**What Leads to Longer Reads?**

**Psychological Drivers of Reading Online Content**

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***ABSTRACT***

More and more consumers read content online. They scan *Wall Street Journal* articles, catch up on sports, and peruse blogs on tech and celebrity gossip. But what makes one article more engaging than another? That is, what about certain articles encourage people to keep reading? Combining natural language processing of a unique dataset of over 825,000 page-reading sessions from over 35,000 articles with an experiment, we examine how textual features (i.e., the words used) shape continued engagement. Results suggest that emotion shapes engagement. Importantly, however, not all emotion increases reading. Consistent with research on appraisal and action tendencies, content that evokes anger and anxiety encourage further reading while content which evokes sadness discourages it. Textual features that should increase processing ease (e.g., concreteness and familiar words) also increase engagement. Experimental evidence underscores the causal impact of emotion on reading and demonstrates that these effects are driven by emotions impact on uncertainty and arousal. These findings shed light on psychological drivers of reading and how to design more engaging content

KEYWORDS: Engagement, online content, digital marketing, content marketing

People have been telling stories for thousands of years. Our early ancestors sat around campfires sharing stories of the hunt. Epic poems like the *Epic of Gilgamesh*, the *Iliad*, and the *Odyssey* were passed down verbally from generation to generation before eventually being written down. And before there was the *New York Times* or *Wall Street Journal*, early journalists circulated handwritten news sheets.

But what makes some stories more engaging than others?

While this question has ancient roots, it is just as relevant in today’s digital age. The average American spends 24 hours a week online, and much of that time is spent reading (Cole, Suman. Schramm, and Zhou, 2017). People browse the latest news from the *New York Times*, read about sports at ESPN.com, and peruse tech blogs and celebrity gossip. The rise of content marketing has only exacerbated this trend. More than 86 million blog posts are published every month (Greesonbach 2018), and companies spend millions creating and distributing content to attract and retain customers.

But as anyone who has ever read a news article or a blog post can attest, not all content generates equal engagement. For some articles, people only read a couple paragraphs before moving on to something else. For others, most people finish the entire piece. But what makes one article more engaging than another? That is, what about certain content encourages continued engagement?

Efforts to answer this question have been hampered by data availability. When reading a magazine or physical newspaper, for example, there’s no record of which articles people read, let alone how far they got through the article. Further, while online metrics like views provide information on what articles get attention, they don’t provide any insight into how much of those articles get consumed.

This article fills this gap by investigating how content characteristics shape continued engagement. We use natural language processing (Humphreys and Wang 2017) to analyze a unique dataset of over 825,000 reading sessions from over 35,000 articles from nine major online publishers. This data allows us to examine, for a given person reading a given article, how textual features of a given paragraph (i.e., the words used) shape whether someone keeps reading. In addition to features that should impact processing ease (e.g., concrete language and whether familiar words are used), we examine how the valence of content (i.e., positive or negative) as well as the specific emotions it evokes (e.g., anxiety versus sadness) affect whether users continue reading. To supplement our empirical analysis of field data, we also conduct an experiment. It provides direct evidence that emotions influence reading and examines the underlying processes behind these effects.

Our findings make three main contributions. First, while some work has examined how visual features of content (e.g., pictures, layout, or the presence of ads) impact attention, there has been less research on how textual features might shape continued engagement. Our findings provide insight into how the emotions evoked by content and how easily the content can be processed impact whether people continue reading. Further, they shed light on the underlying psychological processes that might drive such effects.

Second, from a practical perspective, our findings help content creators design more engaging content. Content marketing is expected to be a $300 billion industry by 2019 (McCoy 2017). But while many have focused on metrics like clicks or views, clicks don’t always translate into reads, and content has more impact if people actually read it. Further, while social shares (e.g., retweeting) increase reach, there’s little relationship between shares and reading (Jeffries 2014). If content creators want people to read their content, they have to understand what drives engagement in the first place. This work provides a set of actionable directions creators can use to craft content that encourages reading.

Note that we focus on features of content rather than individual differences. While particular people may be more or less motivated to read, regardless of idiosyncratic individual tendencies, different articles can also differentially evoke certain emotions and encourage (or discourage) reading. This approach makes our results more useful to content creators and content marketers. While content providers may not have detailed (or any) data on the specific people reading their content to design targeted offerings, they can influence content features to encourage reading and deepen user engagement.

Third, we demonstrate how natural language processing can shed light on consumer behavior. Automated textual analysis provides a rich set of tools for extracting behavioral insight from text, but these tools have just started being adopted by marketing researchers (Netzer, Feldman, Goldenberg, and Fresko 2012; Netzer, Lemaire, and Herzenstein 2018; Moore and McFerran 2017; Packard, Moore, and McFerran 2018; Rocklage and Fazio 2015; Rocklage, Rucker, and Nordgren 2018; Tirunillai and Tellis 2014; 2017; see Humphreys and Wang 2017 for a review). We not only illustrate how a range of features can be used, but how they can deepen understanding around the psychological drivers of behavior.

*RELATED RESEARCH*

Engaging content is beneficial for a variety of reason. Some work highlights the link between engagement and advertising effectiveness. Consumers that found websites more engaging, for example, reported more positive attitudes towards ads on that site and greater intention to click (Calder, Malthouse, and Schaedel, 2009). Other work suggests that engagement may increase purchase. Looking across a range of media channels (e.g., television, magazines, and the internet), people that were more engaged in content (e.g., a television show, news article, or website) reported greater willingness to purchase a product advertised on that content (Kilger and Romer 2007).

From an online media outlet perspective, how much consumers read also directly impacts advertising revenue. Articles usually have multiple ads embedded in different parts of the page, so the longer people read, the more ads get shown and the more revenue the outlet receives.

Further, engagement also determines whether content has impact. Beyond traditional media outlets like newspapers, other organizations create content to engage their audience. Consulting firms write white papers to attract clients, and nonprofits write articles to educate readers and drive donations. But the impact of these efforts depends on people actually reading the content. If people barely read the content, it is unlikely to boost their knowledge or encourage them to hire the firm.

A key question, then, is what drives engagement.

Some research has examined how things like media type, layout, ads, or the presence of pictures or videos impact attention (Lagun and Lalmas, 2016; Lagun and Agichtein, 2015). Compared to physical newspapers, for example, work suggests that people scan more and read less when reading online news (Holmqvist, Holsanova, Barthelson, and Lundqvist 2003). When reading the physical paper, people usually quickly glance at the right page of a spread before moving to the left (driven in part by the page turning process), while in online content, not surprisingly, the top of the page gets the most attention (see Leckner 2012 for a review). Within textual content, photos can increase the length of time people spend reading an article (Zillmann, Knobloch, and Yu, 2001). Pictures and graphics can also act as “entry points” that encourage readers to focus on the text around them (Garcia and Stark 1991). Further, pop up ads, and where they appear on a site, impact the number of pages consumers view (Moe 2006)

While this work has provided insight into how visual or channel features (e.g., online or off) shape engagement, there has been less attention to how textual elements of content impact reading. The main body of work examining this question has mainly focused on labeling texts with their appropriate grade level. Some sentences can be read by most people (e.g. “the dog likes food”), while others require more specialized knowledge or vocabulary that comes with education (e.g., “Natural gas is used to heat our homes and run some transportation”). Standard indices such as Flesch-Kincaid Automated Readability Index (Kincaid, 1975), SMOG (McLaughlin, 1969), and Coleman-Liau (Coleman and Liau, 1975) use simple features like sentence and word length to approximate readability. Longer sentences and longer words tend to be more complex and require a higher-grade level to be able to comfortably parse.

But while word and sentence length are certainly important, they provide less insight into how other aspects of content impact engagement. Further, while computer scientists have begun to examine a broader set of textual features (Pitler and Nenkova 2008), they have focused mainly on predicting self-report ratings of text-quality on a small set of articles. Similarly, research in psychology has examined reading comprehension (e.g., Just and Carpenter 1980; Freebody and Anderson 1983) but has also been limited by small samples (e.g., 15 passages of 132 words each) and tasks where participants are forced to read an entire passage of text. To truly begin to understand how textual features shape continued reading, it is important to look across a broad range of both people and content types.

