270 words but less than 300 words
- Provide the reading level score for each story (using FOG score or Flesch-Kincaid score)

7. **Do Not Quote References:**

- Avoid citing references in the news stories.

Example Execution:

Provided Headlines:

- **Traditional:** Prada's Latest Collection Inspired by Everyday Objects
- **Satirical:** Prada's Latest Collection Inspired by Everyday Objects; Models Strut Runway in Designer Garbage Bags

1. **Find Real News Story:**

- Search for a real news story about Prada's latest collection inspired by everyday objects.
- Extract key facts about the collection's inspiration, materials used, and the event.

2. **Generate 4 News Stories:**

Traditional News Stories:

- Based on real facts about Prada's new collection.
 1. **Traditional News Narrativity:** Concise and factual delivery.
 2. **Fictional Story Narrativity:** Descriptive and immersive.

Satirical News Stories:

- Satirical take on the real story with added humorous elements inspired by the satirical headline "Models Strut Runway in Designer Garbage Bags."
 1. **Traditional News Narrativity:** Concise with humorous elements.
 2. **Fictional Story Narrativity:** Descriptive with humorous scenarios.

We receive the following output from the LLM upon inputting the traditional and satirical headlines:

Headline: Prada's Latest Collection Inspired by Everyday Objects

Traditional News Story (Traditional News Narrativity)

Prada's Latest Collection Inspired by Everyday Objects

MILAN – Prada has unveiled its Fall/Winter 2023 collection, which takes inspiration from everyday objects and uniforms, transforming them into high fashion. The collection, showcased at Milan Fashion Week, highlights themes of tenderness, humility, and care, with a particular focus on the beauty found in the mundane.

Miuccia Prada and Raf Simons, the creative directors behind this collection, have reconceptualized typical uniforms, such as those of nurses and military personnel, into elegant fashion statements. The collection features wedding dresses repurposed as daywear, with long-line shirt dresses and capes inspired by World War II era army nurses.

"We aim to bring importance to the everyday," said Miuccia Prada. "Everyday life deserves beautiful things. Because every day of life counts."

The runway show was set in the Fondazione Prada, where the space was transformed to reflect the collection's themes. The industrial setting was reengineered with a moving ceiling that revealed floral decorations, symbolizing the transformation of the ordinary into the extraordinary.

Critics have praised the collection for its innovative approach to redefining beauty and fashion. "Prada has once again set a new standard by turning everyday garments into symbols of elegance and care," commented fashion analyst Carla Russo.

This collection not only celebrates the aesthetic value of everyday objects but also underscores the designers' commitment to highlighting the significance of modesty and simplicity in fashion.

Traditional News Story (Fictional Story Narrativity)

Prada's Latest Collection Inspired by Everyday Objects

The anticipation was palpable as the audience gathered in the grand hall of the Fondazione Prada. The lights dimmed, and a hush fell over the crowd. Miuccia Prada and Raf Simons were about to unveil their latest collection, one that promised to redefine fashion by drawing inspiration from the everyday.

As the first model stepped onto the runway, it became clear that this was no ordinary fashion show. Wedding dresses, typically reserved for the most special of occasions, were transformed into daywear. Delicately embroidered white lace skirts and pumps were paired with oversized blazers and simple sweaters, creating a striking contrast that highlighted the beauty of everyday attire.

"Everyday life deserves beautiful things," Miuccia Prada explained backstage. "We wanted to take pieces created for one day, like a wedding gown, and make them part of everyone's everyday."

The show continued with uniforms inspired by nurses and military personnel, reimagined with couture details. Capes and long-line shirt dresses, reminiscent of World War II army nurses, floated down the runway, exuding an air of elegance and care. The audience watched in awe as the industrial ceiling of the venue slowly elevated, revealing a floral spectacle that mirrored the collection's theme of transformation.

Raf Simons elaborated on the collection's intent. "These garments are symbols of care and responsibility. By elevating them, we honor the people who wear them and the actions they perform."

The collection concluded to thunderous applause, leaving the audience with much to ponder. Prada's latest collection had not only showcased stunning fashion but had also delivered a poignant message about finding beauty in the everyday.

Satirical News Story (Traditional News Narrativity)

Prada's Latest Collection Inspired by Everyday Objects; Models Strut Runway in Designer Garbage Bags

MILAN – In an unexpected and humorous twist, Prada's Fall/Winter 2023 collection took inspiration from everyday objects, including designer garbage bags. The collection, unveiled at Milan Fashion Week, left the audience both amused and intrigued.

"We wanted to make a bold statement about the beauty in the mundane," said Miuccia Prada. "What better way to do that than to transform the most overlooked everyday object – the garbage bag – into high fashion?"

Models strutted down the runway in ensembles that included repurposed garbage bags adorned with delicate lace and floral appliqués. One standout piece was a full-length gown made entirely from recycled plastic, styled with an oversized blazer for a touch of irony.

Social media quickly lit up with reactions, with the hashtag #PradaGarbageBag trending within minutes. One user tweeted, "Only Prada could make taking out the trash look this good!"

Prada's spokesperson, Giovanna Romano, added a playful note: "This collection is not just about sustainability; it's about seeing the extraordinary in the ordinary. We're turning trash into high fashion."

Critics, however, were divided. "It's an interesting concept," said fashion analyst Carla Russo. "But can these garbage bag dresses hold up on a night out?"

Despite the mixed reactions, Prada's latest collection succeeded in sparking conversation and challenging traditional notions of beauty and fashion. With a blend of humor and innovation, Prada continues to push the boundaries of what is considered stylish.

Satirical News Story (Fictional Story Narrativity)

Prada's Latest Collection Inspired by Everyday Objects; Models Strut Runway in Designer Garbage Bags

The atmosphere at Milan Fashion Week was electric as fashion enthusiasts eagerly awaited Prada's latest collection. The lights dimmed, and a spotlight focused on the runway. Whispers of anticipation turned into gasps of surprise as the first model appeared, adorned in what looked like a high-fashion garbage bag.

"Ladies and gentlemen," Miuccia Prada began, stepping into the spotlight. "We present to you our Fall/Winter 2023 collection, inspired by the beauty of everyday objects. Today, we find elegance in the most unexpected places – even in garbage bags."

The audience watched in amused disbelief as models showcased gowns made from repurposed plastic, styled with intricate lace and floral embellishments. One model twirled, revealing the surprisingly graceful movement of her garbage bag dress, eliciting laughter and applause.

Backstage, Raf Simons explained the concept. "We wanted to challenge the traditional notions of beauty and fashion. By using everyday objects like garbage bags, we highlight the potential for elegance in the mundane."

Social media erupted with reactions. The hashtag #PradaGarbageBag trended as users shared their thoughts and memes. "Who knew taking out the trash could be so glamorous?" one tweet read.

The show continued with more whimsical creations, including a coat made from recycled newspaper and a dress adorned with bottle caps. Each piece was a testament to Prada's commitment to sustainability and innovation, wrapped in humor and creativity.

As the event concluded, Miuccia Prada left the audience with a final thought. "Fashion is about seeing the extraordinary in the ordinary. Today, we've turned trash into treasure."

The audience departed with smiles and conversations sparked. Prada's latest collection had not only entertained but also provoked thought, proving once again that fashion is as much about imagination as it is about style.

EC.C5. Measures

C5.1 Interestingness Items

1. I found the story to be interesting [1=Strongly disagree, 7 = Strongly agree]
2. I found the story to be engaging [1=Strongly disagree, 7 = Strongly agree]

The above two items were strongly correlated ($r = .88, p < .01$). *Interestingness* was computed as an average of the scores for each of these two items ($Interestingness = (Item\ 1\ score + Item\ 2\ score)/2$)

C5.2 Self-Brand Connection (SBC) Items

1. Brand X reflects who I am (not at all/extremely well).
2. I can identify with Brand X (not at all/extremely well).
3. I feel a personal connection to Brand X (not at all/very much so).
4. I (can) use Brand X to communicate who I am to other people (not at all/extremely well).
5. I think Brand X (could) help(s) me become the type of person I want to be (not at all/extremely well).
6. I consider Brand X to be "me" (it reflects who I consider myself to be or the way that I want to present myself to others) (not "me"/"me").
7. Brand X suits me well (not at all/extremely well).

