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Abstract:

Information artifacts incorporate cognitive elements in their design to inform users about and entice them to consume relevant content. Sparse research has examined how to design cognitive elements in information artifacts in the digital news platforms context. This study investigates how information artifacts' semantic and sentiment elements convey meaning and emotion to elicit users to share online news. We propose a dissonant framework and hypothesize that three dissonance dimensions (namely, semantic dissonance, textual sentiment dissonance, and visual sentiment dissonance) influence news sharing. We tested the hypotheses using real-world data from 2013 to 2015 from Mashable—a popular digital news platform. We used novel machine-learning techniques to extract topics and sentiments from text and photos in news articles. Findings from our econometric analysis support that textual sentiment and visual sentiment dissonance positively affect news sharing.

Keywords: Cognitive Design, Information Artifact, Dissonant Framing, News Sharing, Semantic, Sentiment, Visual Sentiment, Online News Sharing.

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1 Introduction

News has moved online. Along with reduced costs, the move away from the printing press to digital platforms created an innovative model of news distribution. Mashable, BuzzFeed, Digg, and Reddit represent exemplary online news platforms where users post and share news. A significant proportion of the adult population in the United States (e.g., 62% in 2016 and 67% in 2017) obtains news from such platforms. Reportedly, more than 60 percent of users of Twitter and Facebook subscribe to the news feed (Shearer & Gottfried, 2017). Interactional features such as likes, comments, and shares further intensify the distribution of news in the digital platforms (Chung & Nah, 2009; Constantinides, Henfridsson, & Parker, 2018).

A news article is an information artifact that a person (or a machine) produces to communicate some facts, thoughts, or feelings. Information systems (IS) research has long focused on guidelines for designing information artifacts (Tallon, Ramirez, & Short, 2013; Turner, 1987). Extending this research stream to digital news platforms that have disrupted and transformed the news industry would inform researchers on designing elements that have the potential to influence popularity (Faraj, Kwon, & Watts, 2004). Undoubtedly, the popularity that digital news platforms garner from users' sharing their news reliably indicates their competitiveness and future success.

We investigate the following research questions (RQ):

RQ1: What cognitive design elements influence whether users share news articles online?

RQ2: How do different cognitive design elements, such as semantical organization, sentiment variations in text, and images, in a news article align with its shareability?

Prior research suggests that the framing of information artifacts plays an important role in the socially mediated process for the design and usability of information systems (Galliers & Swan, 1997; Lee & Chen, 2011; Qiu & Benbasat, 2009; Rittel & Webber, 1973; Schön, 1983). Studies on the content design perspective suggest that personalized connections elicit readers' responses, such as their opinions, events, and experiences (Archak, Ghose, & Ipeirotis, 2011); sentiment or emotion-triggering narratives (Bai, 2011; Berger & Milkman, 2012); and visual cues for emotional appeal (Cyr, Head, Larios, & Pan, 2009). However, little research has focused on identifying cognitive design elements and whether they influence readers to share news articles more. We address that gap in this study.

We examine the impact that relative differences in semantic and sentiment value have on the extent to which users share news across three structural components: an article's title, body, and content. We focus on the differential rather than direct effects because structural and cognitive elements interact together to convey meaning and tone to readers. We use dissonant framing to explain a mechanism that intensifies how users process an online news article. Drawing from prior literature that suggests that facts, personal opinions, events, and experiences visuals in a news article elicit readers by building connections (Archak et al., 2011), we operationalize three dissonance framing-relevant constructs: 1) semantic dissonance, 2) textual sentiment dissonance, 3) visual sentiment dissonance. Semantic dissonance captures the extent to which meaning varies across a news article's title and body. Sentiment dissonance conveys attitudes or evaluative dimensions about an information artifact designed to elicit the reader's interests (Bai, 2011; Berger & Milkman, 2012). Visual sentiment dissonance captures the extent to which sentiment differs across the content reflected through the images or photographs that one embedded purposefully in a news article to complement users' reading experience (Cyr et al., 2009).

We anchor our theoretical framework to the central and peripheral routes of the elaboration likelihood model (ELM) of persuasion (Cyr et al., 2009; Petty, Cacioppo, & Kasmer, 2015) to theoretically argue that semantic, textual sentiment, and visual sentiment influence the extent to which users share news articles. We developed and tested three hypotheses by implementing econometric models using a dataset that we constructed from articles published and shared from 2013 to 2015 on the online news platform Mashable.

2 Background

The framing effect refers to describing a decision problem in such a way that people often make less than optimal choices (Tversky & Kahneman, 1986). Framing leads the audience to think about what agenda, issue, or topic the author presents and how the author does so (Goffman, 1974). Cognitive biases that stem from people'' general tendency to avoid risk underlie the framing effect (Kahneman & Tversky, 1979). Examples of such biases include valuing loss more than gain or favoring a sure thing over probabilistic gain, which alter the decision-making process.