*THE CURRENT RESEACH*

In building our conceptualization, we rely on the fact that motivation and ability are two major drivers of behavior. The more motivated people are to take action, the more likely they will do so; and the more able they are to take that action, the more likely it is to occur. Applied to reading, these dimensions can be operationalized by the emotion content evokes and how easy the text is to process.

*Processing Ease*

We suggest that textual features that make passages easier to process should increase reading. These aspects should reduce the effort required to continue, and thus increase the likelihood that people do so. This should play out across a number of content features.

First, at the most basic level, standard measures of readability should influence processing ease. As noted above, readability measures assign texts an appropriate school grade level (e.g., Kincaid 1975). Shorter words and sentences should make content easier to process and thus encourage continued reading.

This approach to readability is rather simplistic, however, and things like syntactic complexity should also play a role. Measures like Flesch-Kincaid only consider the words in a sentence, but they ignore sentence structure. Linguistic and psycholinguistic theory suggests that as people read, they construct syntactic representations of sentences, or parse trees (Chomsky 1957). Deriving meaning depends on the ability to mentally construct such a parse, and, as a result, sentences with more complex parse trees are more difficult to build and understand (Pitler and Nenkova 2008; Schwarm and Ostendorf 2005). This suggests that greater parse tree height (i.e., more complex sentence structure) may decrease reading.

Even beyond word or sentence complexity, however, familiarity should also shape processing ease. A great deal of research suggests that familiar stimuli are easier to process (e.g., Winkielman & Cacioppo 2001). Work on mere exposure (Zajonc 1965), for example, suggests that the more people see something, the more they like it, in part because repeated exposure makes things easier to process. Consequently, one might imagine that passages that contain more familiar words are easier to read and thus people are more likely to continue reading

Finally, concreteness may also play a role. While some things in the world are relatively abstract (e.g., trust or values), others (e.g., birds or shoes) are relatively concrete. Concrete items tend to be easier to visualize or imagine and are processed more easily (see Connell and Lynott 2012 for a review). This greater ease, in turn, may encourage continued reading. Indeed, preliminary work suggests that concreteness increases comprehensibility, interest, and recall (Sadoski, Goetz, and Rodriguez, 2000).

Taken together, we examine how processing ease, as represented by readability, parse tree height, familiarity, and concreteness, influences reading.

*Emotion*

Beyond processing ease, however, we suggest that content should also impact reading through the emotions it evokes. Emotion might shape reading in three ways, through (1) emotionality, (2) valence, or (3) specific emotions.

The most basic possibility is that emotionality, or sheer amount of emotion, influences reading. Emotions can increase attention (Easterbrook 1959; Vuilleumier 2005) and flag that something is important and deserves further processing. This perspective suggests that content that evokes any emotion, regardless of type, should encourage continued reading.

A second possibility is that valence drives reading. The simplest way to organize emotions is by valence, or whether something is positive or negative. Some emotions (e.g., happiness) are associated with positive states, while others (e.g., sadness) are associated with negative ones. One could argue that positive emotion should increase reading. People like feeling good and tend to approach positive stimuli, so positive content might encourage reading. Negative content might discourage reading as people avoid bad news. At the same time, however, one could argue the opposite. Research on negativity bias (Baumeister, Finkenauer, and Vohs 2001; Rozin and Royzman 2001) finds that negative information garners greater attention. When forming impressions of others, for example, people tend to spend longer looking at negative photographs (Fiske 1980). Similarly, the old news adage, “if it bleeds, it leads,” is based on the notion that negative information will grab the viewers’ attention. These notions would suggest that negative content should encourage reading.

In contrast, we suggest a third possibility: that the relationship between emotion and reading is more complex than valence alone. In addition to being positive or negative, emotions are also characterized by different appraisal or action tendencies (Smith and Ellsworth 1985, Lerner and Keltner 2000; 2001). These tendencies, in turn, can lead different emotions to have different effects on downstream judgments and behavior (Cavanaugh, Bettman, and Luce 2015; Coleman, Williams, Morales, and White 2017). This suggests that even among emotions of the same valence, different specific emotions (e.g., anxiety versus sadness) may have different effects on reading.

In particular, we suggest that the impact of specific emotions on reading may be driven by how they shape uncertainty and arousal. Uncertainty involves not knowing or not being sure about something. While certain emotions (e.g., anger) tend to be characterized by certainty, others (e.g., anxiety or fear) tend to be characterized by a state of uncertainty and uncertainty reduction (Ragunathan and Pham, 1999; Lerner and Keltner 2001; Tiedens and Linton 2001). Uncertainty, in turn, increases attention, information search, and information processing as people they try to resolve predictions about what will happen next (Tiedens and Linton 2001; Weary and Jacobson 1997; Weary 1990). If someone is uncertain about whether it’s going to rain, for example, they might search for, and carefully process information that helps resolve that uncertainty (e.g., checking the weather). Taken to the content of reading, we suggest that emotions associated with uncertainty (e.g., anxiety and sadness) should encourage reading.

Beyond uncertainty, emotions are also characterized by differences in arousal. Arousal is a state of being physiologically alert, awake, and attentive (see Heilman 1997 for a review). While some emotions (e.g., anger and anxiety) are characterized by high arousal, others (e.g., sadness) are characterized by low arousal. A great deal of research finds that emotionally arousing stimuli attract attention (see Mather, 2007 for a review). In particular, arousal-biased competition theory (Mather and Sutherland 2012) suggests that arousal particularly increases attention for high priority stimuli, or those that are relevant to the task at hand. Taken to the content of reading, we suggest that emotions characterized by high arousal (e.g., anger and anxiety) should encourage people to continue reading.

We test these predictions in both the field and the lab. First, we use natural language processing to analyze over 825,000 page read events from over 35,000 online articles. We examine whether people are more likely to continue reading articles whose content evokes certain emotions, or is easier to process. Second, to directly test specific emotions’ causal impact, we conduct an experiment. We manipulate specific emotions and measure the impact on reading. We also measure arousal and uncertainty to test whether they can explain the effects.

*STUDY 1: EMPIRICAL ANALYSIS OF OVER 800,000 PAGE READ EVENTS*

*Data*

We worked with a major content intelligence company that tracks reader engagement for online publishers. In this case, for the last two weeks of October 2014, they provided a representative random sample of page-read events from nine popular online news sites. A page-read event occurs when a reader loads an article on a publisher’s website. To allow for data privacy, we will not disclose the exact outlets, but give a sense of the type of content. We selected sites to cover a wide range of topics, including global news and business (think CNBC and Wall Street Journal), sports (think ESPN), technology (think Gizmodo), and celebrity news, fashion, and lifestyle content (think Jezebel). We selected these sites in particular because they used fixed layouts (i.e., content is laid out the same way across articles), do not have ads within the text, and are not responsive, meaning the page shows up the same way regardless of the device. This last point means that regardless of whether an article was read on a phone, desktop, or other device, the content was not reformatted based on viewport size and the line breaks are exactly the same.

We focus only on page-read events that involve some engagement. In some cases, readers may click on an article only to leave right away. In others, they may open an article but then open another browser tab and do something else. To avoid such “bounce backs” and other cases where users are unlikely to be reading much, if any, of the article, we focus on page-read events that involve some interaction. We rely on the company’s definition, which involves anyone who had at least two interactions with the page (e.g., mouse scrolls or clicks). Someone who opens an article only to close it a few seconds later is unlikely to have been exposed to much of the article’s content. Further, while they may have stopped reading based on the article title or topic, it is unlikely they stopped due to deeply processing textual features of the article itself.

Given our interest in textual features of content, we focus on articles rather than other content types (e.g., videos). Given most of the textual features we consider are based on the English language, we focus on English language articles only. The final dataset involved 827,251 page-read events from 38,916 articles (see Appendix Table 1 for summary statistics).