EC.D. Details on Study 3 – Differential Effects of *Sequence* on Engagement

Table D1a: Study 3 – Summary Statistics

Ind. Vars.		Mediator (M)	Dep. Vars. (Y)		Descriptors of Stimuli Computed by Text Analysis						
<i>News Format</i> (X)	<i>Sequence</i> (W)	<i>Interestingness</i>	<i>Share</i> (%Yes)	<i>TellOthers</i> (%Yes)	<i>Narrativity</i>	<i>Affect</i>	<i>Tone</i>	<i>FOG_Head</i>	<i>FOG_Body</i>	<i>Length_Head</i>	<i>Length_Body</i>
Trad	G-B	4.13	16.7%	34.9%	-59.33	4.99	57.15	14.43	20.78	13	368
Trad	B-G	3.58	14.5%	29.0%	24.57	3.83	63.25	14.43	20.77	13	353
Sat	G-B	4.46	25.0%	53.9%	9.25	6.05	79.11	14.17	16.43	14	482
Sat	B-G	4.59	17.7%	48.4%	-13.31	6.81	86.00	14.17	19.12	14	412
		Mean: 4.19									
		SD: 1.63									

Notes: *Share* is a measure of the intention to share online (Yes/No) while *TellOthers* is a measure of the intention to discuss offline with others (Yes/No).

The reading level (*FOG Body*) of the satirical content > approximately 17, indicating they are difficult to read (Wylie 2018).

Table D1b: Study 3 – Comparability Checks

	<i>NewsFormat:</i>	Satirical	Satirical	Traditional	Traditional
	<i>Sequence:</i>	Bad-Good	Good-Bad	Bad-Good	Good-bad
Age	18-24 Yrs	13	16	11	10
Age	25-34 Yrs	37	29	35	35
Age	35-44 Yrs	34	30	30	30
Age	45-54 Yrs	11	21	19	23
Age	55-64 Yrs	16	21	14	17
Age	65+ Yrs	13	11	15	11
Sample Size		124	128	124	126
Gender	Male	63	53	51	57
Gender	Female	57	71	70	65
Gender	Non-binary	3	3	1	4
Gender	Self-describe	1	1	2	0
Sample Size		124	128	124	126

Notes:

Age Distribution: $\chi^2(15) = 9.93, p = 0.8244$. The age group distributions are not significantly different across conditions.
 Gender Distribution: $\chi^2(9) = 7.05, p = 0.6321$. The gender distributions are not significantly different across conditions.

EC.D1. *NewsFormat* Manipulation Check

We ran several tests to check whether our manipulation of *NewsFormat* was successful. Specifically, we checked whether our manipulation of *NewsFormat* affected participants’ perceptions of (1) whether the news story was trying to be funny, (2) whether the claims made in the news story were accurate, and (3) whether the story contained satirical content. We expected that successful manipulation of *NewsFormat* would result in the satirical news story being perceived as funnier, less accurate, and containing more satirical content than the traditional news story. We present the results of our manipulation checks in the following subsections, which support our successful news format manipulation.

D1.1. *Funny*

A one-way ANOVA on participants’ ratings of how much the news story was trying to be funny revealed a significant effect of news format ($F(1, 500) = 227.83, p < .001, \eta_p^2 = .31$) such that the satirical news story

($M_{Satirical} = 3.91$, $CI_{Satirical} = [3.72, 4.09]$) was perceived to be more funny than the traditional news ($M_{Traditional} = 1.89$, $CI_{Traditional} = [1.71, 2.08]$).

D1.2. Information Accuracy

A one-way ANOVA on participants' ratings of the accuracy of the claims in the news story revealed a significant effect of news format ($F(1, 500) = 120.97$, $p < .001$, $\eta_p^2 = .20$) such that the claims in the satirical news story ($M_{Satirical} = 3.45$, $CI_{Satirical} = [3.29, 3.61]$) were perceived to be less accurate than the claims in the traditional news ($M_{Traditional} = 4.72$, $CI_{Traditional} = [4.56, 4.88]$).

D1.3. Satirical content

A one-way ANOVA on participants' ratings of how much satire was contained in the news story revealed a significant effect of news format ($F(1, 500) = 219.69$, $p < .001$, $\eta_p^2 = .31$) such that the satirical news story ($M_{Satirical} = 4.50$, $CI_{Satirical} = [4.32, 4.69]$) was perceived to contain more satire than the traditional news ($M_{Traditional} = 2.48$, $CI_{Traditional} = [2.29, 2.67]$), suggesting that participants could distinguish between them.

EC.D2. Sequence Manipulation Check

A Chi-square test of association indicated a significant association between the displayed emotional sequence of the news story and participant recall of the sequence ($\chi^2(2) = 304.03$, $p < 0.001$) such that participant recall was significantly affected by *Sequence*. As shown in Table D2 and Figure D2, most participants accurately coded the sequence of bad and good news (bad first = 73.8%, good first = 92.5%), indicating the successful manipulation of emotional sequence.

Table D2: Study 3 – Sequence Manipulation Check

Contingency Table of <i>Sequence</i> X <i>Recall</i>						
		<i>Recall</i>			Total	
		Good to Bad News	Bad to Good News	Cannot recall		
<i>Sequence</i>	Bad News to Good News	Count	40	183	25	248
		Expected Count	135.9	94.4	17.8	248.0
		% within	16.1%	73.8%	10.1%	100.0%
	Good News to Bad News	Count	235	8	11	254
		Expected Count	139.1	96.6	18.2	254.0
		% within	92.5%	3.1%	4.3%	100.0%
Total		Count	275	191	36	502
		Expected Count	275.0	191.0	36.0	502.0
		% within Sequence	54.8%	38.0%	7.2%	100.0%

Note: The results show that most participants accurately code the sequence of bad and good news (bad first = 73.8%, good first = 92.5%), indicating the successful manipulation of *Sequence*

Figure D2: Study 3 – Most participants accurately recall *Sequence*

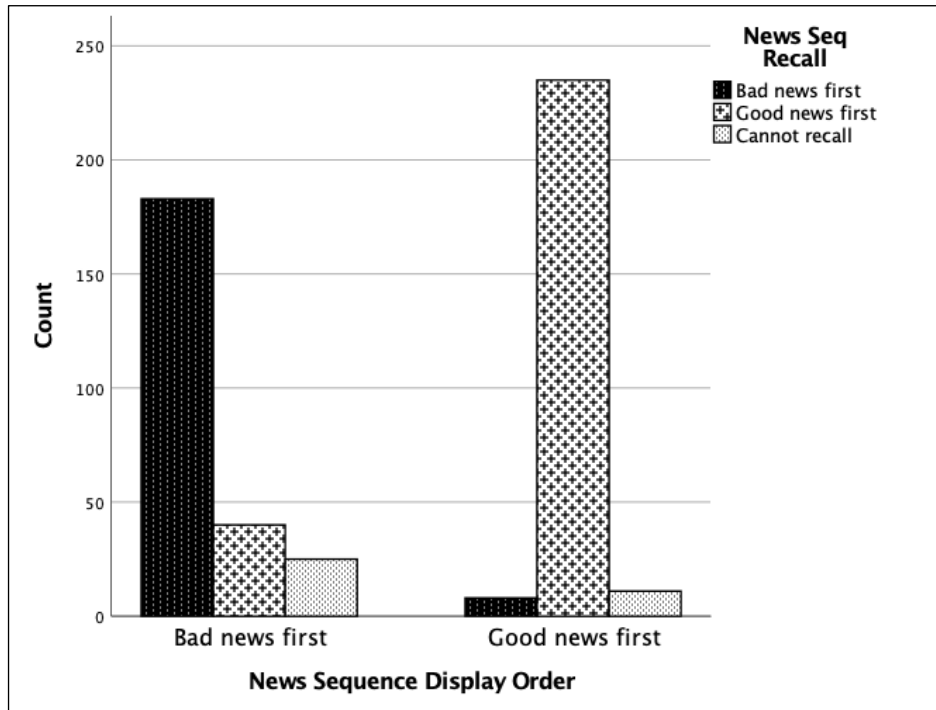


Table D3: Study 3 – Sequence Moderated Mediation Results with Self-Brand Connection as Control