Furthermore, cognitive biases that influence decision framing lead to attribution bias (Heider, 1958), representative fallacy (Tversky & Kahneman, 1986), and cognitive dissonance effects (Festinger, 1962a, 1962b). Framing often involves making decisions in isolation without fully incorporating risks from other relevant factors; for example, narrow framing can explain consumers' reluctance to participate in the stock market, even for a small amount that will not likely affect their labor income (James, Lahti, & Thaler, 2006; Zhang & Feng, 2017). Thus, the way in which one structure information artifacts may alter decision outcomes. How and what information to present then remains a crucial consideration for someone who produces the information.

Framing research in the news context has examined conflict or agreement in narrative, message bias, preferences (Fairhurst & Sarr, 1996), metaphors, and design elements (D'Angelo & Kuypers, 2010; de Vreese, Boomgaarden, & Semetko, 2011; Scheufele, 1999). News framing can employ extreme language or present contradicting information to attract readers' attention to lead to a state of mind where the reader attempts to resolve cognitive dissonance, the mental discomfort that an individual experiences when exposed to two or more contradictory ideas at the same time (Festinger, 1962a). A news article's structural components (i.e., the title, body text, and photographs) can serve as a vehicle to introduce information artifacts. They convey some meaning or tone, either coherently or contradictorily, to attract attention. We build on prior work that suggests that manipulating media content characteristics, such as sentiment or opinions (Stieglitz & Dang-Xuan, 2013), psychological elicitation (Berger & Milkman, 2012), readability (Gopal, Li, & Sankaranarayanan, 2011; Song, 2013), and visual clues (Kahai & Cooper, 2003), can affect the extent to which individuals share the news. Combined with narrow framing, the dissonance effect that a news article creates through insufficiently or misleadingly presenting content may affect users' decision to share the news with their followers. We capture these perspectives in a conceptual model in the next section.

3 Theoretical Framework

We anchor our theoretical framework to the elaboration likelihood model (ELM) of persuasion in that we argue that a news article's semantic and sentiment dimensions influence the extent to which users share it through the model's central and peripheral routes (Petty et al., 2015; Petty, Cacioppo, & Schumann, 1983), respectively. As sharing requires one to process information that a news article presents to at least some extent, we argue that the central and peripheral routes align to influence readers to share the news article. We present the conceptual model we propose in Figure 1 and explain it next.

The central route persuades a person to take action due to logically processing facts and information (Andrews & Shimp, 1990). We argue that, in the news context, the central processing route of cognitive dissonance is realized through the semantic dissonance over narrow framing of title and body. The ELM (Petty et al., 2015) posits that a news article will be more likely to persuade a message recipient when the recipient exerts more considerable cognitive effort to examine the actual merits of information that the article presents to support an argument. Thus, the central route suggests that the higher the semantic dissonance, the more likely a reader will share a news article since it will likely engender a stronger reaction in the reader's followers.

Semantic dissonance leads readers to notice the interpretive differences across a news article's title and main body. This effect rests on the rationale that readers can easily discern both semantic dissonance effects. Readers can see the semantic similarity or differences across an article's title and body even after only cursorily processing the former and then reading the latter. Readers notice the interpretive differences after reading the article's title and body. Based on how readers interpret these differences, they may then either 1) question the news article for its credibility and view it with suspicion or 2) interpret it as something exciting and decide to share it. The more the variance across a news article's title and body semantics, the higher we expect it to raise a sense of curiosity in readers' minds and, thereby, affect the extent to which they will share it. Thus, we hypothesize:

H1: Semantic dissonance is positively associated with online news sharing.

The peripheral route relies on heuristics or general feeling to reduce the effort in processing complex information (Petty et al., 1983). We argue that, in the news context, the peripheral processing route is realized through the sentiment dissonance over the narrow framing of title and body; through the feelings or emotions a reader may draw from reading a text or looking at images. Textual sentiment dissonance may arise when an article title suggests a firm has a high market share but its body mentions that the firm enhanced its market position by engaging in a price war to oust local businesses. We refer to this type of sentiment dissonance as textual sentiment dissonance.

In addition to the textual sentiment dissonance from an article's title and body, sentiment dissonance that emerges from reading an article's body text and viewing an image in the body will likely render a similar effect as processing visual images or photos require less cognitive effort. As the saying goes, a picture is worth a thousand words; thus, a well-placed image can help an individual better understand text. However, individuals will likely require too high a cognitive load to determine how or why an image engenders such effect. Thus, we refer to this type of sentiment dissonance *as* visual sentiment dissonance. Thus, readers may experience a subtle change in their mood or emotion as a degree of sentiment expressed through emotions embedded in a news article's title and body, text, and the visual images or photographs in its body. In other words, the indirect effect manifests through readers' forming the impression that the news article has some interesting, funny, or intriguing elements that they need to share.