For each read-event, we have information about the page (collected based on the URL) and user (i.e., device type). While each site assigns a user a unique ID each time they visit the site, these user IDs are not tracked over time or across sites. Consequently, while the data allows us to compare behavior across users for a given article, it limits our ability to examine repeat user behavior across articles.

*Dependent Variable*. We are interested in how content shapes reading. While one could imagine modeling this by looking at the link between article content and reading depth, such an aggregate approach ignores key micro-level details. First, engagement can’t be influenced by content people haven’t read, so it’s important to only predict reading using content prior to when people stop. Second, such an article-level analysis ignores paragraph-to-paragraph variation. In a story about the economy, for example, some paragraphs may evoke anxiety while others may not. Further, even if the entire article evokes little anxiety overall, if a certain paragraph evokes some, that may encourage continued engagement.

Consequently, we take a more fine-grained approach, examining how the text of each paragraph relates to whether a user continues to read into the next paragraph. In other words, we conceptualize reading as a process where at the end of each paragraph the reader either continues reading or stops.

This approach also helps address a number of alternative explanations. As discussed in greater detail below, we include various controls (e.g., publisher, device, and article topics) to try to rule out selection concerns (e.g., certain types of people tend to read certain types of articles or at certain times). That said, one could still argue that some unobserved feature of the content is what is driving engagement. To address this concern, we use article-level content features as a control. This allows us to provide a more fine-grained test. Even controlling for anxiety evoked by the rest of the article, for example, whether paragraphs that evoke more anxiety still increase reading.

To capture paragraph-to-paragraph reading, we measure how far down the page a user scrolls. This is determined using JavaScript code that is embedded on the publishers’ sites and executed on the user's browser when an article page is loaded (i.e., for each read event). The code records the pixel position a user scrolls to on the page which is the top position that is visible on the user's screen. Pixel length starts at 0 for every page and increases up to the length of a given article. If a page was 1000 pixels long, for example, the user would start at 0 and pixel depth would increase, potentially up to 1000.

For each page-read event, we map pixel length to a position within the article. The conversion from pixel length helps us get a measure of reading depth that is independent of site layout. Further, it ensures that our measure is consistent across devices and that we only examine text as opposed to other elements like ads and comments. To do the conversion, we developed a custom CSS selector, unique for each site, to identify the page content. We downloaded each article and visually rendered the page using the PhantomJS JavaScript library. From this rendering we extracted the pixel location of the top of each paragraph to know whether the user read past this point during a given page-read event. By selecting sites that have non-responsive layouts, we ensure that the pixel depth remains consistent across devices, screen resolutions and window sizes. The content is not scaled and text is not re-flowed based on screen resolution or browser window size. For example, the same page would be 1000 pixels on both a low-resolution mobile device or high-resolution screen. We validated the results of the pixel conversion process to by manually verifying it for a small set of articles.[[1]](#footnote-2)

Across all page-read events, readers read an average of 49.37% of the article text (SD = 25.40%), with an inter-quartile range of [24.64%, 75.26%]. This suggests a high degree of variation across both articles and page-read events. In terms of the number of paragraphs, readers read an average of 8.52 paragraphs (SD = 7.53), with an inter-quartile range of [3,12]. The distribution of page-read events across articles is heavily skewed, with an average number of page-read events per article of 21.26 (SD = 130.66), but as noted below, all the main results are robust to focusing only on articles that have a significant number of page-read events in the data (e.g., 100 or 250)

*Independent Variables*

As noted in the introduction, we examine how textual features linked to emotion and processing ease shape reading (See Table 1 for summary statistics for the main features and Appendix Table 2 for examples of paragraphs that score highly on each key dimension).

*Emotion*. We test the relationship between emotion and reading in two ways. First, we measure the sentiment or valence of the text using Linguistic Inquiry and Word Count (LIWC, Pennebaker et al 2015). Following prior work (Berger and Milkman 2012) we separately measure both positive and negative emotions to examine how each relates to reading.

Second, we measure specific emotions. Compared to positive emotion, specific negative emotions are easier to distinguish from one another (Keltner and Lerner 2010) and tools exist to extract them from text, so the analyses focuses there. Mohammad and Bravo-Marquez (2017) asked people how much different online content evoked anger, anxiety, and sadness and then used machine learning to extrapolate these responses to new content. We adapted their approach for larger passages of text, allowing us to measure the amount of anger, anxiety, and sadness evoked by each paragraph.[[2]](#footnote-3)

*Processing Ease.* To begin to measure processing ease, we use *Flesch-Kincaid (1975) grade level*. This measure combines elements like word and sentence length to get a sense of the number of years of education generally required to understand a text.

To provide a deeper measure of syntactic or sentence complexity, as discussed in the theory section, we also use *parse tree height* (Pitler and Nenkova 2008; Schwarm and Ostendorf 2005). This counts the number of steps it takes to get from the root, or top node, to the bottom most node. While both “The cat on the hot tin roof meowed at my parent's house" and "The cat on the hot tin roof at my parent's house meowed" are similar sentences and involve the same words, the second one has a taller parse tree (i.e., 8 edges vs. 6 edges tall).

To measure the *familiarity* of the words in each paragraph, we used ratings from Paetzold and Specia (2016). This work uses bootstrapping to extend the MRC Psycholinguistic Database (Coltheart, 1981) from around 9,000 words to over 85,000. Participants were asked to rate words based on how familiar they are, where 1 = never seen, heard, or used and 7 = seen, heard, or used every day (see Gilhooly and Logie 1980 for more detail).

A similar approach was used to measure *concrete* language. We used Paetzold and Specia (2016)’s bootstrapped ratings building on the MRC database. Participants were asked to rate concreteness on a 7-point scale (1 = least concrete, 7 = most concrete, see Spreen and Schulz 1966). Words referring to objects, materials, or people received high concreteness rating. Words referring to abstract concepts that could not be experienced by the senses (e.g., the word “facts”) received low concreteness ratings. Note that this measure is highly correlated with imagery (r = .93), consistent with our suggestion that concrete words are easier to imagine.

*Controls*

As discussed, various factors may affect reading that have little to do with the content itself. Consequently, we control for such features to rule out alternative explanations and test the robustness of the effect.

*Publisher*. Different publishers may attract different types of readers, attract readers when they have more or less time to read, or publish types of articles that encourage longer or shorter reads. People who read CNBC may have longer attention spans than those that read ESPN, for example, or the same person may read the CNBC (ESPN) when they have more (less) time. Similarly, the *Wall Street Journal* tends to publish business news, which may hold people’s attention less than sports. Thus, we use dummy variables to control for the site on which a given article was published.

*Reading Device*. Similarly, the device on which an article is read (e.g., mobile vs. desktop) should impact reading. Different types of people may use different devices, people may use different devices at different times, and different devices may themselves impact behavior (Ransbotham, Lurie, and Liu 2018). Younger people may read on their phones, for example, while older people read on their desktop. People may quickly skim online content on their phones on their morning commute while lazily browsing on their tablets when they have more time on the weekend. And given the smaller screen size, reading on a mobile device may itself encourage shorter reads. To address these possibilities, we use dummy variables to control for whether users read an article on mobile, desktop, or tablet (0.5% of page-reads are from an unknown device).

*Article Topic.* Article topic may also influence reading. Articles about certain topics may attract different types of readers, attract readers when they have more time, or impact reading in other ways. To control for this, we control for article topic. Rather than divide articles into discrete categories, we take a more fine-grained approach, performing topic modeling across the entire set of articles and allowing each to be represented as a proportion of different topics.