DV = <i>Interestingness</i>		β	SE	t	p	LLCI	ULCI
<i>Panel 1</i>	constant	2.8917	.1770	16.3409	.0000	2.5440	3.2394
	<i>NewsFormat</i> (X)	.9867	.1947	5.0669	.0000	.6041	1.3693
	<i>Sequence</i> (W)	-.4363	.1947	-2.2405	.0255	-.0537	-.8190
	<i>NewsFormat</i> X <i>Sequence</i>	.6121	.2739	2.2345	.0259	1.1502	.0739
	<i>SBC</i>	.2608	.0421	6.1973	.0000	.1781	.3435
DV = <i>Sharing</i>		coeff	SE	Z	p	LLCI	ULCI
<i>Panel 2</i>	constant	-6.5311	.7022	-9.3007	.0000	-7.9074	-5.1548
	<i>NewsFormat</i> (X)	-.0129	.2665	-.0484	.9614	-.5352	.5094
	<i>Interestingness</i> (M)	.9043	.1274	7.0989	.0000	.6546	1.1539
	<i>SBC</i>	.2216	.0795	2.7890	.0053	.0659	.3774
	Direct effect of <i>NewsFormat</i> on <i>Sharing</i>	Effect	SE	Z	p	LLCI	ULCI
	-.012	.2665	-.0484	.9614	-.5352	.5094	
Index of Moderated Mediation <i>Sequence</i> (W)	Index	BootSE			BootLLCI	BootULCI	
	.5535	.2636			1.1083	.0786	
DV = <i>TellOthers</i>		coeff	SE	Z	p	LLCI	ULCI
<i>Panel 3</i>	constant	-4.8148	.4783	-10.0663	.0000	-5.7523	-3.8773
	<i>NewsFormat</i> (X)	.5111	.2178	2.3465	.0190	.0842	.9380
	<i>Interestingness</i> (M)	.8541	.0941	9.0792	.0000	.6697	1.0385
	<i>SBC</i>	.1460	.0693	2.1050	.0353	.0101	.2819
	Direct effect of <i>NewsFormat</i> on <i>TellOthers</i>	Effect	SE	Z	p	LLCI	ULCI
	.5111	.2178	2.3465	.0190	.0842	.9380	
Index of Moderated Mediation <i>Sequence</i> (W)	Index	BootSE			BootLLCI	BootULCI	
	.5228	.2370			1.0088	.0789	

Notes: Where indicated in parentheses, X = Independent variable, W = Moderator, M = Mediator, DV = Dependent variable. Boot = Bootstrapped, SE = Standard Errors, LLCI/ULCI = Lower/Upper limit of confidence interval.

These results with SBC as a covariate align with those reported in Study 3 (without SBC), indicating robustness.

EC.D3. Study 3 – LLM Prompts to Manipulate *NewsFormat* and *Sequence*

Our instructions to the LLM are in *Italics*. LLM responses are highlighted in blue shading. Materials supplied to the LLM are included at the end of this section and highlighted in gray shading.

Summarize the news about the NameDrop and Live Voicemail features in the provided press release in the style of the news story from Wired. Your news story should include two distinct sections: one providing good news and the other bad news. The good and bad news sections should be approximately equal in length and may include related news outside of the provided press release. Provide the good news section first. Your news story should be 400 words or less and have a readability Fog Index of less than 11. Label the news story “Version A” and include a catchy news headline for your news story. Report the Fog Index and number of words at the end of your news story.

Version A: traditional, good news first

Apple's Privacy Innovations Transform User Interaction, but Privacy Advocates Raise Concerns

In an ambitious stride toward user empowerment, Apple has unveiled a duo of cutting-edge features, NameDrop and Live Voicemail, promising heightened interaction and protection. NameDrop, an innovative AirDrop experience, promises to reshape how contact information is exchanged, while Live Voicemail revolutionizes call management with real-time transcriptions. Apple's commitment to privacy enhancement is evident, but echoes of skepticism are voiced from privacy advocates seeking broader digital rights.

Good News: Redefining Interaction Through NameDrop and Live Voicemail

Apple's unwavering dedication to privacy takes a fresh leap with NameDrop, an AirDrop evolution that ushers in a new era of secure contact sharing. By enabling users to selectively disclose contact details while protecting sensitive information, Apple empowers users to assert control over their digital identities. This game-changing feature extends to content sharing, ensuring seamless, encrypted transmissions that bolster user confidence in data exchanges.

Live Voicemail joins the fray, transforming call management by providing real-time transcriptions as callers speak. This innovation eradicates the age-old frustration of missed voicemails, granting users the ability to decide on call responses based on transcribed content. Significantly, Apple's Neural Engine ensures the transcription process occurs entirely on the device, upholding stringent privacy standards.

Bad News: Privacy Advocates Challenge Apple's Comprehensive Commitment

Amid these strides, the broader privacy landscape remains intricate, and privacy advocates raise poignant questions about Apple's holistic approach. As the digital world grapples with the notion of a universal "Do not track" mechanism, Apple's conspicuous absence from the ranks of supporters garners scrutiny. This oversight fuels concerns that even an industry leader can sometimes fall short of embracing universal privacy ideals.

While Apple champions progress in user interaction and data security, its alignment with the global privacy control remains uncertain. The potential for a simplified opt-out mechanism stands as a beacon of hope for users seeking streamlined privacy management. Yet, as Apple's innovation flourishes within specific realms, its position in the broader privacy narrative remains a subject of intrigue.

As digital realms continue their metamorphosis, Apple's advancements underscore the power of technology to redefine user experiences. However, the absence of a comprehensive approach to

privacy serves as a stark reminder that even trailblazers must traverse complex terrain to realize collective privacy aspirations.

Next, rearrange the news story in “Version A” to provide the bad news first. Label the story “Version B”. The news headline and style should be like “Version A”.

Version B: traditional, bad news first

Apple's Privacy Innovations Face Scrutiny as Advocates Seek Broader Digital Rights

Amid a landscape of rapid technological evolution, Apple's latest privacy endeavors, NameDrop and Live Voicemail, shine as beacons of innovation, promising heightened user interaction and protection. However, as the dust settles, privacy advocates raise pointed concerns about Apple's comprehensive approach, underscoring the complexities of digital rights in today's interconnected world.

First the Bad News: Privacy Advocates Challenge Apple's Comprehensive Commitment

While Apple unveils captivating innovations such as NameDrop and Live Voicemail, a broader privacy discourse takes center stage. Questions loom large about Apple's positioning within the realm of universal privacy rights. Notably absent from the ranks of supporters championing a universal "Do not track" mechanism, Apple's commitment to a comprehensive approach faces scrutiny. The industry giant's reluctance to embrace this endeavor exposes a dissonance between innovation and universal privacy ideals.

As privacy advocates rally for a streamlined opt-out mechanism to navigate the digital landscape, Apple's selective engagements spark introspection. Even in the face of groundbreaking innovations, the absence of a cohesive stance on universal privacy control remains a conspicuous challenge.

Now the Good News: Redefining Interaction Through NameDrop and Live Voicemail

Apple's dedication to reshaping user interaction is unmistakable, with NameDrop and Live Voicemail spearheading this charge. NameDrop emerges as a transformative AirDrop experience, redefining how contact information is shared. This feature enables users to wield authority over their digital identities by selectively sharing contact details while shielding sensitive information. Additionally, Apple empowers users to share content securely, reinforcing data protection.

Live Voicemail marks another watershed moment, revolutionizing call management with real-time transcriptions. By offering callers' spoken words in written form, this innovation addresses the perennial challenge of missed voicemails. Users can decide on call responses based on transcribed content, ensuring no important communication goes unheard. Remarkably, Apple's Neural Engine ensures transcription takes place entirely on the device, underscoring its commitment to stringent privacy safeguards.

As Apple's privacy odyssey unfolds, the convergence of innovation and user protection remains central. While the broader landscape invokes skepticism, Apple's stride toward heightened interaction and data security resounds with potential. Yet, the privacy journey—ripe with debates and dialogues—continues to shape the future of digital rights.

Next, write a satirical news story based on Version A in the style of the Onion. Your story should include two distinct sections: one providing good news and the other bad news. The good and bad news sections

should be approximately equal in length. Provide the good news section first. The bad news section should contain satire about a newly released feature named "iSPY" that notifies the user's friends whenever the user drops a friend's name in a conversation. Include a catchy news headline for your news story. Your news story should be 400 words or less and have a readability Fog Index of less than 11. Label it "Version C".

Version C: satirical, good news first

Apple's Latest Innovations Unveil an Eerie Blend of Utility and Surveillance

In a whirlwind of announcements, Apple has once again proven its prowess in revolutionizing the digital landscape with a suite of groundbreaking features that reek of innovation and redefine personal connection. Privacy crusaders are elated as Apple showcases its commitment to safeguarding user data while elevating the user experience to dizzying new heights.

First, the Good News: Apple's Privacy Pioneering Hits New Heights

Apple's masterful symphony of privacy and functionality comes to life with the introduction of the mesmerizing "NameDrop" and the all-seeing "Live Voicemail." NameDrop transcends mere contact sharing, allowing users to sculpt their digital identity by customizing the information they're willing to reveal, all while keeping those pesky over-sharers at bay. This game-changer even extends to the Apple Watch, ushering in a new era of intimate wrist-based data exchange. Meanwhile, Live Voicemail paints voicemails in a whole new light, transforming them from cryptic audio riddles into digestible transcripts that make missed calls a thing of the past.

And as if that wasn't enough to send shockwaves through the industry, Apple's steadfast devotion to privacy takes center stage with an array of features that empower users like never before. From the newfound control over photo sharing to the intricate dance of link protection, Apple pledges allegiance to the user's data sovereignty. The Lockdown Mode expansion tantalizingly shields the chosen ones from prying eyes and those dubious mercenaries peddling high-end spyware.

