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Judging a Book by Its Cover: Understanding the Phenomenon of Fake News Propagation from an Evolutionary Psychology Perspective

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Abstract

With fake news now a serious concern facing researchers, practitioners, and policymakers alike, research is increasingly exploring the factors that lead to its proliferation. However, there is limited research on the role of temporal orientation. i.e., emphasis on time. This paper examines whether a future temporal orientation (FTO), defined as a relative emphasis on the future observed in fake news titles and content, is associated with fake news sharing. We bring arguments grounded in evolutionary psychology to understand the underlying rationale driving this phenomenon. Our analysis of a Twitter dataset comprising 465519 tweets suggests that FTO characterizes fake news and is positively associated with fake news sharing. Notably, fake news titles and the accompanying text differ in their FTO. Specifically, we show an inverted U-shaped relationship between fake news sharing and the difference in FTO between the title and accompanying text. As a practical implication of this analysis, efforts to limit the spread of fake news should pay more attention to how such news emphasizes the future.

Keywords: Fake News, Future, Temporal Orientation, Evolutionary Psychology

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"*Fake news*" *could worsen infectious disease* "*epidemic*" (February 17, 2020, PharmaTimes)

1 Introduction

The growth of the internet and social media over the last decade has led to increasing concern about the phenomenon of fake news. Fake news is defined as deliberate disinformation or hoaxes spread through traditional news media and online social media (Zeynep, 2018). Recent studies indicate that false information spreads more quickly than factual news on Twitter (now known as X), a popular social media platform. In fact, tweets that contain fake news are 70% more likely to be retweeted than tweets that convey truthful information (Langin, 2018). While fake news has been observed throughout history as a propaganda tool for psychological manipulation, the vast reach of the internet and social media platforms—as well as their capability to spread any message—has made fake news a pressing problem facing modern society and policymakers alike. The magnitude of this problem can be gauged from some statistics. For example, 37% of Europeans report that they encounter fake news on an almost daily basis (Statista, 2020) and over 80% of US adults aged 18-29 perceive fake news as a major problem (Statista, 2019). Fake news has motivated crimes (e.g., shootings) and caused unnecessary panic and subsequent responses (e.g., unjustified fears of the Ebola virus in the US) (Akpan, 2016). The severity of the problem has motivated us to understand the factors that promote sharing fake news which, hopefully, can help control its proliferation.

We reason that a relatively high emphasis on the future, which we term a future temporal orientation (FTO), is a key factor that promotes the sharing of fake news. Specifically, we predict that fake news with a greater FTO is more likely to be shared. Fake news with a greater FTO makes readers ponder the future, including its possibilities and challenges. Our principal argument is that the inherent uncertainty about the future provides a backdrop for negative emotions like fear, which leads to the sharing of fake news. Recent studies such as Oh et al. (2023) have found that people are more likely to read news with negative sentiment. Fake news propagandists leverage this propensity to spread negative news through enhanced FTO. Although the future may be associated with both positive emotions (e.g., excitement and hope) and negative emotions (e.g., fear), negative emotions play a strong role in spreading fake news (Bakir & McStay, 2018). Hence, fake news propagandists may leverage negative emotions through the use of FTO. By focusing on FTO—an aspect that fake news propagandists can exploit—we extend a growing body of research examining the phenomenon of fake news from various perspectives, such as identification and detection (Conroy et al., 2015; Shu et al., 2017; Wang, 2017); characteristics associated with its spread (Bryanov & Vziatysheva, 2021); and biases, emotions, and the inherent sentiment in fake news (Bakir & McStay, 2018; Kim & Dennis, 2019; Safadi et al., 2020). In this work, we focus on FTO as a specific underlying factor responsible for fake news sharing.

To understand the role of FTO, we combine temporal logic with arguments from evolutionary psychology to argue why FTO may be salient in the spread of fake news. Grounded in evolutionary psychology, we argue that humans naturally fear the future due to the role that potential physical and emotional dangers have played in human evolution. This fear is ingrained in the human psyche, as our ancestors were always alert to uncertainty ahead (Lents, 2016). Fake news articles with high FTO thus appeal to this specific aspect of human nature, motivating people to share this content. As one of the eight primary emotions (Pico, 2016), fear has widespread communicative power: Messages that arouse fear are often leveraged in traditional nondigital communication (Dillard, 1994). Fear is a very powerful emotion (Dillard, 1994; Dillard et al., 1996; Witte, 1996) that significantly influences belief in fake news (Salvi et al., 2021), leading to increases in its production and consumption in recent years (Shirish et al., 2021). Furthermore, fear leads to an increased tendency to share fake news and increased pseudo-profound existential beliefs (Salvi et al., 2021). In this study, we build on prior research and focus specifically on the FTO of articles shared on microblogging platforms such as Twitter (now X), as these platforms are often criticized for spreading fake news (Passy, 2020).