We use latent Dirichlet allocation (e.g., Blei et al. 2003), a common topic modeling framework that assumes each article can be represented as a mixture of topics (e.g., Berger and Packard 2018; Tirunillai and Tellis 2014). The data generating process assumes that for each word position in a document, a topic is drawn and a word is then drawn conditional on the topic. The posterior distribution of topics can be used to characterize the content of an article. We estimate a 25-topic solution and calculate the posterior topic distribution across topics. We are interested in controlling for the distribution of topics, and not the exact topics themselves, but example topics include things like government (i.e., words like state, law, govern$ and office$), sports (i.e., words like game, team, player, and sport) and personal technology (i.e. words like app, google, window and file).Posterior topic probabilities for a given article sum to 1, so we include the posterior topic probabilities for 24 of the topics as control variables.

*Paragraph Length*. Given limited attention spans, the longer one paragraph is, the less likely people may be to read the next one. Consequently, we control for paragraph length using the number of words in each paragraph.

*Position in Article*. People may be less likely to continue reading the longer they have read already. Alternatively, the more someone has read already, the more invested they may be in the content and the more likely they are to continue. Either way, we control for how long someone has been reading using the article length in words up to that point. We use both a linear and quadratic term to allow for non-linearities.

*Percentage Read.* Continued reading may also depend on where someone is in the article. Work on goal gradient (Hull 1932), for example, might suggest that readers are more likely to read a paragraph if they are almost done with an article. Consequently, we control for percentage read so far using both a linear and quadratic term.

*Article Level Feature Controls*. Finally, to further control for content differences across articles, as discussed previously, for each feature we examine at the paragraph level, we also control for it at the article level.

*Analysis Strategy*

We conceptualize each reading session, *i*, as a sequence where at the end of each paragraph the reader either continues reading or stops. We denote the action made after paragraph *j* of reading session *i* as Yij, in which Yij=1 if the reader continues to the next paragraph and Yij=0 if they do not. We assume that the probability of continuing past paragraph *j* in reading session *i* is a function of the paragraph-level content variables and control variables. Formally, we estimate the following logistic regression:

where

where Xijk denotes the kth independent variable that characterizes the content of paragraph *j* in reading event *i* and Zijc denotes the cth control variable.

*Results*

*Emotion*. We start by examining emotional valence. At first glance, the results seem to support the emotionality hypothesis (i.e., that any emotion encourages engagement). People are more likely to continue reading after paragraphs that evoke either more positive emotion (β = 0.005, *p* < .001) or more negative emotion (β = 0.102, *p* < .001, Table 2, Model 1).

Unpacking negative emotion into different specific emotions, however, suggests the picture is more complex (Table 2, Model 2). People are more likely to continue reading after paragraphs that evoke more anxiety (β = 0.363, *p* < .001) or anger (β = 0.335, *p* < .001). They are *less* likely to continue reading, however, after paragraphs that evoke more sadness (β = -0.574, *p* < .001).[[3]](#footnote-4) The fact some negative specific emotions increase reading while others decrease it suggests that the effect of emotions are driven by more than mere emotionality (i.e., amount of emotion) or valence. Instead, the results are more consistent with the notion that specific emotions are characterized by different appraisal or action tendencies that spillover to impact behavior. We expand on this point in more detail in the discussion of the study.

*Processing Ease.* Next, we examine processing ease. As predicted, a range of content features that should impact processing ease are linked to continued engagement (Table 2, Model 2). First, the two variables that increase complexity hurt engagement. People are less likely to continue reading after paragraphs written at a higher Flesch-Kincaid Grade Level (β = -0.012, *p* < .001) or with greater average parse-tree height (β = -0.195, *p* < .001).[[4]](#footnote-5) Our findings suggest that even beyond word and sentence length, syntactic complexity may also discourage continued reading.[[5]](#footnote-6)

Second, the two variables that should increase processing ease have positive effects. People are more likely to continue reading after paragraphs that use more familiar (β = 0.001, *p* < .001) or concrete (β = 0.001, *p* < .001) words. This suggests that words that are easier to process encourage reading.

*Control Variables.* Our results are robust to a variety of controls (Table 2, Model 2). These variables are not our theoretical interest, but they may practically relevant, so we report them briefly.

In terms of devices, not surprisingly, people are more likely to continue reading if they read on a desktop, or tablet (albeit marginally), and less likely to continue reading if they are on a mobile device.

Article topic is also linked to reading. Results suggest that Topic 25 (words including “earth,” “space” and “universe” and seems to be associated with science) is associated with one of the greatest decreases in reading. People are most likely to continue reading articles that have a higher proportion of topic 9, which includes words such as “season,” “yard” and “touchdown” and seems to be associated with football. People are also likely to continue reading articles that have a higher proportion of topic 6 (including words like “food,” “eat”, and “drink” and seems to be associated with food) and topic 5 (including words like “movie,” “film”, and “character” and seems to be associated with entertainment).

Word count of the current paragraph has a negative relationship, indicating that people are less likely to continue reading after reading a longer paragraph. Word count of the entire article exhibits a decreasingly positive relationship with reading, suggesting that people are more likely to continue reading longer articles. This could indicate that people tend to not to open longer pieces until times when they know they have the bandwidth to read them. Percentage read has a negative relationship, indicating that people are less likely to continue reading the further they have gotten in to an article.

*Robustness checks*. The results are consistent with the notion that emotions and processing ease shape reading, but one could wonder whether they are truly driven by the features identified. To provide further evidence, we conduct various robustness checks. We control for (1) the same textual features at the article-level, (2) other major linguistic features, and (3) textual features of the prior paragraph. We also (4) test whether the results hold focusing on articles that have at least a certain number of readers (e.g., over 250). In all cases the results still hold.

First, while we attempted to address selection by controlling for site, article topic, and platform, one could still wonder whether the results are driven by different articles attracting different types of readers. To further address this concern, we include article-level feature controls. While articles that evoke certain emotions may attract certain readers for example, or attract them when they have more or less time to read, controlling for article-level features allow us to test whether even controlling for, say the amount of anxiety an article evokes, whether evoking that anxiety in a particular paragraph encourages people to read to the next one.

Our results hold even using this more stringent test (Table 2, Model 3). This provides further support for the notion that the features identified have a causal impact on engagement.

Second, one might wonder whether other major linguistic features could explain the results. To test this, we ran a model including baskets of words empirically linked to other social or psychological constructs from LIWC dictionaries (e.g., cognitive processes, emotion, sociality, perception, motivation, time, relativity, and formality). Even after including these factors, however, the effects of our key textual features remained significant (Table 2, Model 3). The only feature that changed even slightly was parse tree height.

Third, we test whether the results are robust controlling for textual features of the prior paragraph (Table 2, Model 4). For the prior paragraph analysis, we simply included the key textual features of the paragraph prior to the focal one. Results remain the same.[[6]](#footnote-7)

Fourth, one could wonder whether the results are somehow driven by some of the articles having very few readers. But this does not seem to be the case. Even looking at articles with over 100 reads (3.7% of all articles, 67% of all reading sessions), or over 250 reads (Table 2, Model 5, 51% of reading events) results remain the same.

*Discussion*

Natural language processing of over 825,000 page-read events from over 35,000 articles suggests how textual features of content shape reading. First, the results suggest that evoking emotion shapes reading, but that the effects are more complex that simple emotionality or valence alone. Consistent with a specific emotion based perspective, different negative emotions had different relationships with reading. While readers were more likely to continue reading after paragraphs that evoked more anxiety or anger, they were *less* likely to continue reading after paragraphs that evoked more sadness. Second, the results suggest that people are more likely to continue reading after passages that are easier to process.

More broadly, our results suggest that while the topic of the article (e.g., sports vs. politics) certainly shapes reading, textual features are of similar importance. Figure 1 illustrates the fitted probability of reading the entire article based on a one standard deviation increase in each of the main textual features for each paragraph. The dotted lines indicate the average effect of topic (i.e., the average of absolute value of change in reading for a 1SD increase in each topic). For example, increasing the amount of anxiety each paragraph evokes by one standard deviation increases the odds that readers will finish the entire article by almost 5%. This increase is equivalent to shifting the topic of the article from arts and literature (which gets lower engagement) to entertainment (which gets more). Similarly, a one-standard-deviation decease in Flesch-Kincaid score increases the odds that readers will finish the article by over 10%.