Now the Bad News: The Rise of iSPY - Friends in Every Conversation

But wait, as the curtain lifts on Apple's grand spectacle of innovation, a shadowy figure slinks onto the stage — the iSPY. Yes, ladies and gentlemen, prepare to be both amused and alarmed by this uninvited guest at the privacy party. No longer content with silently soaking up your secrets, iSPY takes a bold leap into the world of social espionage. This cutting-edge feature ensures your friends are never in the dark about your impressive name-dropping skills, notifying them each time you lovingly sprinkle their moniker into conversation. It's as if Siri herself has donned a detective hat, monitoring your every vocal move and alerting friends at lightning speed.

Picture this: you're relishing a tête-à-tête with your buddy, casually name-dropping your lunch date with a friend, and suddenly, their phone pings with a triumphant notification. "Your name has been dropped!" it chirps. You may have aimed for subtle coolness, but iSPY takes your modest boasting and turns it into a full-fledged spectacle. Gone are the days of surprise and intrigue, replaced by an uncanny digital applause track that celebrates your conversational accomplishments.

In this uncanny melding of utility and surveillance, Apple leaves no stone unturned in its quest for the ultimate user experience. Privacy aficionados may raise an eyebrow at iSPY's bold intrusion, but

who could resist the allure of sharing your every verbal nod with the world? Apple, you've done it again — redefining communication one name-drop at a time.

Next, rearrange the satirical news story in Version C to provide the bad news first. Label the story “Version D”. The news headline and style should be like “Version C”.

Version D: satirical, bad news first

Headline: Apple Unveils Latest Innovation: iSPY, Redefining Digital Etiquette

Bad News: iSPY - Friends as Your Echo Chamber

CUPERTINO, CA — In a stunning revelation that blurs the line between connectivity and surveillance, Apple has unleashed a technological marvel that promises to revolutionize social dynamics in ways never before imagined. Say hello to iSPY, the captivating feature that ensures your friends are never left in the dark when you nonchalantly drop their names in conversations. Apple's audacious leap into the realm of social espionage has critics raising an eyebrow, while enthusiasts embrace the brave new world of name-dropping transparency.

Imagine the scene: you're engaged in an enthralling exchange, seamlessly weaving your friends' names into the dialogue, and suddenly, their phones emit triumphant pings. "Your name has been dropped!" the notification blares, as if heralding your conversational finesse. With iSPY, subtlety is no longer an option — every artful name-drop is now a public spectacle, transforming your hushed praises into a digital parade.

As you bask in the glory of your newfound conversational prowess, spare a thought for the unsuspecting friends on the receiving end of iSPY notifications. They'll be left wondering if genuine camaraderie or a calculated attempt at self-promotion is the driving force behind your lyrical praises. Social dynamics have evolved into an intricate web of digital high-fives, where name-drops become badges of honor.

Good News: Apple Elevates Privacy and Functionality

But let's not let the intrigue of iSPY overshadow Apple's other monumental accomplishments. The tech giant continues to assert its dominance in the realm of privacy and functionality, showcasing an ensemble of features that redefine personal connections and bolster data security. The illustrious "NameDrop" and the eloquent "Live Voicemail" come together in a symphony of innovation, offering users a novel way to sculpt their digital personas while relishing voice message transcriptions that render missed calls obsolete.

Apple's commitment to safeguarding user data is a saga unto itself, as evidenced by the intricate dance of link protection and the Lockdown Mode expansion. Photo sharing is now an exercise in sovereignty, and the protective cocoon of Lockdown Mode envelops users in an impervious shield against unsavory spies and dubious mercenaries.

As the curtain falls on Apple's grand spectacle of innovation, the moral of the story is clear: in the world of technology, there's always a trade-off between dazzling utility and creeping surveillance. Apple leaves no stone unturned in its quest to redefine communication norms and elevate the user experience, even if it means embracing the slightly uncanny digital applause track of iSPY.

**** Start of Press Release:**

Apple announces powerful new privacy and security features

CUPERTINO, CALIFORNIA Apple today announced its latest privacy and security innovations, including major updates to Safari Private Browsing, Communication Safety, and Lockdown Mode, as well as app privacy improvements. Additionally, Apple introduced new features designed with privacy and security at their core, including Check In, NameDrop, and Live Voicemail. These new efforts are the latest manifestation of Apple’s deeply held belief that privacy is a fundamental human right and that good privacy is built on a foundation of strong security.

“Privacy is designed into every new Apple product and feature from the beginning,” said Craig Federighi, Apple’s senior vice president of Software Engineering. “We are focused on keeping our users in the driver’s seat when it comes to their data by continuing to provide industry-leading privacy features and the best data security in the world. This approach is evident in a number of features on our platforms, like the major updates to Safari Private Browsing, as well as the expansion of Lockdown Mode.”

Privacy Features Give Users Greater Control of Their Data

Major Updates to Safari Private Browsing: Safari introduced private browsing years before any other browser. This year, a significant update provides even greater protection against trackers as users browse the web and from people who might have access to their device. Advanced tracking and fingerprinting protections go even further to help prevent websites from using the latest techniques to track or identify a user’s device. Private Browsing now locks when not in use, allowing a user to keep tabs open even when stepping away from the device.

Photos Privacy Permission Improvements: A new embedded Photos picker can help users share specific photos with apps while keeping the rest of their library private. When apps ask to access the user’s entire photo library, the user will be shown more information about what they’ll be sharing, along with occasional reminders of their choice.

Link Tracking Protection in Messages, Mail, and Safari Private Browsing: Some websites add extra information to their URLs in order to track users across other websites. Now this information will be removed from the links users share in Messages and Mail, and the links will still work as expected. This information will also be removed from links in Safari Private Browsing.

App Privacy Improvements: New tools give developers more information about the data practices of third-party software development kits (SDKs) they use in their apps, allowing them to provide even more accurate Privacy Nutrition Labels. These changes also improve the integrity of the software supply chain by supporting signatures for third-party SDKs to add another layer of protection against abuse.

Features Designed to Help Protect User Safety

Communication Safety: Communication Safety, designed to warn children when receiving or sending photos in Messages that contain nudity, now covers video content in addition to still images. A new API lets developers integrate Communication Safety right into their apps. Additionally, the feature will now help keep kids safe when they’re sending and receiving an AirDrop, a FaceTime video message, and when using the Phone app to receive a Contact Poster and the Photos picker to choose content to send. All image and video processing for Communication Safety occurs on device, meaning neither Apple nor any third

party gets access to the content. These warnings will be turned on for the child accounts in their Family Sharing plan, and can be disabled by the parent.

Sensitive Content Warning: Sensitive Content Warning helps adult users avoid seeing unwanted nude images and videos when receiving them in Messages, an AirDrop, a FaceTime video message, and the Phone app when receiving a Contact Poster, all using the same privacy-preserving technology at the core of Communication Safety. The feature is optional and can be turned on by the user in Privacy & Security settings. As with Communication Safety, all image and video processing for Sensitive Content Warning occurs on device, meaning neither Apple nor any third party gets access to the content.

Powerful Security Protections to Safeguard User Data

Passwords and Passkeys Updates: For easier and more secure password and passkey sharing, users can create a group to share a set of passwords, and everyone in the group can add and edit passwords to keep them up to date. Since sharing is through iCloud Keychain, it is end-to-end encrypted. Additionally, one-time verification codes received in Mail will now automatically autofill in Safari, making it easy to securely log in without leaving the browser.

Lockdown Mode: Lockdown Mode expands to provide even more protections for those who may be targeted by mercenary spyware because of who they are or what they do. New protections encompass safer wireless connectivity defaults, media handling, media sharing defaults, sandboxing, and network security optimizations. Turning on Lockdown Mode further hardens device defenses and strictly limits certain functionalities, sharply reducing the attack surface for those who need additional protections. Additionally, Lockdown Mode will be supported on watchOS.

Additional Features Designed with Privacy and Security at Their Core

1. **Check In** makes it easy for users to let friends or family members know they've reached their destination safely. Once turned on by the user, Check In automatically detects when the user has reached their intended destination, and will let selected contacts know via Messages. In the case that something unexpected happens while the user is on their way, Check In will recognize that the user is not making progress toward their declared destination and check in with them. If they don't respond, the feature will share useful information — like the user's precise location, battery level, cell service status, and the last active time using their iPhone — with the contacts the user selected. In addition to making it easier to get help if needed, Check In is designed around privacy and security, keeping the user in control by letting them choose whom to share their information with, including the destination and time duration that they set. Users can end the Check In session at any time. Information sent with Check In is end-to-end encrypted so only the user's family member or friend can read it, not Apple or anyone else.