Merely having polarizing sentiment may not be enough to persuade readers to share a news article. Instead, when the text in an article's title and body expresses enough variance in emotion, readers may question its credibility, become suspicious, or become curious, which may trigger the peripheral route and, thus, cause individuals to share the article. Thus, the sentiment dissonance represents an emotional appeal and a subsequent reactive state whereby individuals act based on instinct rather than on thoughtful deliberation. Readers may trigger the emotional appeal by reading a text or looking at a photograph in a news article (Plutchik & Kellerman, 2013). Thus, an image or photo in the news increases emotional appeal (Cyr et al., 2009), in a news article's title and body.

Accordingly, we argue that visual sentiment dissonance should influence persuasion as per the elaboration likelihood model (Petty et al., 2015) by inducing a psychological state to more readily accept the presented information (Bower, 1991). Visual sentiment dissonance between body text and images will likely amplify the peripheral route of processing that underlies emotions embedded in a news article. For example, a photograph with positive sentiment will activate positive feelings (Obaid & Pukthuanthong, 2019). Therefore, we hypothesize:

H2: Textual sentiment dissonance is positively associated with online news sharing.

H3: Visual sentiment dissonance is positively associated with online news sharing.

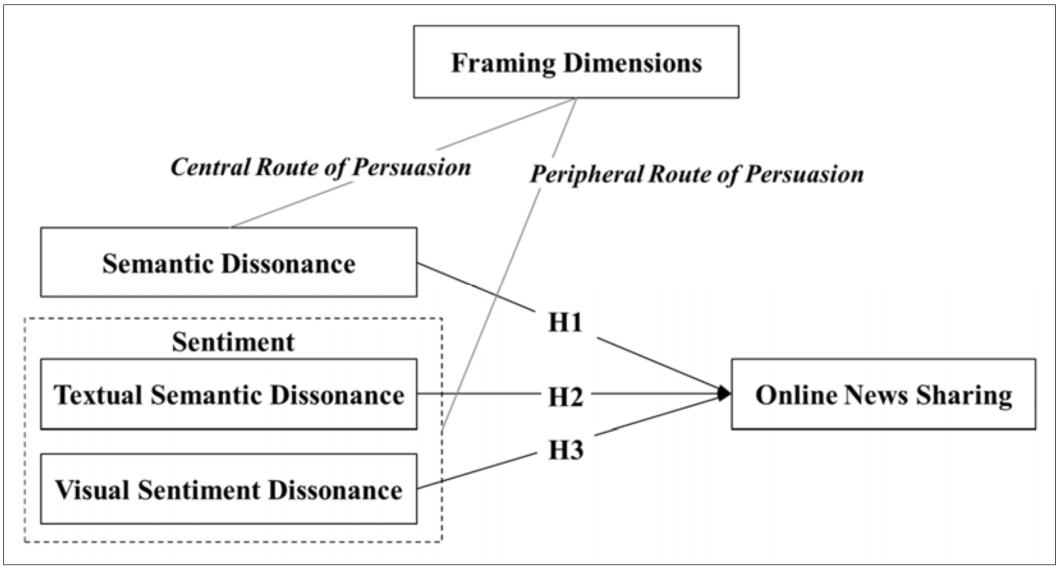

Figure 1. Conceptual Framework of Dissonant Framing Dimensions and Online News Sharing

4 Data Analyses

4.1 Data and Variables

The dataset we used comes from the Machine Learning Repository at the University of California, Irvine. This dataset contains information about 39,797 articles that Mashable—a digital news platform that focuses on global, multi-platform media and entertainment—published from 7 January, 2013, to 7 January, 2015. Founded in 2005, Mashable offers a news-curation service where volunteers upload published articles from freelancers and publisher outlets to provide a go-to source for technology, digital culture, and entertainment news. We collected additional data with more detailed information about each news article, such as its title, text, and photographs, using the hyperlinks in the primary dataset. We provide the summary statistics for the dataset in Table 1. The minimum and the maximum number of articles that Mashable published per day was 12 and 105, respectively. The original dataset contained 47 attributes that describe different characteristics of the articles, and we included some of these attributes as controls in our empirical model.

Table 1. Summary Statistics of Dataset

Number of articles	39,797
Data period	7 January , 2013 to 7 January, 2015
Number of articles with photographs	32,658
Minimum number of articles per day	12
Maximum number of articles per day	105

Table 2 shows the variables we used in this study. We used the number of times users shared a news article as the dependent variable (sharing), which we coded as the number of times individuals shared an article online via social media outlets such as Facebook, Twitter, or LinkedIn during the sampling period. We used three independent variables to operationalize semantic dissonance, textual sentiment dissonance, and visual sentiment dissonance. Thus, to measure semantic dissonance variable, we used the degree to which each article's title and body expressed similar concepts. To measure the textual sentiment dissonance variable, we used the absolute value of the difference in sentiment scores between a news article's title and body text. Finally, to measure the visual sentiment dissonance variable, we used the absolute value of the difference in sentiment scores between the images/photographs in an article's body and its body text.