All fake news tweets have two components: (1) the title of the news item and (2) the accompanying text that the person posting the tweet writes to support, argue with, or discuss the news item. Figure 1 shows an example of a fake news tweet with the title and accompanying text. Both components may include FTO elements that influence sharing. However, as crafting the title and accompanying text require different amounts of effort, the two components may differ in their FTO. This difference could influence the sharing of fake news.

Against this background, we aim to answer the following research question:

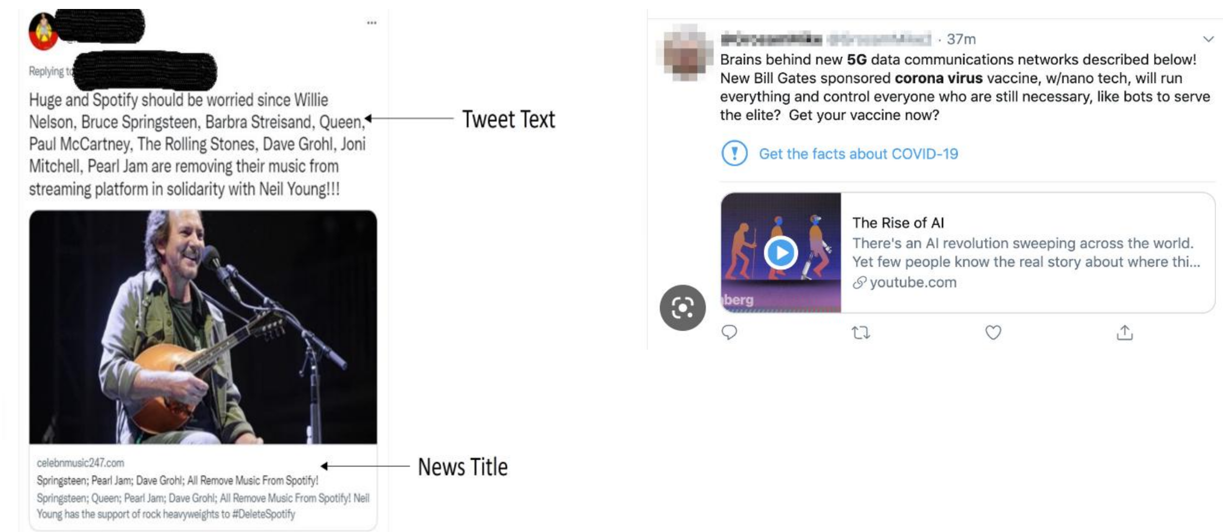
RQ: What is the effect of depicted FTO in the title and content on fake news sharing on Twitter?

Through this work, we make the following contributions. First, we extend the literature on fake news by examining an aspect that leads to sentiment and emotions, which directly appeal to human nature. As temporal orientation is inherent to any communication, it can play a significant role in its success. We demonstrate that FTO characterizes fake news and that fake news with higher FTO results in higher anxiety, supporting our proposed mechanism.

Second, we offer new empirical insights into how specific linguistic characteristics can contribute to the spread of fake news. With the growing prevalence of large language models (LLMs), which make content generation easier and faster than ever before, it has become increasingly important to understand the mechanisms that lead to the proliferation of fake news.

Third, we explore how temporal orientation contributes to various aspects of fake news examined in prior work. Our robustness checks show that FTO plays a crucial role in the sharing of fake news in different contexts and when other aspects, such as videos and images, are present.

Finally, we leverage FTO to propose a framework for fake news identification and management. Our approach addresses the limitations of the platforms commonly used to share fake news and incorporates insights from prior studies on human responses to different aspects of content. Overall, this approach can enhance the effectiveness of existing frameworks and online tools to manage fake news.



Note: Fake news is often taken down or blocked after being reported or identified. Hence, many fake news tweets from the studied time period were not available in late 2022. The source for the fake news presented here is: https://www.vox.com/recode/2020/5/11/21254889/twitter-coronavirus-covid-misinformation-warnings-labels (accessed Nov 29, 2022).

Figure 1. Examples of Fake News Tweets

2 Literature Review

While gossiping and rumor-mongering have a long history as integral human pastimes, the ability to connect with a broader audience through social media has magnified both the scale and scope of these activities (McNair, 2017). By asking varied questions, extant research has attempted to understand the phenomenon of fake news through multiple lenses. Table A1 (Appendix) and Table 1 provide a nonexhaustive snapshot of the most relevant literature in the field. Although the field is not new, it has seen enhanced interest since the 2016 US presidential election when the term "fake news" entered common parlance (Cerf, 2016). Several studies in the base disciplines of sociology and communication have aimed to unearth rumors and misinformation (Sunstein, 2014), while studies in computer science have developed novel algorithms to detect and classify misinformation (Lazer et al., 2018).