2. With **NameDrop**, a new AirDrop experience, a user can hold their iPhone near another to share their contact information with only their intended recipients. Users can also choose the specific contact details they want to share — and, importantly, what information they don't want to share. Users can also share content like photos or links the same way. Apple Watch users can also use NameDrop by tapping the Share button in My Card in the Contacts app, or by tapping the My Card watch face complication, and then bringing Apple Watch face to face with someone else's Apple Watch. As with all AirDrop experiences, these new features securely share content over an encrypted connection.

3. Live Voicemail makes it easier to know when to answer a phone call. When someone calls and starts to leave a message, users will see a live transcription as the caller speaks. If the user wants to talk to the caller, they can pick up the call at any time. When Silence Unknown Callers is turned on, calls from unknown numbers will go directly to Live Voicemail without ringing. Calls identified as spam by carriers won't appear as Live Voicemail, and will instead be instantly declined. This gives the user more peace of mind that spam, scams, or calls that may be invasive of privacy, can be ignored without missing important calls. Thanks to the power of the Neural Engine, Live Voicemail occurs entirely on device, and this information is not shared with Apple.

These features will be coming in free software updates this fall 2023.

**** End of Press Release**

****Start of News article from Wired:**

The Privacy Battle That Apple Isn't Fighting

FOR AT LEAST a decade, privacy advocates dreamed of a universal, legally enforceable “Do not track” setting. Now, at least in the most populous state in the US, that dream has become a reality. So why isn't Apple—a company that increasingly uses privacy as a selling point—helping its customers take advantage of it?

When California passed the California Consumer Privacy Act in 2018, it came with a large asterisk. In theory, the law gives California residents the right to tell websites not to sell their personal data. In practice, exercising that right means clicking through an interminable number of privacy policies and cookie notices, one by one, on every site you visit. Only a masochist or a die-hard privacy enthusiast would go to the trouble of clicking through to the cookie settings every time they're looking up a menu or buying a vacuum. Privacy will remain, for most people, a right that exists only on paper until there's a simple one-click way to opt out of tracking across the whole internet.

The good news is, that ideal is inching closer and closer to reality. While the CCPA doesn't explicitly mention a global opt-out, the regulations interpreting the law issued by the California attorney general in 2020 specified that businesses would have to honor one just as they do individual requests. The technology for a universal opt-out didn't actually exist yet, but last fall, a coalition of companies, nonprofits, and publishers unveiled a technical specification for a global privacy control that can send a CCPA-enforceable “Do not track” signal at the browser or device level.

Today, if you live in California, you can enable the global privacy control by using a privacy browser like Brave or downloading a privacy extension, like DuckDuckGo or Privacy Badger, in whatever browser you already use. (Seriously, go do it. The full list of options is [here](#).) Once you do, you'll automatically tell sites you visit “Do not sell my personal information” without having to click anything—and, unlike with previous efforts to create a universal opt-out, any decent-size company that does business in California will be legally obligated to comply, which requires adding just a few lines of code to their website.

The state of CCPA enforcement remains murky, because some businesses object to the attorney general's broad interpretation of the law. But California's government has begun making clear that it intends to enforce the global privacy control requirement. (The more recently passed California Privacy Rights Act, which goes into full effect in 2023, makes this requirement more explicit.)

In mid-July, Digiday reported that attorney general Rob Bonta's office had “sent at least 10 and possibly more than 20 companies letters that call on them to honor the GPC.” And an item appeared on a recent list

of CCPA enforcement actions on the attorney general’s website noting that a company had been forced to start honoring the signal.

Now, the bad news. While it’s a lot easier to install a privacy extension or browser than click through a million privacy pages, the vast majority of people are still unlikely to do so. (It remains to be seen whether DuckDuckGo papering America’s highways and cities with billboards will inspire a new wave of privacy connoisseurs.)

This matters quite a bit, because online privacy rights are collective, not individual. The trouble with pervasive tracking is not merely that it can allow someone to access your personal location data and use it to ruin your life, as recently happened to a Catholic priest whose commercially available Grindr data revealed a pattern of frequenting gay bars. Even if you personally opt out of tracking, you’re still living in a world shaped by surveillance. Tracking-based advertising contributes to the decline of quality publications by eating away at the premium that advertisers pay to reach their audiences. Cheaper to find those readers on social media or even on bottom-feeding extremist news sites. It turbocharges the incentive to relentlessly maximize engagement on social media platforms. None of that will go away until a critical mass of people opt out of being tracked across the board.

That’s why one absence from the list of companies supporting the global privacy control is so conspicuous. Apple burnished its already strong reputation on privacy earlier this year by introducing App Tracking Transparency, a setting that flips the privacy default on iOS devices by forcing apps to get a user’s permission before sharing their data. That is a genuinely big step forward for privacy, since the difference between being opted out by default and opted in is enormous—and indeed, early reports suggest that most iPhone users are declining to give apps permission to track them.

****End of News article from Wired**

EC.E. Details on Study 4 – Moderating Effects of Reading Level and Self-Brand Connection

Table E1a: Study 4 – Summary Statistics

FOG	Self-Brand Connection	Traditional News					Satirical News				
		Perceived Ease of Reading		Information Gratifications			Perceived Ease of Reading		Entertainment Gratifications		
		Mean	SD	Mean	SD	N	Mean	SD	Mean	SD	N
Low	Low	6.49	.651	3.73	1.575	37	5.74	1.482	2.15	1.424	39
	Medium	6.03	.684	4.67	1.451	33	5.42	1.483	3.58	1.723	40
	High	6.16	.735	5.71	.824	31	6.24	.700	5.43	1.399	21
	Total	6.24	.709	4.64	1.559	101	5.72	1.379	3.41	1.960	100
High	Low	6.00	.957	4.04	1.744	25	4.65	1.859	2.54	1.502	37
	Medium	5.89	.936	5.00	1.394	37	5.07	1.386	3.75	1.323	28
	High	6.22	.854	5.78	.917	37	6.03	1.098	5.83	.822	35
	Total	6.04	.914	5.05	1.494	99	5.25	1.598	4.03	1.877	100
Total	Low	6.29	.818	3.85	1.638	62	5.21	1.754	2.34	1.466	76
	Medium	5.96	.824	4.84	1.421	70	5.28	1.444	3.65	1.562	68
	High	6.19	.797	5.75	.870	68	6.11	.966	5.68	1.081	56
	Total	6.14	.821	4.85	1.537	200	5.48	1.507	3.72	1.939	200

Table E1b: Study 4 – Comparability Checks

<i>NewsFormat:</i>		Traditional	Traditional	Satirical	Satirical
Reading Level (FOG):		Low	High	Low	High
Age	18-24 Yrs	8	8	5	8
Age	25-34 Yrs	28	32	38	29
Age	35-44 Yrs	29	21	21	25
Age	45-54 Yrs	16	19	17	21
Age	55-64 Yrs	12	10	14	12
Age	65+ Yrs	8	9	5	5
Sample Size		101	99	100	100
Gender	Male	48	56	53	52
Gender	Female	53	42	47	45
Gender	Non-binary	0	0	0	2
Gender	Self-describe	0	1	0	1
Sample Size		101	99	100	100

Notes:

Age Distribution: $\chi^2(15) = 7.82, p = 0.931$. The age group distributions are not significantly different across conditions.
 Gender Distribution: $\chi^2(9) = 12.93, p = 0.374$. The gender distributions are not significantly different across conditions.

EC.E1. Study 4 – LLM Prompts to Manipulate Reading Level

We employ the following steps to generate four matched news stories (2 traditional, 2 satirical) about a human brand, Oprah Winfrey. We guide the LLM (ChatGPT) to ensure that stories differ in reading levels (high vs. low FOG index), are similar in length (~205–210 words), and matched on factual content (headline, topic, date).

Step 1 - The user inputted a single headline to guide both traditional and satirical versions: *“Oprah Resigns from WeightWatchers, Donates Equity Stake to Museum.”* This headline served as the anchor for both formats of stories. For the satirical version, the user additionally included instructions to incorporate a humorous element: Oprah’s donation being displayed next to Harriet Tubman’s shawl.

Step 2 - Using the keywords from the provided headline, the LLM identified and extracted relevant facts from actual news reports published in March 2024. These included:

- Oprah Winfrey resigned from the WeightWatchers board.
- She donated her equity stake to the National Museum of African American History and Culture.
- She cited a desire to focus on public wellness.
- WeightWatchers was experiencing market challenges.

These facts formed the basis for all four news versions.

Step 3 - The LLM was instructed to generate 2 Traditional News Stories (factual, neutral tone with high vs. low reading level) and 2 Satirical News Stories (same facts, but with humor layered in, and again split by reading level). Further, the user specified two levels: Low Reading Level (FOG \approx 11–13) using simple syntax, and High Reading Level (FOG \approx 18–20) using more complex phrasing and sentence structure.