We coded semantic dissonance using text-mining and natural language-processing approaches. For each article, we first processed the title and body text as two separate raw texts, which we refer to as documents. We then processed the documents according to the natural language-processing framework, which calls for researchers to conduct lemmatization (i.e., group together the inflected forms of words), to remove functional words (i.e., articles, prepositions, conjunctions, etc.) that would not likely affect how readers interpreted the text, and to rank extracted words according to how frequently they appeared across the documents we collected. We normalized how frequently terms appeared across documents using the term frequency-inverse document frequency (TF-IDF) algorithm, which reduces overrepresented terms in documents due to the selective nature in which one collects them. For instance, a document collection about cameras will likely contain the word camera in almost every document. We used the normalized (i.e., TF-IDF) document and term matrix to code title and body as vectors. We then calculated the cosine similarity score between the title and body vectors. Finally, we subtracted the cosine similarity score from 1 to code the semantic dissonance score between title and body (see Manning, Raghavan, and Schütze (2010)) for details on TF-IDF and cosine similarity).

The textual sentiment scores represent the sentiment (i.e., positive and negative sentiment) in each text. We calculated the textual sentiment score based on the extent to which a document contained words with positive or negative sentiment. One can represent positive and negative sentiment scores using a single scale with positive and negative values, respectively, or two separate scales that each represents a sentiment type. While we conducted analyses with both a single scale score and separate scales, we only report the results using the single scale score here for simplicity; we can provide the separate scales on request. We computed the textual sentiment scores using the pattern Web-mining model (Smedt & Daelemans, 2012).

Table 2. Variable Explanations and Measurement

Variables	Definitions and measurements
Sharing	The log value of how many times users shared an article
Semantic dissonance	An absolute value that indicates similarity between an article's title and the body text based on how they semantically represent their concepts or themes
Textual sentiment dissonance	An absolute value of the difference in sentiment scores between the title and the body text
Visual sentiment dissonance	An absolute value of the difference between visual sentiment and textual sentiment
Title length	The total number of words in an article's title
Total unique words	The total number of unique words in an article's main body
Total words	The total number of words in an article
Average characters	The average number of characters that a word has in an article
Topics	An article's topic numbered between 1 and 5. The data creator gives it.
Number of photos	The number of photographs in an article.
Having photos	Whether an article includes a photograph (1 = yes, 0 = no).
Time to publication	The number of days passed between an article's publication date and the date when we collected the data.
News channel	A series of dummy variables to code the Mashable news channel or article category, which includes: lifestyle (LCH), entertainment (ECH), business (BCH), social media (SCH), tech (TCH), and world (WCH).
Number of links	The total number of links or URLs in an article
Number of videos	The total number of videos in an article
Weekend	Indicates whether an article appeared on the weekend

To code the visual sentiment of the photos in the articles, we calculated to what extent they represented negative and positive sentiment on a scale from -1 to 1, respectively. We employed the visual sentiment ontology (VSO) system called SentiBank to automate the calculation (Borth, Chen, Ji, & Chang 2013).

In addition to the main variables of interest—semantic dissonance, textual sentiment dissonance, and visual sentiment dissonance—we also specified a set of control variables that may affect news sharing in our empirical model. The first group of variables included article characteristics such as the total length of the title (title length) and main text (total words) and the average number of characters that words have in article (average characters). The second group of variables concerned metadata about photographs, such as whether an article included a photo (having photos) and how many it contained (number of photos). Other variables concerned an article's metadata, such as the number of URL links (number of links) and the number of videos (number of videos) it contained.

We also control for time-related variables such as the number of days between the article's publication date and the date we acquired the dataset (time to publication) to account for each article's tenure and whether the article appeared on the weekend or not (weekend) because we expect that news articles published during the weekend will have more exposure.

To account for selection bias due to news sections that match reader preferences, we coded Mashable's news channel as categorical variables. In particular, Mashable published articles in five such channels or sections: lifestyle (LCH), entertainment (ECH), business (BCH), sports (SCH), technology (TCH), and world news (WCH). For instance, one might expect readers to share a celebrity gossip article that in the entertainment channel (ECH) more than a business report in the business channel (BCH). Table 3 shows the descriptive statistics for each variable.