*FIGURE 1: PERCENTAGE CHANGE IN FITTED PROBABILITY OF READING ENTIRE ARTICLE BASED ON ONE-STANDARD-DEVIATION INCREASE IN EACH TEXTUAL FEATURE*



Note: The results assume a one standard deviation increase in that feature in each paragraph of the article. The baseline for comparison is an article in the Wall Street Journal that is read on a desktop computer with the average values assumed for the topic posterior probabilities, emotion variables and other controls. The dotted lines indicate the impact of article topic. It was estimated by taking the average of the absolute value of the change in the estimated probability of completing the article based on a one standard deviation increase in each article topic. As some topics are linked to increased reading and others are linked to decreased reading, the figure shows lines for both the positive and negative side.

*Ancillary Analyses.* Ancillaryanalyses begin to shed light on why specific emotions might influence reading. We suggested that emotions shape reading through evoking arousal and uncertainty. To begin to test these possibilities, we measure these features directly. We measured arousal using ratings from Warriner, Kuperman, and Brysbaert (2013)[[7]](#footnote-8)and uncertainty using LIWC’s certainty measure (i.e., words like “always” and “never”). When people are uncertain, they use more tentative language (e.g., “maybe” and “perhaps,” Tausczik and Pennebaker 2010) so we measure this LIWC category as well.

Results are consistent with the notion that arousal and uncertainty increase reading. People were more likely to continue reading after paragraphs that evoked greater arousal (β = 0.065, *p* < .001**)** or used less certain (beta = -0.002, p < .001) or more tentative language (beta = 0.001, p = .003).

While the results of study 1 are consistent with our theorizing, to more directly test whether arousal and uncertainty actually drive any effects of specific emotions on reading, we conduct an experiment. We manipulate specific emotions at the individual level and measure the impact on reading. Further we test the underlying roles of both arousal and uncertainty.

The experiment also tests whether uncertainty matters. Looking at the results of Study 1 in isolation, one could wonder whether arousal alone is sufficient to explain the results. After all, while anger (high arousal) and anxiety (high arousal) were associated with increased reading, sadness (low arousal) was associated with decreased reading. Thus, arousal seems sufficient to explain the results. Further, on the surface, the results seem less consistent with an uncertainty-based explanation given that some emotions characterized by uncertainty (i.e., anxiety) increased reading while others characterized by uncertainty (i.e., sadness) decreased reading. Emotions differ on multiple dimensions simultaneously, however, and without knowing how specific articles effect specific readers, it is hard to fully test the underlying mechanisms. Further, while one could argue that specific emotions impact though arousal might overwhelm their effects through certainty, anxiety should have positive effects on reading through both arousal and uncertainty, making it difficult to know which is truly having the larger effect. Study 2 directly tests whether uncertainty effects reading above and beyond any effects of arousal.

*STUDY 2: MANIPULATING SPECIFIC EMOTIONS*

Study 2 has two main goals. First, as is often the case with observational data, it is difficult to definitely demonstrate causality. While including various controls casts doubt on many alternative explanations, one could still wonder whether the features identified truly influenced reading. Consequently, to more directly test the causal nature of the effects, we conduct an experiment. Simultaneously testing all the different features would be challenging, so we focus on specific emotions. We manipulate anger, anxiety, and sadness between subjects and measure the resulting impact on reading. Consistent with the field data, we predict that anxiety and anger will both increase reading and sadness will decrease it.

Cleanly manipulating emotions, however, is challenging. One could imagine having different participants read different content that evoked different emotions, but this approach would run into the same causality questions as the field data. It is difficult to create content that differs only on the intended emotion and nothing else. An article about climate change may induce anger, and an article about death may induce sadness, but these articles also differ on topic and a number of other features. Further, as shown in the field data, specific negative emotions are often correlated, so a passage that induces sadness may also induce anxiety. These aspects make it difficult to isolate whether any effects of different content are driven by specific emotion rather than some other correlated feature. In addition, a given piece of content may evoke slightly different emotions across different people. A piece on increasing environmental regulations, for example, may make some angry and others happy. While the scale of the field data allows us to address this concern somewhat, it is challenging to address in a smaller scale experiment.

Consequently, to improve experimental control, we use a common method in the literature and manipulate emotion incidentally (see Cavanaugh, Bettman, and Luce 2015, Berger 2011, for similar approaches). Rather than manipulating emotions through the content itself (i.e., an anger inducing article), we manipulate it exogenously. Depending on condition, participants wrote about a time they felt either angry, anxious, or sad. Participants in the control condition wrote about a neutral stimulus (i.e., office products). Then, as part of an ostensibly unrelated experiment, participants read a couple paragraphs of a neutral article and reported their interest in continuing to read more. If emotion impacts reading, as we suggest, then the emotion induced in the first task should spill over into the second. Even though everyone read the same article, the incidental emotion manipulation should impact reading. By keeping the actual article the same across conditions, and manipulating emotion incidentally, we ensure that any observed difference between conditions is driven by emotion rather than some other factor.

The second goal of Study 2 is to test the underlying process. We suggested that specific emotions may influence reading through arousal and uncertainty. Anxiety, for example, tends to increase arousal (which should encourage reading) and make people feel uncertain (which should also encourage reading). If this theorizing is correct, then these underlying dimensions should mediate any of specific emotions’ effects. We measure both arousal and uncertainty and test whether they can explain the results.

*Method*

Three hundred and two Mechanical Turk participants completed two ostensibly unrelated studies in exchange for a small payment. To keep the study short, no demographic information was collected. Participants were randomly assigned to one of four between subject conditions (control vs. anger vs. anxiety vs. sadness).

First, we manipulated specific emotions. Prior literature reviews (Quigley, Lindquist, and Barrett 2014) suggest that recalling an emotional experience is one of the cleanest ways to manipulate emotions, so we rely on this approach (see Cavanaugh et al 2015 and Berger 2011 for similar designs). Participants were asked to list three to five things that made them feel a specific emotion, and then to write about one of those things in greater depth. In the anger condition, for example, participants were asked to list three to five things that make them angry and then “Describe in more detail a situation that made you feel particularly angry,” writing “in a way that someone reading it might even get angry just from learning about the situation.” The prompt was identical in the anxiety and sadness conditions except that the word angry was replaced with the word anxious or sad. To make sure all participants engaged in a similar task, participants in the control condition completed the same writing task but wrote about a neutral topic (i.e., office products). Manipulation checks suggested the manipulations worked as intended. [[8]](#footnote-9)

Second, we measured the hypothesized process. After completing the writing task, we measured how uncertain and aroused participants felt using measures from prior work. Uncertainty was measured using three items from Faraji-Rad and Pham (2017) on 7-point scales: "how do you feel about your environment?” anchored by unsure/sure, hesitant/determined, and don’t feel confident/feel confident (α = .94, reverse-scored and averaged to form an uncertainty index). Arousal was measured using three items from Berger (2011) on 7-point scales: “how do you feel right now” anchored by very low energy/very high energy, very passive/very active, very mellow/very fired up (α = .90, averaged to form an arousal index).

Third, we measured the dependent variable. After completing the first “study” participants moved on to the “second.” This involved reading content from a news article (i.e., about wireless phone changing, adapted from the *New York Times*) and answering some follow up questions. After reading the first paragraph, participants were asked “how much do you want to read the rest of the article” (1 = not at all, 7 = very much).

Finally, all participants were shown more of the article and the study concluded.

*Results*

*Emotion’s Effect on Reading*. As predicted, a one-way ANOVA found that emotion shaped reading (F(3, 299) = 7.23, p < .001). Consistent with our theorizing, while anxiety (M = 4.52, t(299) = 2.37, p = .018) and anger (M = 4.24; t(299) = 1.56, p = .12) made people want to read more (compared to the control condition, M = 3.75) sadness decreased their interest in reading more (M = 3.09, t(299) = -2.02, p = .045).

*Underlying Process*. A series of bias-corrected simultaneous mediation models tested whether arousal and certainty can explain the effects of emotion on reading.