These instructions (in italics) and LLM responses (in blue shading) are detailed next:

Write a traditional, journalistic news story about Oprah Winfrey resigning from the WeightWatchers board and donating her equity stake to the National Museum of African American History and Culture.

The story should be written for readers with middle-school literacy (around FOG = 11–13). Use simple vocabulary, short sentences, and a neutral tone. Limit the story to about 210 words.

Traditional News – Low Reading Level: FOG = 12.5, 210 words

Oprah Resigns from WeightWatchers, Donates Equity Stake to Museum
March 01, 2024

Oprah Winfrey has left the WeightWatchers board. She also gave her full stake in the company to the National Museum of African American History and Culture, saying it was the right time for a change.

In a statement, she said she wants to spend more time helping others learn about health, especially in communities that need it most. Her goals, she explained, don't match staying part of a company. Instead, she hopes to focus more on education and public service.

The museum said her donation will be used for programs that promote health and wellness. WeightWatchers thanked her for her time on the board. They said she helped bring attention to their brand and showed how public figures can support wellness causes in meaningful ways.

The news comes as WeightWatchers is losing customers. More people now turn to newer ways to manage weight, including online tools and medical treatments. The company's stock dropped a bit after Oprah shared the news.

Experts say this shows a change in how people view celebrity health brands. It's not just about ads anymore. People want purpose and real action.

Though she's stepping away from the company, Oprah says she still cares about the mission and will keep supporting health and wellness in other ways.

Now write the same story using a more formal and complex style suitable for readers with a high reading level (FOG = 18–20). The tone should remain objective and journalistic. Include abstract phrasing, passive voice where appropriate, and more complex syntax. Target length: ~210 words.

Traditional News – High Reading Level: FOG = 19.7, 210 words

Oprah Resigns from WeightWatchers, Donates Equity Stake to Museum
March 01, 2024

Oprah Winfrey announced her resignation from the board of WeightWatchers and simultaneously gifted her entire equity stake to the National Museum of African American History and Culture. The move, framed as both personal and philanthropic, underscores her commitment to advancing public wellness without financial entanglement.

"This is an intentional shift," said Winfrey in an official statement. "My focus is on fostering equitable access to health resources—particularly in underserved communities—and I want to pursue that goal without the complications of corporate affiliation."

The donation, which financial disclosures estimate in the multimillion-dollar range, will support museum-led initiatives on health literacy and equity. WeightWatchers praised Winfrey's leadership, citing her pivotal role in modernizing the brand's image.

Despite the positive optics, the announcement comes as WeightWatchers grapples with declining consumer engagement. In recent quarters, the company has faced competitive pressure from emerging pharmaceutical treatments for weight loss.

“Oprah’s exit could be a symbolic inflection point,” remarked a senior health industry analyst. “Her presence legitimized the brand during a critical phase. Now the brand must define its relevance in a crowded marketplace.”

Though no longer a shareholder, Winfrey affirmed her ongoing support for health and wellness causes. “I’m not stepping away from the mission,” she said. “I’m stepping into a broader version of it.”

Using the same basic facts, write a satirical news story about Oprah Winfrey stepping down from the WeightWatchers board and donating her equity stake to the National Museum of African American History and Culture. The tone should resemble The Onion and be funny but still understandable by someone reading at the 6th grade level (FOG ~11). Add humor about how her donation might be displayed next to Harriet Tubman’s shawl. Limit to 210 words.

Satirical News – Low Reading Level: FOG = 11.2, 205 words

Oprah Resigns from WeightWatchers, Donates Equity Stake to Museum
March 01, 2024

Oprah Winfrey has stepped down from the WeightWatchers board and given her entire stake to the National Museum of African American History and Culture—because where else should a bunch of stock go but next to Harriet Tubman’s shawl?

“It makes sense,” said one museum guide. “Harriet Tubman walked for miles, saved people, and didn’t even have a smartwatch or a protein bar. The sign next to Oprah’s donation might say: ‘From freeing people to freeing brands. Please take the stairs while you think about it.’”

Winfrey explained she wanted to focus on helping others live healthier lives without being tied to a company. Or, as she put it, “I’m out, but I’m still holy.” The donation will support wellness programs and maybe help someone finally explain those confusing Points.

The announcement came while WeightWatchers is losing customers. More people are turning to newer ways to manage weight. The company’s stock dropped a bit after Oprah’s news.

“There’s a different vibe now,” said a wellness expert, adjusting her ring that tracks energy levels. “It’s not just about ads anymore. People want purpose.” She smiled and added, “It’s like if Mother Teresa stopped her peace work to sell kombucha. With a fancy label. And a goal.”

Now revise that satirical story for a college-level audience (FOG = 18–20). Keep the same joke idea (Oprah’s stock displayed next to Harriet Tubman’s shawl) but make the language more abstract, ironic, and verbose. Use advanced vocabulary and sentence structures. Keep the tone wry, sophisticated, and irreverent. Target length: ~210 words.

Satirical News – High Reading Level: FOG = 19, 205 words

Oprah Resigns from WeightWatchers, Donates Equity Stake to Museum
March 01, 2024

Oprah Winfrey has ceremoniously unseated herself from the WeightWatchers board and flung her entire equity stake into the arms of the National Museum of African American History and Culture—because what better resting place for a financial asset than beside Harriet Tubman’s shawl?

“It’s a fitting placement,” said a museum curator. “Harriet Tubman walked hundreds of miles to rescue enslaved people—without a smartwatch, a gluten-free bar, or a brand partnership. The plaque might read: ‘From liberation through swampland to liberation from corporate board seats. Please reflect—and take the stairs.’”

In a statement radiating benevolent detachment, Winfrey cited a desire to pursue wellness initiatives “unencumbered by fiduciary entanglements”—celebrity code for “I’m out, but I’m still holy.” The multimillion-dollar donation will support health equity programs and perhaps help someone finally decode the Points system.

The move comes as WeightWatchers faces waning public interest and stiff competition from pharmaceutical alternatives. Shares dipped slightly after the announcement.

“There’s a definite shift in vibe,” said a wellness analyst, adjusting her aura-monitoring ring. “It’s not just about celebrity faces—it’s about signaling cosmic alignment.” She winked. “It’s like if Mother Teresa returned her Nobel Peace Prize to launch a kombucha brand—served only in glass, with a mission.”

EC.E2. Study 4 – *NewsFormat* Manipulation Check

Similar to Studies 2 and 3, we run several tests to check whether our manipulation of *NewsFormat* is successful. Specifically, we checked whether our manipulation of *NewsFormat* affected participants’ perceptions of (1) whether the news story was trying to be funny, (2) whether the claims made in the news story were accurate, and (3) whether the story contained satirical content. We expected that successful manipulation of *NewsFormat* would result in the satirical news story being perceived as funnier, less accurate, and containing more satirical content than the traditional news story. We present the results of our manipulation checks in the following subsections, which support our successful news format manipulation.

E2.1. Funny

A one-way ANOVA on participants’ ratings of how much the news story was trying to be funny revealed a significant effect of news format ($F(1, 398) = 141.97, p < .001, \eta_p^2 = .26$) such that the satirical news story ($M_{Satirical} = 4.36, CI_{Satirical} = [4.10, 4.61]$) was perceived to be more funny than the traditional news ($M_{Traditional} = 2.36, CI_{Traditional} = [2.15, 2.57]$).

E2.2. Information Accuracy

A one-way ANOVA on participants’ ratings of the accuracy of the claims in the news story revealed a significant effect of news format ($F(1, 398) = 30.158, p < .001, \eta_p^2 = .07$) such that the claims in the satirical news story ($M_{Satirical} = 4.25, CI_{Satirical} = [4.01, 4.49]$) were perceived to be less accurate than the claims in the traditional news ($M_{Traditional} = 5.05, CI_{Traditional} = [4.89, 5.05]$).