An analysis of the literature on fake news and misinformation—especially in the era of social media—identifies specific patterns of questions raised and examined by researchers. As the focus of this study is broader research in information systems, we conducted a systematic literature review in this domain. We used the Business Source Complete Database provided by EBSCOhost for this purpose and searched for articles including any of the three keywords "misinformation" or "disinformation" or "fake news" in the abstract. We limited our search to the Senior Scholars' List of Premier Journals in the field (11 journals),[1] which identified 30 published papers. We then read the full text of these 30 papers and eliminated those that did not directly relate to our phenomenon, e.g., papers about fake product reviews (Ananthakrishnan et al., 2020). We also eliminated review papers and editorials. This exclusion process left us with 26 papers, which we organized in the research buckets discussed below. After reading these papers, we included additional relevant and critical papers outside the inclusion criteria to form a more comprehensive list of relevant studies.

We classified the papers identified by the review process into the five major categories[2] in Table 1. The first category describes research that attempts to identify fake news algorithmically. Many studies in this category are in the domains of computer science and information science (IS), with researchers attempting to use text analytics, data mining, and lab experiments to understand the characteristics of fake news and create automated identifiers for such news items. Some studies (e.g., Kim et al., 2019) have proposed mechanisms to identify fake news to make digital platforms safer for all users. The second category attempts to understand the personalities of users who spread misinformation, mostly through experimental and survey-based methods. Within this category, we also find computational studies that attempt to understand the questions of "who spreads fake news" and "how" by studying the role of social network patterns in fake news dispersion.

[1] https://aisnet.org/page/SeniorScholarListofPremierJournals

[2] We thank an anonymous reviewer for suggesting useful references on different categories of research.

Table 1. Classification of Extant Studies in the Fake News Domain

Research bucket	Major research questions	Probable domains of study	Indicative papers*
1. "What is fake news"	How to identify fake news? What are the different characteristics of fake news? Veracity assessment techniques	Computer science, IS	Zhang et al. (2016); Shu et al. (2017); Wang (2017); Kim et al. (2019); Kim & Dennis (2019); Deng and Chau (2021); Lozano et al. (2020); Gopal et al. (2022); Yuan et al. (2021)
2. "Who spreads fake news and how?"	What are the traits of people sharing false information? Identification of fake reviewer/fake news sources. What is the mechanism of fake news spread?	Psychology, IS, journalism, communication studies	Effron & Raj (2020); Pennycook & Rand (2020); Ginting et al. (2018); Vosoughi et al. (2018); Shin et al. (2018); Grinberg et al. (2019); Dennis et al. (2023); (Dennis et al., 2023); Horner et al. (2021); Miller et al. (2024); Ng et al. (2021); Ross et al. (2019); Karami et al. (2021)
3."Why does fake news spread?"	Why do individuals share fake news? What are the motives for fake information sharing?	IS, psychology	Oh et al. (2013);Kim & Dennis (2019); Kim et al. (2019);Laato et al. (2020); Shirish et al. (2021); Talwar et al. (2019); Talwar et al. (2020); Turel and Osatuyi (2021);
4."What impact does fake news have"	How does fake news impact firms? How does fake news impact business, society, and governance?	Marketing, IS, sociology	Visentin et al. (2019); Clarke et al. (2020); Lutz et al. (2024)
5. "who "believes" in fake news"	Why do individuals believe fake news? Can individuals detect fake news? Can interventions such as asking users to rate stories affect their belief in fake news?	IS	Beisecker et al. (2024); Gimpel et al. (2021); Moravec et al. (2018); Moravec et al. (2020); Moravec et al. (2022); Safadi et al. (2020); Schuetz et al. (2021); Wang et al. (2022);Gupta et al. (2023);Mirhoseini et al. (2023)

Note: * As the name suggests, the "indicative papers" column, as is an indicative and not an exhaustive list of all papers in this domain, when referring to non-IS domain papers. We have attempted to include all IS-specific papers as per the inclusion criteria of systematic literature review described in the paper. It should be noted that several papers could be classified into more than one category, as they attempt to answer multiple questions. These papers have been classified into the category with the best fit.