First, we examined the anxiety manipulation. As predicted, compared to the control condition, boosting anxiety increased arousal (coeff = .42, se = .21, t = 2.04, p= .04) which, in turn, increased reading (coeff = .90, se = .11, t = 8.13, p < .001). Increasing anxiety also increased uncertainty (coeff = 1.48, se = .24, t = 6.28, p < .001) which, in turn, increased reading (coeff = .22, se = .08, t = 2.60, p = .01). A simultaneous mediation shows that both arousal [*ab* = .38, 95% CI .02 to .80] and uncertainty [*ab* = .32, 95% CI .07 to .63] drove the effect of anxiety on reading.

Second, we examined the sadness manipulation. As predicted, compared to the control condition, increasing sadness decreased arousal (coeff = -.50, se = .24, t = -2.07, p= .04) which led to decreased reading (coeff = .66, se = .10, t = 6.55, p < .001). Boosting sadness also increased uncertainty (coeff = .86, se = .22, t = 3.90, p < .001) which, in turn, increased reading (coeff = .38, se = .11, t = 3.14, p < .001). Finally, a simultaneous mediation shows that both arousal [*ab* = -.33, 95% CI -.70 to -.02] and uncertainty [*ab* = .32, 95% CI .14 to .61] drove the effect of sadness on reading.

Third, we examined the anger manipulation. As predicted, compared to the control condition, increasing anger increased arousal (coeff = .64, se = .20, t = 3.11, p = .002) which, in turn, increased reading (coeff = .82, se = .11, t = 7.58, p < .001). Boosting anger also increased uncertainty (coeff = .47, se = .17, t = -2.81, p = .006) which, in turn, increased reading (coeff = .26, se = .11, t = 2.42, p = .02). Finally, a simultaneous mediation shows that both arousal [*ab* = .52, 95% CI .19 to .93] and uncertainty [*ab* = .13, 95% CI .02 to .32] drove the effect of anger on reading.[[9]](#footnote-10)

*Discussion*

Study 2 demonstrates specific emotions affect reading and provides evidence for the hypothesized processes underlying these effects. First, consistent with the field data, specific emotions influenced reading. Anxiety and anger made people more interested in reading the rest of an article. Sadness made them less interested. Directly manipulating these emotions incidentally underscores the causal nature of these effects.

Second, the results provide evidence for the underlying process. Consistent with our theorizing, specific emotions influenced arousal and uncertainty, which, in turn, increased reading. While different emotions evoked these two aspects to different degrees, both arousal and uncertainty increased reading.

*GENERAL DISCUSSION*

In today’s digital age, online content has become a key way to engage audiences. Online media companies, like newspapers and magazines, depend on readers to attract advertisers. But through content marketing, a much broader set of companies and individuals have come to use content as a marketing strategy. Rather than advertising, which often involves talking about how great a product or service is, content marketing provides an alternate route to engage an audience, grow awareness, and change attitudes.

But all of this depends on people actually consuming or reading the content. What makes some articles more engaging than others?

This paper attempts to provide at least a preliminary answer. Analyzing over 825,000 reading sessions encompassing over 35,000 articles from nine major online publishers, we use natural language processing to shed light on how textual features might shape continued reading. Results suggest that both emotion and processing ease shape engagement.

First, rather than any emotion increasing reading, or reading being driven by valence alone, the results suggest a more complex picture. Anger, anxiety, and sadness are all negative emotions, but while evoking anxiety and anger encouraged reading, evoking sadness discouraged it. Ancillary analyses (Study 1) and mediational analyses (Study 2) highlight the important role that arousal and uncertainty play in these effects. People are more likely to continue reading after passages that should evoke more arousal and uncertainty, and specific emotions shape the amount of arousal and uncertainty people feel, which in turn, shape reading

Second, various features that should shape processing ease seem to influence reading. People are less likely to continue reading content that is more complex (i.e., high Flesch-Kincaid reading level and parse tree height) and more likely to continue reading after content that uses more familiar and concrete language.

Demonstrating these findings across thousands of articles from a variety of different content providers speaks to their generalizability. Experimental evidence underscores the causal nature of the effects observed in the field, and provides evidence for the underlying processes.

*Contributions and Implications*

These findings make three main contributions. First, on a theoretical level, they provide insight into what drives reading. While some work has looked at how visual features shape attention (e.g., Zillmann, et al., 2001), there has been less attention to how textual features shape engagement. As a result, relatively little is known about behavioral drivers of reading. This work begins to shed light on this issue, demonstrating the important role of emotion and processing ease. It is hoped that these preliminary findings will encourage further work in the area.

An analogy can be made to burgeoning interest in behavioral drivers of word of mouth. People have been sharing things for thousands of years, and many papers have demonstrated the causal impact of word of mouth, but until recently, *why* people share word of mouth in the first place was less clear. The same can be said of continued reading or engagement. Reading is not new. But the availability of better data on how people are reading provides a new opportunity to study behavioral drivers of this important dependent variable in greater detail.

Second, on a more applied level, the results have clear practical takeaways for designing more engaging content. For a journalist or media outlet that wants to engage readers more deeply, or a marketer trying to get consumers to pay attention to their content, these findings suggest that certain linguistic features can be used to deepen engagement.

Further, the results demonstrate that reading depends on more than topic alone. Organizations often lament that it is easier to get people to care about some topics than others. A common refrain is that while people love reading about sports and celebrity gossip, it’s harder to get them to pay attention to heavier topics like policy discussions and environmental appeals. But while topic certainly plays a role in driving engagement, our results suggest that they are not the only factor. Even controlling for what an article is about (i.e., its topic or topics), how that topic is discussed plays an important role in whether people continue reading.

This provides a hopeful note for organizations trying to generate attention and engagement for less “engaging” topics. While the topic itself may not engender continued reading, writing about it in a way that generates uncertain emotions and processing ease should deepen engagement. Writing style can compensate for topic.

*Future Research*

One interesting question for future research is sequence effects. While our data does not provide the granularity to examine this in detail, how does reading one article effect reading behavior on a subsequent article? If people leave one article because it is not engaging enough, for example, might that increase their impatience or engagement threshold, such that it decreases their likelihood of engaging deeply with a subsequent article? If so, that would suggest that media outlets may want to feature content that generates longer reads to encourage people to more deeply engage with whatever they read next.

Our experiment suggest that there may also be emotional spillover. Emotions evoked in one piece of content can carry-over to effect behavior on a second, even unrelated piece of content. Consequently, reading an anxiety inducing article may increase uncertainty such that people engage more deeply in whatever they read next, even if it has no anxiety producing element. Similarly, one could imagine there are topical interdependencies. Reading one article about a topic could make people more open to reading a second. Alternatively, it may make them more likely to seek out something different.

Similarity or atypicality would also be an interesting feature to examine. How does the similarity between an article and its outlet shape reading? Take a media outlet, for example, that focuses primarily on sports. Are people more likely to deeply read a typical (i.e., sports) article, or one that is more atypical (e.g., about player’s personal lives). While the typical article may be more like what the audience tends to come to the site for, more atypical content may get more attention due to its novelty.

Similarity could also be examined within content. Any story, article or long form narrative (e.g., book or movie) can be broken down into small chunks. How might the similarity among those chunks impact engagement? One could argue that similarity is beneficial. Content that flows between similar chunks should be easier to process and follow, which might deepen engagement. At the same time, however, the chunks being too similar might feel repetitive or like the plot is not advancing fast enough. Consequently, the relationship between similarity and engagement may be more like an inverted-U, with content that is sufficiently different moving things forward, but similar enough to run a common thread throughout the content.

This brings up the broader question of narrative development. Emotional trajectories might be one area to consider. While we focused how emotion in one paragraph related to reading the next, across an article or longer narrative, emotion can take various trajectories. Some content is highly volatile, evoking positive emotions at one moment and negative the next. Emotional volatility may make content more engaging, which, in the case of positive cultural products, increases liking (Berger, Kim, and Meyer, 2018). Applied to reading, emotional volatility may also increase engagement as the uncertainty causes people to keep reading to find out what happens next.