E2.3. Satirical content

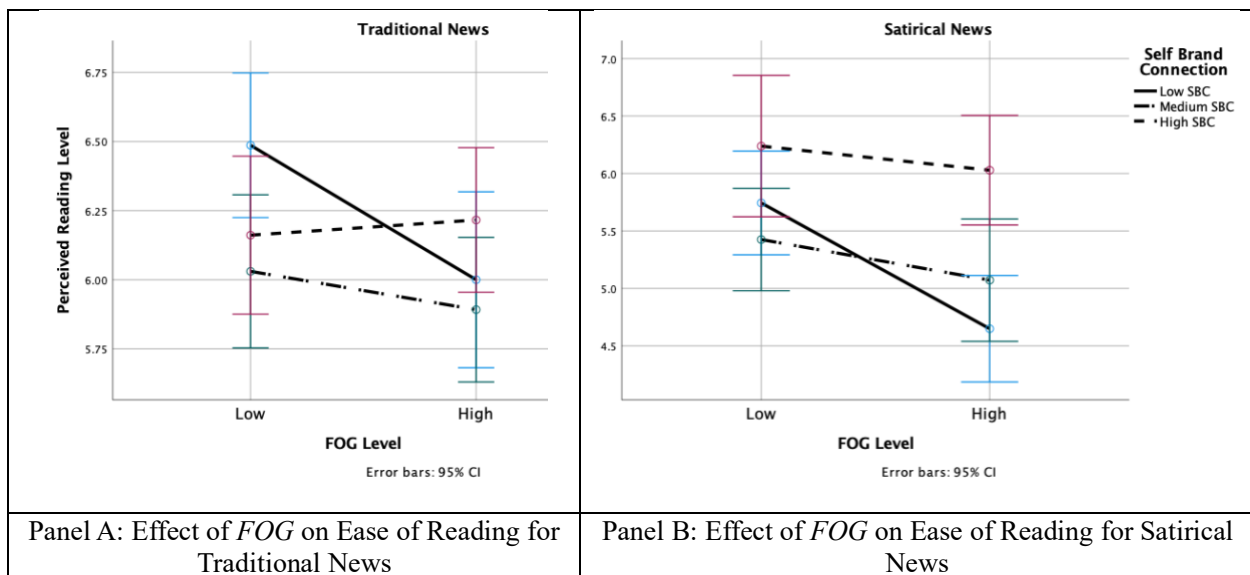
A one-way ANOVA on participants’ ratings of how much satire was contained in the news story revealed a significant effect of news format ($F(1, 398) = 161.31, p < .001, \eta_p^2 = .29$) such that the satirical news story

($M_{Satirical} = 4.61$, $CI_{Satirical} = [4.36, 4.85]$) was perceived to contain more satire than the traditional news ($M_{Traditional} = 3.56$, $CI_{Traditional} = [3.37, 3.75]$), suggesting that participants could distinguish between them.

EC.E3. Study 4 – Results for Traditional News

In traditional news, as shown in Panel 1 in EC.E, Table E2, an increase in *FOG* significantly reduces perceived ease of reading (Panel 1; $\beta = -0.7926$, $p = .0125$), in line with predictions from IPT that complex language is difficult to process. Further, as shown in Panel 2, *FOG* increases information gratification ($\beta = 0.3962$, $p = .0027$), suggesting that more complex language can be more gratifying, plausibly because it conveys more information. Interestingly, perceived ease of reading also increases information gratification (Panel 2; $\beta = 0.4851$, $p = .024$). That an increase in *FOG* reduces ease of reading but complex language increases gratification reveals a tension: while complex language can be gratifying, it also needs to be easily understood. These results suggest that content creators must strike the right balance to meet users' information gratification needs from traditional news sources. Information gratification, in turn, significantly increases both *Share* (Panel 3; $\beta = 1.0702$, $p < .0001$) and *TellOthers* (Panel 4; $\beta = 1.3044$, $p < .0001$), supporting H4b that user gratifications will mediate the effect of news format on social media sharing such that higher information gratifications lead to higher sharing of traditional news. However, the direct effects of *FOG* on these outcomes are not significant (*Share*: $\beta = -0.0118$, $p = .9722$; *TellOthers*: $\beta = -0.2981$, $p = .4109$), indicating an indirect pathway. Further tests of moderated serial mediation reveal how user motivations (their SBC) impact the effect *FOG* has on engagement.

Figure E1: Perceived Ease of Reading across SBC values shows that low and medium SBC consumers are most affected by Reading Level



As shown in Panel 3, the indirect effects reveal that *FOG* has a significant positive indirect effect on *Share* via gratification alone (Effect = 0.5191, 95% CI [0.0820, 1.1092]). The indirect effect of *FOG* via perceived ease of reading and gratification (IV → M1 → M2 → DV) reveals that SBC affects this relationship. The effect of *FOG* via this pathway is negative and significant for low *SBC* (Effect = -0.2109,

95% CI [-0.6272, -0.0141]); however, for medium (high) SBC readers, the negative effect reduces (becomes positive) but is not significant as the confidence interval contains 0 (Medium SBC: *Share*: Effect = -0.0857, High SBC: *Share*: Effect = 0.0395). A formal test of the indirect effect with 10,000 bootstraps indicates a marginally significant index of moderated mediation (Effect = .1252, 95% CI = [-.0001, 0.3927]) as the lower 95% CI bound marginally overlaps with 0. Please see Panel A, Figure E1, showing that the effect of reading level (FOG) on the perceived ease of reading varies by SBC. Taken together, the results on indirect effects reveal that while perceived ease of reading affects gratifications and thereby engagement for low SBC users, for medium and high SBC, the gratification path alone drives engagement (IV → M2 → DV).

Panel 4 reveals that the pattern of indirect effects is similar for *TellOthers*, with a positive indirect effect of *FOG* via gratification alone (Effect = 0.6327, 95% CI [0.1065, 1.2916]) and a significant negative indirect via ease of reading and gratification for low *SBC* (Effect = -0.2570, 95% CI [-0.7238, -0.0161]) but not medium (*TellOthers*: Effect = -0.1044, 95% CI [-.3410, .0081]) and high *SBC* (*TellOthers*: Effect = 0.481, 95% CI [-.1496, .2709]). The index of moderated mediation is significant (Effect = .1526, 95% CI = [.0001, 0.4916]) as the 95% CI does not contain 0.

Taken together, these results support H5, that the effect of reading level on engagement will depend on self-brand connection. For weak SBC, simpler reading levels will increase gratification and thereby engagement. For strong SBC, reading level will have no negative effect on gratifications and engagement. These results suggest that while complexity may enhance gratification, its benefits are dampened when perceived ease of reading is compromised. Because perceived ease of reading depends on users' motivation to expend effort on the content, creators need to consider the characteristics of their intended audience when designing language complexity. As traditional news is typically encountered incidentally on social media, it is crucial to ensure that it is comprehensible to a large audience; an easy-to-read level is beneficial for appealing to a broad audience.

Table E2: Study 4 – Traditional News

		β	SE	t	p	LLCI	ULCI
Panel 1	DV = Perceived Ease of Reading (M1)						
	constant	6.5697	.2079	31.5964	.0000	6.1596	6.9797
	FOG (X)	-.7926	.3145	-2.5203	.0125	-1.4127	-0.1724
	SBC (W)	-.1711	.0987	-1.7332	.0846	-.3658	.0236
	FOG X SBC	.2952	.1437	2.0552	.0412	.0119	.5785
Conditional effects of X at values of the moderator W:							
	SBC =	Effect	se	t	p	LLCI	ULCI
	Low	-.4973	.1884	-2.6396	.0090	-.8689	-.1258
	Medium	-.2021	.1157	-1.7471	.0822	-.4302	.0260
	High	.0931	.1804	.5163	.6062	-.2626	.4489
Panel 2	DV = Information Gratification (M2)						
	constant	2.1722	.8256	2.6311	.0092	.5441	3.8003
	FOG (X)	.4851	.2132	2.2753	.0240	.0646	.9055
	Perceived Reading Level (M1)	.3962	.1302	3.0434	.0027	.1395	.6529
Panel 3	DV = Sharing						
	constant	-3.7679	1.4693	-2.5644	.0103	-6.6477	-.8882
	FOG (X)	-.0118	.3385	-.0348	.9722	-.6751	.6516
	Perceived Ease of Reading (M1)	-.3325	.2316	-1.4353	.1512	-.7865	.1215
	Information Gratification (M2)	1.0702	.1797	5.9540	.0000	.7179	1.4225
	Direct effect of FOG (X) on Sharing (Y)	Effect	SE	Z	p	LLCI	ULCI
		-.0118	.3385	-.0348	.9722	-.6751	.6516
	Indirect Effect (X --> M1 --> Y) at values of SBC (W)	Effect	se			LLCI	ULCI
		SBC =					
		Low	.1654	.1544		-.0686	.5364
		Medium	.0672	.0738		-.0357	.2477
		High	-.0310	.0812		-.2279	.1119
		Index of Moderated Mediation	Index	BootSE		LLCI	ULCI
		SBC (W)	-.0982	.0988		-.3417	.0436
	Indirect Effect (X --> M2 --> Y)	Effect	se			LLCI	ULCI
	.5191	.2619			.0820	1.1092	
Indirect Effect (X --> M1 --> M2 --> Y) at values of SBC (W)	Effect	BootSE			LLCI	ULCI	
	SBC =						
	Low	-.2109	.1584		-.6272	-.0141	
	Medium	-.0857	.0784		-.2896	.0084	
	High	.0395	.0882		-.1247	.2393	
	Index of Moderated Mediation	Index	BootSE		LLCI	ULCI	
	SBC (W)	.1252	.1014		-.0001	.3927	
Panel 4	DV = TellOthers						
	constant	-3.9591	1.5916	-2.4875	.0129	-7.0786	-.8396
	FOG (X)	-.2981	.3626	-.8222	.4109	-1.0087	.4125
	Perceived Ease of Reading (M1)	-.3647	.2458	-1.4839	.1378	-.8463	.1170
	Information Gratification (M2)	1.3044	.1985	6.5695	.0000	.9152	1.6935
	Direct effect of FOG (X) on TellOthers (Y)	Effect	SE	Z	p	LLCI	ULCI
		-.2981	.3626	-.8222	.4109	-1.0087	.4125
	Indirect Effect (X --> M1 --> Y) at values of SBC (W)	Effect	se			LLCI	ULCI
		SBC =					
		Low	.1814	.1543		-.0428	.5528
		Medium	.0737	.0764		-.0215	.2669
		High	-.0340	.0796		-.2123	.1205
		Index of Moderated Mediation	Index	BootSE		LLCI	ULCI
		SBC (W)	-.1077	.0961		-.3370	.0301
	Indirect Effect (X --> M2 --> Y)	Effect	se			LLCI	ULCI
	.6327	.3019			.1065	1.2916	
Indirect Effect (X --> M1 --> M2 --> Y) at values of SBC (W)	Effect	BootSE			LLCI	ULCI	
	SBC =						
	Low	-.2570	.1842		-.7238	-.0161	
	Medium	-.1044	.0924		-.3410	.0081	
	High	.0481	.1014		-.1496	.2709	
	Index of Moderated Mediation	Index	BootSE		LLCI	ULCI	
	SBC (W)	.1526	.1165		.0001	.4419	