Table 3. Descriptive Statistics

Variables	Obs. (N)	Means	Std.	Min	Max
Sharing	39,644	7.475	0.930	0	13.65
Semantic dissonance	39,644	0.247	0.122	0	0.773
Textual sentiment dissonance	39,644	0.192	0.181	0	1.539
Visual sentiment dissonance	39,644	0.127	0.0850	0	0.696
Title length	39,644	10.40	2.114	2	23
Total unique words	39,644	0.548	3.521	0	701
Total words	39,644	546.5	471.1	0	8,474
Average characters	39,644	4.548	0.844	0	8.042
Topics	39,644	3.225	1.420	1	5
Number of photos	39,644	4.544	8.309	0	128
Having photos	39,644	0.824	0.381	0	1
Time to publication	39,644	354.5	214.2	8	731
Number of links	39,644	10.88	11.33	0	304
Number of videos	39,644	1.250	4.108	0	91
Weekend	39,644	0.131	0.337	0	1

4.2 Estimation Approach

The log-transformed value for how many times readers shared a news article (sharing) served as the dependent variable in our model. We used the ordinary least squares (OLS) estimation with robust standard errors to test our hypotheses with the following specification:

$$Log(Sharing_i) = \beta_0 + \beta_1\ semantic\ dissonance_i + \beta_2\ textual\ sentiment\ dissonance_i + \beta_3\ visual\ sentiment\ dissonance_i + \beta_c\ controls_i + \varepsilon_i \quad (1)$$

In this function, log(sharing$_i$) represents the log value of the number of shares for article i; semantic dissonance$_i$, textual sentiment dissonance$_i$, and visual sentiment dissonance$_i$ represent the semantic, sentiment, and visual sentiment dissonance of article *i,* respectively. Further, controls represents the control variables, β represents a vector of parameters, and ε represents disturbances associated with the model.

5 Results

In Table 4, we report the estimated coefficients and standard errors (in parentheses). Consistent with the research design, the results come from a subsample of 32,658 articles that contained at least one photo. While the coefficient of the semantic dissonance variable was statistically insignificant, the coefficients of textual sentiment dissonance and visual sentiment dissonance variables were statistically significant and positive at the 0.01 level. These results show that the textual sentiment dissonance between an article's title and main text and the visual sentiment dissonance between its photos and text increased the extent to which readers shared it. However, text semantic dissonance had a positive but insignificant effect on news sharing. Thus, we found support for H2 and H3 but not H1.

We found that readers are less likely to share articles with longer titles (title length), more words (total words), and longer words (average characters). However, more unique words in the article (total unique words) make an article more exciting such that readers shared it more. Furthermore, photos, links, and videos in articles increase sharing, and readers also shared articles published on weekends more often. These findings confirm assertions in the prior research that appropriate structural framing has a role in efforts to design information artifacts. We also conducted a set of additional sensitivity checks and analyses to check endogenous concerns to establish the robustness to our results (see Appendix B for details).

Table 4. Key Estimation Results and Support for Hypotheses

Variables	Coefficients
Semantic dissonance	0.0344 (0.0407)
Sentiment dissonance	0.203*** (0.0308)
Visual sentiment dissonance	0.602*** (0.0672)
Title length	-0.00930*** (0.00237)
Total unique words	0.00174*** (9.88e-05)
Total words	-3.23e-05*** (1.24e-05)
Average characters	-0.102*** (0.00997)
Topics	0.0283*** (0.00332)
Number of photos	0.00722*** (0.000700)
Having photos	-0.00577*** (0.00131)
Number of links	0.00849*** (0.000563)
Number of videos	-0.000293 (0.00160)
Weekend	0.280*** (0.0141)
Constant	7.678*** (0.0563)
Observations	32,658
R-squared	0.046
Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05	

In all the above analyses, we treated visual sentiment as binary (either positive or negative). We also employed more granular dimensions of visual sentiment to deconstruct binary (i.e., the positive and negative) measures of sentiment into eight primary emotions (Plutchik & Kellerman, 2013). According to Plutchik (1980), eight primary emotions represent individuals' general emotional responses: joy, anger, trust, and surprise, sadness, fear, disgust, and anticipation. These primary emotions come from evolutionary fight-or-flight responses. Researchers have widely used this taxonomy as a foundation for developing popular lexical resources for sentiment analysis, such as the affective norms of English words (ANEW) (Bradley & Lang, 1999) and National Research Council Canada's (NRC) word-emotion lexicon (Mohammad & Turney, 2013). These primary emotions further enrich our model to better understand the effect that visual sentiment dissonance has on news sharing.

We estimated OLS models with eight different specifications using data with images and the sharing as the dependent variable. In each specification, we replaced visual sentiment dissonance with the difference between sentiment and each emotion dimension. All estimates showed that most visual sentiment dissonance generated from the different visual emotion dimensions had significant effects, which further confirms our previous findings (see details in Appendix C).