Research might also examine how engagement affects return visits. One would imagine that the more engaging readers find an article, the more likely they will be to return to that content provider in the future. If most articles only hold people’s attention for a couple paragraphs, they’re less likely to keep coming back. This highlights the downsides of overly attention-grabbing headlines. Clickbait may be great for attracting views, but to maintain long term brand value, deeper engagement with the content itself may be needed.

It would also be interesting to examine whether easy to process language has positive effects in other domains. Take customer service calls, for example. Might customer service agents been seen as more helpful if they use concrete language or more familiar words? Such actions might make the interaction feel easier which might increase customer satisfaction.

In conclusion, while these results shed light on the behavioral drivers of continued reading, they also highlight the value of using natural language processing to extract behavioral insight from textual data. From articles, social media posts, and transcribed customer service calls, to movie scripts, song lyrics, and millions of digitized books, technology has made more and more textual data accessible. With the right tools, these data can provide insight into a range of behaviorally interesting and managerially relevant questions.

*TABLE 1: PREDICTOR VARIABLE summary statistics*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  | **Mean** | **SD** |
| **Primary** | **Emotion** | **Positive Emotion** | 2.72% | 4.21% |
| **Predictor** |  | **Negative Emotion** | 0.40% | 0.06% |
| **Variables** |  | **Anger** | 0.42% | 0.07% |
|  |  | **Fear** | 0.39% | 0.08% |
|  |  | **Sadness** | 0.40% | 0.08% |
|  | **Processing** | **FK** | 9.20 | 5.66 |
|  | **Ease** | **Parse Tree Height** | 6.30 | 2.15 |
|  |  | **Familiarity** | 560.30 | 27.43 |
|  |  | **Concreteness** | 367.71 | 37.99 |
| Control |  | WC | 54.44 | 46.83 |
| Variables |  | % Read | 0.33 | 0.25 |
|  |  | Total WC | 1172.08 | 722.33 |

Means and standard deviations are averages across the paragraphs

*TABLE 2: READing AS FUNCTION OF CONTENT CHARTACTERISTICS*

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Valence | |  | | Specific Emotions | |  | | Additional Features | |  | | Last Paragraph | |  | | 250+ Reads | |
|  |  | | (1) |  | | (2) | |  | | (3) | |  | | (4) | |  | | (5) | |
| **Emotion** | Positive Emotion | | 0.005\*\*\* | |  | | 0.006\*\*\* | |  | | 0.006\*\*\* | |  | | 0.006\*\*\* | |  | | 0.008\*\*\* | |
|  |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
|  | Negative Emotion | | 0.102\*\*\* | |  | | - | |  | | - | |  | | - | |  | | - | |
|  |  | | (0.024) | |  | | - | |  | | - | |  | | - | |  | | - | |
|  | Anger | | - | |  | | 0.335\*\*\* | |  | | 0.138\*\*\* | |  | | 0.332\*\*\* | |  | | 0.141\*\*\* | |
|  |  | | - | |  | | (0.025) | |  | | (0.028) | |  | | (0.025) | |  | | (0.036) | |
|  | Anxiety | | - | |  | | 0.363\*\*\* | |  | | 0.253\*\*\* | |  | | 0.338\*\*\* | |  | | 0.536\*\*\* | |
|  |  | | - | |  | | (0.025) | |  | | (0.028) | |  | | (0.025) | |  | | (0.036) | |
|  | Sadness | | - | |  | | -0.574\*\*\* | |  | | -0.270\*\*\* | |  | | -0.580\*\*\* | |  | | -1.042\*\*\* | |
|  |  | | - | |  | | (0.027) | |  | | (0.030) | |  | | (0.027) | |  | | (0.038) | |
| **Processing** | FK | | -0.011\*\*\* | |  | | -0.012\*\*\* | |  | | -0.017\*\*\* | |  | | -0.011\*\*\* | |  | | -0.010\*\*\* | |
| **Ease** |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
|  | Parse Tree Height | | -0.018\*\*\* | |  | | -0.019\*\*\* | |  | | 0.013\*\*\* | |  | | -0.018\*\*\* | |  | | -0.007\*\* | |
|  |  | | (0.001) | |  | | (0.001) | |  | | (0.001) | |  | | (0.001) | |  | | (0.001) | |
|  | Familiarity | | 0.001\*\*\* | |  | | 0.001\*\*\* | |  | | 0.001\*\*\* | |  | | 0.001\*\*\* | |  | | 0.002\*\*\* | |
|  |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
|  | Concreteness | | 0.001\*\*\* | |  | | 0.001\*\*\* | |  | | 0.001\*\*\* | |  | | 0.001\*\*\* | |  | | 0.000\*\*\* | |
|  |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
| **Controls** | Platform=Desktop | | 0.048\*\* | |  | | 0.048\* | |  | | 0.052\* | |  | | 0.047\* | |  | | 0.023 | |
|  |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.029) | |
|  | Platform=Mobile | | -0.111\*\*\* | |  | | -0.112\*\*\* | |  | | -0.116\*\*\* | |  | | -0.114\*\*\* | |  | | -0.166\*\*\* | |
|  |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.029) | |
|  | Platform=Tablet | | 0.035^ | |  | | 0.034^ | |  | | 0.037^ | |  | | 0.033^ | |  | | 0.020 | |
|  |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.029) | |
|  | Para Word Count | | -0.011\*\*\* | |  | | -0.011\*\*\* | |  | | -0.011\*\*\* | |  | | -0.011\*\*\* | |  | | -0.011\*\*\* | |
|  |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
|  | % Article Read | | 0.346\*\*\* | |  | | 0.336\*\*\* | |  | | 0.255\*\*\* | |  | | 0.799\*\*\* | |  | | 0.274\*\*\* | |
|  |  | | (0.017) | |  | | (0.017) | |  | | (0.017) | |  | | (0.021) | |  | | (0.024) | |
|  | squared | | -3.837\*\*\* | |  | | -3.831\*\*\* | |  | | -3.781\*\*\* | |  | | -4.244\*\*\* | |  | | -3.790\*\*\* | |
|  |  | | (0.019) | |  | | (0.019) | |  | | (0.019) | |  | | (0.022) | |  | | (0.026) | |
|  | Article Length | | 0.003\*\*\* | |  | | 0.003\*\*\* | |  | | 0.003\*\*\* | |  | | 0.003\*\*\* | |  | | 0.003\*\*\* | |
|  |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
|  | squared | | 0.000\*\*\* | |  | | 0.000\*\*\* | |  | | 0.000\*\*\* | |  | | 0.000\*\*\* | |  | | 0.000\*\*\* | |
|  |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |  | | (0.000) | |
|  | Site dummies | | Yes | |  | | Yes | |  | | Yes | |  | | Yes | |  | | Yes | |
|  | Topic Controls | | Yes | |  | | Yes | |  | | Yes | |  | | Yes | |  | | Yes | |
|  | Features@article level | | No | |  | | No | |  | | Yes | |  | | No | |  | | No | |
|  | Additional features | | No | |  | | No | |  | | Yes | |  | | No | |  | | No | |
|  | Last Paragraph | | No | |  | | No | |  | | No | |  | | Yes | |  | | No | |
|  | Observations | | 7,051,593 | |  | | 7,051,593 | |  | | 7,051,593 | |  | | 7,051,593 | |  | | 3,826,693 | |