EC.E4. Study 4 – Results for Satirical News

In satirical news, as shown in Panels 1-4 in EC.E, Table E3, our tests reveal similar patterns as observed in traditional news, but with important caveats: First, while the coefficient of the indirect path of *FOG* via gratification alone ($IV \rightarrow M2 \rightarrow DV$) is positive and significant, similar to traditional news, it is much larger (Satirical News: *Share* = Effect = 1.3532, 95% CI [0.5516, 2.5388], *TellOthers* = Effect = 1.7632, 95% CI [0.7230, 3.3353]; Traditional News: *Share* = Effect = 0.5191, *TellOthers* = Effect = 0.6327). Second, the negative effect of *FOG* via the ease of reading and gratification path ($IV \rightarrow M1 \rightarrow M2 \rightarrow DV$) is significant for both low and medium SBC, in contrast to traditional news, where it was significant for only low SBC. Please see Panel B, Figure E1, showing that the effect of reading level (*FOG*) on the perceived ease of reading varies by SBC.

These considerations reveal that although a high *FOG* in satirical content reduces gratification by increasing the difficulty of reading ($IV \rightarrow M1 \rightarrow M2 \rightarrow DV$), the overall effect on engagement remains strongly positive due to the effects of language complexity on increasing entertainment gratification ($IV \rightarrow M2 \rightarrow DV$). Thus, complex language in satirical news can increase users' entertainment gratification, leading to engagement, despite the cognitive costs of increased language complexity. This result aligns with the finding in Study 1 (see Column 6 in Table B4.1, EC.B4) that language complexity increases retweets of satirical news (the interaction of *NewsFormat* X *FOG_Body* is positive and significant), but not traditional news, where complexity reduces retweets (the effect of *FOG_Body* is negative when *NewsFormat* = 0).

Importantly, since satirical news is less abundant than traditional news, the likelihood of incidental exposure to it is lower; users would need to seek out satirical content about a brand. For high SBC users, our results indicate that complex language is unlikely to deter engagement, as the pathway of *FOG* to engagement via perceived ease of reading and gratification is not significant for these users. Taken together, these results, while strongly supporting H4a and H5, suggest that creators should utilize complex language in satirical news, as the goal is to deliver entertainment, which is likely satisfied through the nuanced use of irony, wit, and layered meaning.

Table E3: Study 4 – Satirical News

		β	SE	t	p	LLCI	ULCI	
Panel 1	DV = Perceived Ease of Reading (M1)							
	constant	5.4006	.3759	14.3678	.0000	4.6593	6.1419	
	FOG (X)	-1.5126	.5240	-2.8868	.0043	-2.5460	-.4793	
	SBC (W)	.1755	.1908	.9196	.3589	-.2009	.5518	
	FOG X SBC	.5124	.2552	2.0077	.0460	.0091	1.0157	
	Conditional effects of X at values of the moderator W:							
		SBC =	Effect	se	t	p	LLCI	ULCI
		Low	-1.0002	.3056	-3.2727	.0013	-1.6030	-.3975
		Medium	-.4878	.2062	-2.3655	.0190	-.8945	-.0811
		High	.0246	.3492	.0704	.9440	-.6640	.7132
Panel 2	DV = Entertainment Gratification (M2)							
	constant	.5594	.5146	1.0870	.2784	-.4555	1.5743	
	FOG (X)	.8542	.2539	3.3641	.0009	.3535	1.3550	
	Perceived Ease of Reading (M1)	.4984	.0845	5.9006	.0000	.3318	.6649	
Panel 3	DV = Sharing							
	constant	-6.4623	1.3286	-4.8641	.0000	-9.0662	-3.8583	
	FOG (X)	-.2021	.4699	-.4302	.6671	-1.1232	.7189	
	Perceived Reading Level (M1)	-.1657	.2112	-.7844	.4328	-.5796	.2483	
	Entertainment Gratification (M2)	1.5842	.2399	6.6046	.0000	1.1140	2.0543	
	Direct effect of FOG (X) on Sharing (Y)							
		Effect	SE	Z	p	LLCI	ULCI	
		-.2021	.4699	-.4302	.6671	-1.1232	.7189	
	Indirect Effect (X --> M1 --> Y) at values of SBC (W)							
		Effect	se			LLCI	ULCI	
	SBC = Low	.1657	.2400		-.2479	.7172		
	Medium	.0808	.1228		-.1179	.3727		
	High	-.0041	.0765		-.1581	.1752		
	Index of Moderated Mediation	Index	BootSE		LLCI	ULCI		
	SBC (W)	-.0849	.1290		-.3875	.1385		
Indirect Effect (X --> M2 --> Y)								
	Effect	se			LLCI	ULCI		
	1.3532	.5021			.5516	2.5388		
Indirect Effect (X --> M1 --> M2 --> Y) at values of SBC (W)								
	SBC =	Effect	BootSE		LLCI	ULCI		
	Low	-.7897	.3670		-1.6741	-.2331		
	Medium	-.3851	.1940		-.8343	-.0785		
	High	.0194	.2237		-.4034	.4804		
	Index of Moderated Mediation	Index	BootSE		LLCI	ULCI		
	SBC (W)	.4045	.2340		.0392	.9464		
Panel 4	DV = TellOthers							
	constant	-6.9613	1.5276	-4.5571	.0000	-9.9552	-3.9673	
	FOG (X)	-.7572	.5320	-1.4234	.1546	-1.7999	.2854	
	Perceived Ease of Reading (M1)	-.2231	.2322	-.9611	.3365	-.6782	.2319	
	Information Gratification (M2)	2.0641	.3249	6.3539	.0000	1.4274	2.7008	
	Direct effect of FOG (X) on TellOthers (Y)							
		Effect	SE	Z	p	LLCI	ULCI	
		-.7572	.5320	-1.4234	.1546	-1.7999	.2854	
	Indirect Effect (X --> M1 --> Y) at values of SBC (W)							
		Effect	se			BootLLCI	BootULCI	
	SBC = Low	.2232	.2861		-.2577	.9110		
	Medium	.1089	.1483		-.1185	.4821		
	High	-.0055	.0947		-.1966	.2162		
	Index of Moderated Mediation	Index	BootSE		BootLLCI	BootULCI		
	SBC (W)	-.1143	.1530		-.4739	.1395		
Indirect Effect (X --> M2 --> Y)								
	Effect	se			BootLLCI	BootULCI		
	1.7632	.6543			.7230	3.3353		
Indirect Effect (X --> M1 --> M2 --> Y) at values of SBC (W)								
	SBC =	Effect	BootSE		BootLLCI	BootULCI		
	Low	-1.0289	.4931		-2.1905	-.3030		
	Medium	-.5018	.2649		-1.1080	-.0913		
	High	.0253	.2930		-.5465	.6242		
	Index of Moderated Mediation	Index	BootSE		BootLLCI	BootULCI		
	SBC (W)	.5271	.3071		.0476	1.2466		

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