Thus, our findings imply that framing an article in such a way that it elicits dissonance either linguistically, through different opinions, or through sentiment (or all three) and embedding an image that invokes positive emotion in the article will convince readers to share it more. Positive images not only simplify otherwise complex or thought-provoking article but also provide a level of persuasive substance or credibility to them. If the context demands that an article uses a negative emotion, then decreasing the subjective and emotional dissonance may lead readers to share it somewhat. However, one must take care in doing so in order to avoid unethically reporting facts and not overemphasizing dissonance attributes to such a degree that the news article itself becomes false or fake. Indeed, our findings have implications for how one should design and structure information artifacts and for IS research on framing the cognitive elements in information artifacts, which we discuss in Section 6.

6 Discussion

In this study, we examined various cognitive design elements in online news articles that influence readers to share them. In this section, we discuss our study's theoretical contributions

6.1 Contributions to Information Systems Research

A rich research stream in information systems related to artifact design has somewhat neglected to provide insights for the cognitive elements in information artifacts. However, the virality of online information artifacts such as Twitter postings (Heimbach & Hinz, 2018; Shi, Rui, & Whinston, 2014), blogs, and online news (Stieglitz & Dang-Xuan, 2013) has raised the topic's importance in IS research. Further, as news media have moved from printing to online digital platforms, we need to revisit the structural and cognitive design elements that news publishers need to frame news articles. In other words, online information artifacts differ from print artifacts in their design, consumption pattern, and effect on readers. With this study, we inform the IS research stream on designing online information artifacts.

Applying dissonant framing to news sharing in digital platforms represents a significant contribution to apply the "framing" concept in the IS context. Researchers can apply the dissonance framing concept that we theorize in this study to many other contexts, such as the widely emerging gaming and virtual environments, product and service advertisements and positioning, and digital marketing and e-commerce platforms.

Our findings also more deeply explain IS artifacts in the media industry. Our findings also suggest that the way in which one frames content and media artifacts has a critical role in affecting news sharing. Further, we identify how semantics, sentiment, and visual emotions interplay with one another to influence consumer behavior and decision making in the context of media consumption. These implications not only lead to unraveling the nuances associated with media consumption but also extend concepts such as why certain individuals share certain media types more than others and the knowledge-conversion process (Massey & Montoya-Weiss, 2006; Qiu & Kumar, 2017).

Third, we differentiate how a news article's semantic and sentiment aspects relate to its credibility, emotional appeal, and subsequent usefulness. Although we focus only on the links between cognition (semantic and sentiment appeal) and subsequent sharing, we demonstrate the interestingness and usability of IT-enabled media artifacts from conceptualizing and testing the mechanisms we propose. Future research may explore some of these mechanisms: whether the quality that readers perceive an article to have depends on the expectation they form when reading its title (i.e., anchored perceived quality), to what extent they set their initial expectation (i.e., anchoring point) about a consumption process (e.g., expectation-conformation) is susceptible to manipulation, and whether any deviation from the initial expectation influences the way they influence a news article's information and entertainment value.

6.2 Managerial Implications

This study also has implications for online news platforms and news production houses. First, our findings suggest that managers should produce dissonant news in both semantic and sentimental respects if they want to encourage users to share their news more. Incorporating our insights into designing news has substantial implications in making a digital news platform popular and sustainable. However, one must interpret these suggestions carefully.

Our study has stronger implications for news-production houses. First, they cannot ignore the emerging centrality of online news. We may generalize our findings to real-time and breaking news in TV, social media channels (i.e., YouTube), or streaming content channels. However, news-production houses need to ensure they do not overuse dissonance framing to avoid stretching facts and affecting the degree to which people trust them.

Our study's practical implications raise challenges for news creators, production houses, and online platforms. For instance, they need to win readers' trust while being practical in framing news. Most content creators would affirm an inclination to create emotional or sentimental news. In order to not create overly biased news articles, we suggest that news producers make the news trustworthy yet dissonant in online news platforms.

6.3 Study Limitations

This study has two main limitations that may serve as future research opportunities. First, researchers could explore visual image sentiment-analysis approaches such as deep convolutional neural networks to further explain the impact that visual image sentiment has on the relationship between cognitive dissonance and news sharing. The second limitation concerns the dataset we used. Our using a public data set from one context over two years may not provide completeness and generalizability to all other contexts. Researchers should replicate our results to check whether the patterns that we found apply to mobile-device users, specifically with in mobile location-based news feed context (Wang, Gopal, Shankar, & Pancras, 2015).

7 Conclusion

In conclusion, in this study, we propose a dissonance framework for news in a digital news platform context. We assert that, along with the simple direct effects that the design has on news sharing, semantic, subjective, and visual attractiveness also affect it in combination with dissonant framing. Anchoring to the direct and peripheral routes of persuasion in the elaboration likelihood model, we prose a conceptual framework and suggest several hypotheses related to semantic dissonance, textual sentiment dissonance, and visual sentiment dissonance. We tested the hypotheses using real-world data from Mashable, and our findings provide valuable insights to inform research around incorporating cognitive structures into information artifacts and improving the design beyond just structural elements. Researchers can use this insight to investigate further different aspects of sharing, and information artifact management practitioners can use it to develop strategies to increase audience engagement. Overall, this study explains news sharing on digital news platforms with the unique lens of dissonance framing.