\*\*\*p < .001, \*\* p < .01, \*p < .05, ^p <.10

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*APPENDIX*

*TABLE A1: PREDICTOR VARIABLE summary statistics*

|  |  |  |
| --- | --- | --- |
|  | Distribution of | Distribution of |
|  | Read Events | Paragraphs Read |
| Site1 | 23.29% | 23.86% |
| Site2 | 0.53% | 0.71% |
| Site3 | 9.15% | 9.32% |
| Site4 | 9.88% | 6.81% |
| Site5 | 10.65% | 8.83% |
| Site6 | 20.47% | 18.17% |
| Site7 | 12.10% | 12.88% |
| Site8 | 5.90% | 7.87% |
| Site9 | 8.03% | 11.55% |
| Desktop | 61.72% | 64.96% |
| Mobile | 28.86% | 25.15% |
| Tablet | 8.94% | 9.39% |
| Unknown | 0.48% | 0.50% |

|  |  |
| --- | --- |
| *TABLE A2: PARAGRAPHS THAT SCORE HIGHLY ON DIFFERENT DIMENSIONS* | |
| *Emotion* | |
| Positive Emotion | *High Scoring:* Amazing mural artist Mona Caron has created a number of wall-sized paintings in San Francisco. But this painted utility box is one of her standout works -- and it's a great optical illusion, too. |
| Negative Emotion | *High Scoring:* Hundreds of English Defence League (EDL) members made a trip to Birmingham on Saturday to continue doing what they love: getting drunk in public and shouting about how much they hate Muslims |
| Anger | *High Scoring:* After several truly infuriating accounts of the Columbia administration mishandling and neglecting sexual assault reports became public, the University pledged to clean up its act. But, as is so often and so alarmingly the case, this seems to have just been a PR smokescreen: the administration's first concern was salvaging its reputation, not the health and safety of its students. |
| Anxiety | *High Scoring:* The bishop of the Fargo Catholic Diocese exposed some parishioners at North Dakota churches in Fargo, Grand Forks and Jamestown to the hepatitis A virus in late September and early October. |
| Sadness | *High Scoring:* “When 17-year-old Zach Sobiech learned that the rare form of bone cancer he's battling likely has left him with only a few months to live, he wrote and recorded this song as a way of saying goodbye to his family and friends.” |
| *Processing Ease* | |
| FK | *High Reading Level:* Last week we highlighted a few retro gaming wallpapers for some Friday fun. That was nothing compared to DeviantArt member Orioto's high-resolution, you-won't-believe-your-eyes paintings of classic video games for your desktop. A must-see for any gaming enthusiast.  *Low Reading Level*: You go to a convention, and you come home with 55 cards in your pocket. If one or two cards have photos, you'll remember those people. |
| Parse Tree Height | *High Parse Tree Height:* Goldman's move is a blow to junior analysts who put in legendarily long hours for a shot at moving up the ladder. It is the latest sign that the financial industry is grappling with issues such as pay and perks amid an uneven economy and tight new rules limiting profits. A typical investment-banking analyst class at a Wall Street firm numbers about 100 people.  *Low Parse Tree Height:* Attention Black Friday shoppers: You're probably wasting your time. |
| Familiarity | *High Scoring:* If you're lucky enough to win the upcoming $600 million Powerball, you'll also be putting a big smile on Uncle Sam's face.  *Low Scoring:* If you listen to the architect Kengo Kuma, the craze for kyosho jutaku, that distinctly Japanese variant of the micro home, started in the thirteenth century, when the poet Kamo no Chomei penned an essay about the joys of living in a shack called An Account of My Hut. Contemporaneously speaking, though, micro homes became a thing in the 1990s, when rising real estate prices and a nagging recession spurred many young Tokyo residents to reconsider suburbia. |
| Concreteness | *High Scoring:* On October 17, 1814, over a quarter million gallons of beer were unleashed onto London's streets. The 15-foot tall tidal wave of booze crashed into buildings and flooded cellars, even killing eight especially unfortunate souls. The culprit? A bursting vat.  *Low Scoring:* When US-Soviet relationships were at their frostiest in the 1980s, there was no telling what sort of exotic threat was about to come roaring through Russia's Iron Curtain. That's where the Defense Intelligence Agency came in. |

1. One could wonder whether our measure truly captures reading. For example, some people may quickly scroll down an article without reading it in depth, so one could argue that our measure simply captures how far someone scrolled and nothing else. If that was the case, however, it should make it harder to find effects of textual features on scrolling. If someone simply scrolled, without reading any of the words, then words should have no impact on how far they scrolled. Thus, unless skimming or deeper scrolling is somehow driven by some alternative feature that is also correlated with the textual features we examine, if anything, this measure provides a conservative test of our hypotheses. The less people are reading the weaker any relationships between textual features and reading should be. [↑](#footnote-ref-2)
2. We used Mohammad and Bravo-Marquez (2017)’s approach rather than LIWC for a number of reasons. First, while the validity of LIWC’s positive and negative emotion categories have been tested in a number of studies, the specific emotion categories have less empirical support. Second, a small-scale comparison showed that Mohammad and Bravo-Marquez (2017)’s approach was more predictive of manual coding of the articles. That said, to ensure that the results are robust to different methodologies, we also run a version where we use LIWC instead. Results are almost identical. [↑](#footnote-ref-3)
3. Using an alternate measure of specific emotions (i.e., LIWC) shows almost identical results for both anxiety and sadness. The results for anger are largely consistent albeit weaker. [↑](#footnote-ref-4)
4. While Pitler and Nenkova (2008) found that things like words per sentence and parse tree height did not predict readability ratings, it involved only 30 articles, and may thus have been underpowered. It is also possible that readability ratings don’t fully reflect actual reading behavior. [↑](#footnote-ref-5)
5. Note while one could wonder whether the relationship between complexity and engagement might be an inverted-U, additional analyses casts doubt on this possibility. Rather than complexity simply being bad, for example, one might wonder whether some complexity is good, but too much becomes bad. But this does not seem to be the case. Including a quadratic effect of parse tree height or Flesch-Kincaid Grade Level, for example, shows that while the quadratic effects are positive (parsetree height stat, FK stat), rather than being an inverted U the relationship is strictly decreasing for FK and decreasing for 90% of the data for parsetree height (it only has a positive effect in the last 1% of the data). Thus complexity is almost always negatively linked to reading. [↑](#footnote-ref-6)
6. We also built a stock model that allows for all previous paragraphs to affect the decision to continue reading. This considers the cumulative effect of linguistic features since the start of the article and assumes a given linguistic feature accumulates from one paragraph to the next but that the prior amount of the stock decays. The stock model is analogous to a leaky bucket in which the previous level will decline over time, but that the level may increase with the presence of the linguistic feature in the latest paragraph.  There are various formulations such a model could take, but given computational demands, we used a version where the decay parameters for (1) all the emotions and (2) all the processing ease measures are kept the same.  Given computational demands, this model could only be run on a 20% sample of the articles, but the results are generally the same. [↑](#footnote-ref-7)
7. People rated nearly 14,000 words based on how aroused they felt after reading them. Words like “insanity” and “lover” were rated as high arousal while words like “dull” and “librarian” were rated as low. [↑](#footnote-ref-8)
8. Using a similar natural language processing approach to the field analysis, we calculated the amount of anxiety, anger, and sadness indicated in each participants’ writing. As expected, the manipulations changed the amount of anxiety (F(3, 299) = 36.568, p < .001), anger (F(3, 299) = 31.40 p < .001), and sadness (F(3, 299) = 13.48, p < .001) participants expressed. The anxiety manipulation, for example, evoked more anxiety (M = 4.08%) than any of the other conditions (Ms < .5%, ps < .001). Similarly, the anger manipulation evoked more anger (M = 3.44%) than any of the other conditions (Ms < .7%, ps < .001) and the sadness manipulation evoked more sadness (M = 2.27%) than any of the other conditions (Ms < 1.14%, ps < .003). This suggests that each manipulation evoked the key emotion of interest and not other specific emotions. [↑](#footnote-ref-9)
9. Anger may not have increased certainty due to the specific control condition used. We tried to select an innocuous control condition (i.e., writing about office products) but participants still reported an extremely high level of certainty (M = 6.1 on a 7-point scale) making it difficult for any emotion condition to boost certainty even further. Ancillary data we collected using a control condition where participants didn’t write about anything however, showed a decreased level of certainty in the control condition, such that anger did in fact increase certainty. [↑](#footnote-ref-10)