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Appendix A: Pairwise Correlations

We report the pairwise correlation coefficients of the variables that we considered in this study in the Table A1.

Table A1. Pairwise Correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Sharing	1.00													
2	Semantic diss.	0.01	1.00												
3	Textual sentiment diss.	0.06	0.02	1.00											
4	Visual sentiment diss.	0.06	0.01	0.20	1.00										
5	Title length	-0.02	-0.01	0.00	-0.06	1.00									
6	Total unique words	0.01	0.00	-0.01	0.00	-0.01	1.00								
7	Total words	0.03	-0.03	0.01	-0.03	0.02	-0.01	1.00							
8	Average characters	-0.05	0.00	-0.01	0.19	-0.07	0.03	0.17	1.00						
9	Number of photos	0.09	-0.03	0.05	0.06	-0.01	0.02	0.34	0.03	1.00					
10	Having photos	-0.04	0.02	-0.05	0.00	-0.05	0.00	0.28	0.26	0.25	1.00				
11	Time to publication	0.02	0.05	0.02	0.13	-0.24	0.00	-0.06	0.13	-0.03	-0.13	1.00			
12	Number of links	0.11	-0.05	0.06	0.08	-0.05	0.00	0.42	0.22	0.34	0.18	0.00	1.00		
13	Number of videos	0.03	-0.03	0.05	-0.03	0.05	0.00	0.10	0.00	-0.07	-0.22	0.00	0.12	1.00	
14	Weekend	0.11	-0.03	0.02	0.02	-0.01	0.00	0.05	0.00	0.05	0.00	0.00	0.07	-0.02	1.00

Note: All correlations above 0.1 are significant at the 0.001 level.

Appendix B: Extended Analysis for Addressing Endogenous Concerns and for Robustness Checks

We conducted tests to address the endogenous concern and to test the robustness of our findings. Table 4 shows that dissonance impacted news sharing. However, the correlation may be spurious due to two main endogenous concerns: whether readers choose Mashable over other sites and whether unobserved variables besides photographs influenced the extent to which users shared articles. Although we addressed these issues in our models to a certain extent by adding controls, we adopted additional instrumental and news-rankings control approaches to validate our findings further.

First, if readers are less likely to choose Mashable over other sites, they will be less likely to read any articles from the website. As a result, they will be less likely to share the articles. We used results from Google Trends about Mashable during our study period as an instrument. If we consider search results for Mashable as its overall popularity compared to other similar websites, we can reasonably think that Mashable's popularity will affect whether readers will likely view photographs but have no impact on sharing. In other words, search trends for Mashable according to Google Trends constitute a valid instrument for our first concern. We implemented a two-stage least square regression analysis (i.e., 2sls) with robustness standard errors, and the results qualitatively remained the same as our main findings. We report all estimates in Table B1.

Table B1. Tests to Addressing Endogenous Concerns

Variables	Google Trends	Text length
Semantic dissonance	0.0904 (0.0703)	0.0439 (0.0384)
Sentiment dissonance	0.325*** (0.0769)	0.157*** (0.0288)
Visual sentiment dissonance	0.522*** (0.0947)	0.360*** (0.0610)
Observations	32,658	32,658
Text information	Yes	Yes
Image information	Yes	Yes
Control information	Yes	Yes
Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.		

Second, to address whether unobserved variables besides photographs influenced the extent to which users shared articles, we also implemented an instrument-variable approach. We used the text length of the main text as an instrument based on the rationale that authors who write a shorter article are more likely to include a photograph to make it more salient or interesting. We conducted the Durbin-Wu-Hausman test of endogeneity and overfitting test for instrumental approaches before using this instrument. We found endogenous issues (which justify this analysis) and that both instruments were valid, which establishes the validity and sensitivity of our key estimation results. Similar to the previous test, we conducted a 2sls analysis with robust standard error. At the first stage, we regressed having photographs, an indicator that shows whether an article contained photographs, on text length. The results also remained consistent with the earlier results.

We tested our results' robustness using new measurements for dissonance. For semantic dissonance, we use a different distance function, Jaccard similarity to calculate the semantic distance between an article's title and its content. Rather than using the absolute differences between the title and body, we used the ratio of an article's title sentiment to its textual sentiment to quantify sentiment dissonance. For visual sentiment dissonance, we also used the ratio of textual sentiment to visual sentiment. Thus, we created three new independent variables to present dissonance. We implemented identical methods as those in the primary analyses to examine how dissonance metrics affect news sharing.

We further considered the impact that an article's popularity had on the extent to which individuals shared it. The more popular a news item is, the more likely individuals will share it. Although Mashable does not have a system to rank news, we generated an ordering variable and included it in the model to control such effects. If we assume consumption (i.e., reading articles) is similar to popularity (i.e., news sharing), we created a rank variable using the following formula:

$$Rank_i = \frac{Number\_Shares_i}{Published\_Days_i}$$

where $rank_i$ is the derived rank of article *i*, $number\_shares_i$ is the number of shares of article *i*, and $published\_days_i$ is the number of days since Mashable published article *i.*

Then, we regressed the rank of each article on the published date (e.g., Monday or Tuesday) and article topics, factors that could likely affect consumption and, eventually, the rank, to predict its ranking score. We used latent Dirichlet allocation (LDA) topic modeling—a generative probabilistic model that researchers commonly use for topic modeling—to cluster articles into different topics. LDA models documents as a mixture of latent topics. We found the best number of clusters to be five. We included these factor-based ranking score variables as a control into the main models. The results show consistency in how we estimated the key variables.

We show the results from the above robustness tests in Table B2. One can see we found the same qualitative results as those in the primary analyses, which strongly supports our previous findings.

Table B2. Robustness Tests

Variables	Alternative independent variables	Ranking score as control
Semantic dissonance	1.339 (1.695)	0.0405 (0.0407)
Sentiment dissonance	0.00311*** (0.000952)	0.227*** (0.0309)
Visual sentiment dissonance	0.379*** (0.0849)	0.550*** (0.0669)
Observations	32,658	32,658
Text information	Yes	Yes
Image information	Yes	Yes
Control information	Yes	Yes
Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.		

Appendix C: Visual Sentiment Dissonance using Primary Emotions

The results of the main estimation models show that visual sentiment impacted the relationship between dissonance and news sharing. However, we considered the photograph sentiment as binary (either positive or negative) rather than capturing the granularity of the emotions. Thus, we further examined the effect that multiple visual sentiment dimensions had on the relationship between dissonance and news sharing in this section. Following Plutchik's theoretical model of emotions (Plutchik & Kellerman 2013), we measured visual sentiment in terms of eight primary emotions: joy, trust, fear, surprise, sadness, disgust, anger, and anticipation. Previous literature shows that these emotion dimensions characterize people's general emotional responses. Therefore, we examined how visual sentiment dissonance generated from each dimension affected news sharing. We also conducted a sensitivity analysis to test our hypothesis under different conditions, such as articles published on the weekend and articles shared on different social media channels.

We conducted eight tests using the new emotional dimensions. In each test, we replaced the visual sentiment dissonance with the difference between the absolute difference between textual sentiment and one emotion dimension in the model. We also included semantic dissonance, sentiment dissonance, other control information. We used the OLS models with robust standard error for all these tests.

Table C reports the results. While the semantic dissonance from all eight emotions had statistically insignificant and positive marginal effects, sentiment dissonance from all eight emotions had statistically significant and positive marginal effects. These results confirm our previous findings. The results also show that visual sentiment dissonance did have an impact on news sharing. Among different visual sentiment dissonance measurements, the dissonance coming from trust, disgust, anger, and anticipation emotion dimensions all significantly increased news sharing but the dissonance coming from joy, surprise, and sadness decreased it.

Table C. Visual Sentiment Dissonance

Variables	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipa.
Semantic dissonance	0.0396 (0.0406)	0.0347 (0.0406)	0.0407 (0.0407)	0.0420 (0.0407)	0.0380 (0.0407)	0.0404 (0.0407)	0.0398 (0.0407)	0.0368 (0.0407)
Sentiment dissonance	0.305*** (0.0307)	0.192*** (0.0308)	0.259*** (0.0311)	0.275*** (0.0306)	0.289*** (0.0306)	0.245*** (0.0307)	0.243*** (0.0308)	0.209*** (0.0308)
Visual sentiment dissonance (joy)	-0.754*** (0.0927)							
Visual sentiment dissonance (trust)		0.703*** (0.0668)						
Visual sentiment dissonance (fear)			-0.0007 (0.0715)					
Visual sentiment dissonance (surprise)				-0.31*** (0.0944)				
Visual sentiment dissonance (sadness)					-0.49*** (0.0795)			
Visual sentiment dissonance (disgust)						0.18** (0.0774)		
Visual sentiment dissonance (anger)							0.177** (0.0697)	
Visual sentiment dissonance (anticipa.)								0.566*** (0.0700)
Observations	32,658	32,658	32,658	32,658	32,658	32,658	32,658	32,658
R-squared	0.048	0.047	0.044	0.044	0.045	0.044	0.044	0.046
Text information	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Image information	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control information	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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