The third category attempts to understand why individuals indulge in misinformation campaigns. In other words, what are users' motives for spreading fake news? This category includes work such as Oh et al.'s (2013) study on the motives behind spreading rumors on social media. However, their study focuses on rumors, not the institutionalized fake news that has become particularly topical post-2016. This category also includes recent work, such as Laato et al. (2020), conducted against the background of COVID-19. Such studies attribute individuals' propensity to share unverified information to trust in online information sources and perceived information overload due to the proliferation of online content. The fourth category attempts to understand the impact of the spread of fake news. This category includes limited studies from business and management. Although some studies in the finance and economics domains have examined the impact of rumors on stock reactions (e.g., Kamins et al., 1997), the broader impact of fake news peddled as real news and its implications for business and society warrant deeper analysis. The final category attempts to understand why individuals believe in fake news. The findings suggest that individuals' reasons for belief in fake news are manifold, ranging from confirmation bias (Moravec et al., 2020, 2022) to social media homophily that reduces fact-checking (Schuetz et al., 2021).

It should be noted that most of the included studies are from the IS domain or related management disciplines, which warrants consideration in the literature analysis. A significant amount of research on fake news has taken place in computing fields.[3] Hoy and Koulouri (2021) conducted a systematic literature review in the computer science domain, identifying and analyzing 81 articles focused on the lexical aspects of news content to determine fake news. These features include

[3] These studies from the field of computer science were not included in Table 1 if they were not directly related to the categorizations created to analyze the management/IS research.

words, numbers, occurrences, etc. Notably, less than five articles in their dataset used any form of linguistic inquiry and word count (LIWC)-based analysis to extract linguistic features, and no articles focused on the fundamental reasoning behind the sharing phenomenon. In a recent literature review of misinformation intervention studies in the computer science domain, Hartwig et al. (2023) analyzed 108 studies and identified different intervention designs proposed for tackling misinformation. These studies analyzed the phenomenon of fake news using complex experiments and machine learning models and proposed interventions but did not analyze the factors driving individuals to engage in sharing. We also specifically analyzed the computer science literature using linguistic features and LIWC software in fake news research to understand the landscape. The most relevant identified study was by Karami et al. (2021), who used LIWC and linguistic analysis to profile users who retweet fake news according to specific psychological characteristics. While this study sheds light on the psychological profiles of users who regularly share fake news, it did not analyze linguistic characteristics at the tweet level to explore why those specific tweets were shared. Other studies like Castelo et al. (2019) and Qiao et al. (2020) used LIWC to create linguistic features to predict the determinants of fake news itself. Compared to these existing studies, our study is unique in its use of tweet-level linguistic features to identify why specific fake news tweets are shared and their link to a future temporality, as well as for its theoretical links with evolutionary psychology.

Our study exists at the intersection of Categories 1 and 3. Through its focus on higher FTO in fake news, our study contributes to both the identification of fake news and the understanding of why FTO is a salient factor in its spread. We empirically demonstrate that FTO characterizes fake news and establish a theoretical basis for why individuals share fake news. We argue that the use of FTO is a strategy grounded in human evolutionary history for fake news propagandists to spread fake news, as fear of the future leads to heightened anxiety and impairs critical thinking. In doing so, we explicate an underlying mechanism that makes it difficult for individuals to distinguish between fake and real news and—by appealing to the basic emotion of fear—increases sharing. Given these strong theoretical foundations, our study contributes to the theoretical richness of a field with several empirical studies, as seen in Table 1 (and Table A1 in the Appendix).

2.1 Theoretical Background

2.1.1 Fake News and EP Perspective

In this study, we consider how humans respond to fake news from an evolutionary psychology (EP) perspective. EP is grounded in biological foundations for studying human behavior (Downes, 2018). Its central premise is that internal psychological mechanisms can be attributed to human adaptations that are the product of evolution. EP attributes any psychological trait to our evolutionary past and its role in surviving the challenges arising from the environment, where environment refers to nongenetic factors and includes social, nutritional, climatic, and other related factors (Kock, 2009; McElreath & Boyd, 2007). Any psychological trait that helped humans survive environmental challenges would have been passed on to future generations, who then also exhibit the trait. Thus, the evolution of a specific trait has a hereditary foundation (Kock, 2009). Although our evolutionary past also shapes how we respond to technology (Kock, 2009), modern humans do not experience threats to our survival at a similar magnitude as in the past. To theorize about human responses to technology, one must focus on three elements: psychological traits, environment, and task performance, where task performance refers to an individual's ability to perform a task. The modern task environment—i.e., the environment surrounding humans when they perform modern tasks—influences the relationship between psychological traits and task performance.

This study specifically seeks to understand if FTO, defined as a relative emphasis on the future in fake news titles and content, is associated with sharing fake news. We contextualize our study in the setting of social media platforms, specifically Twitter. Twitter is a microblogging service that allows users to share 280[4] character messages termed "tweets" (Murthy, 2013). When users share a tweet with others, it is termed a "retweet." Notably, Twitter has been blamed as an important source of disinformation and fake news campaigns (Grinberg et al., 2019).

We argue that FTO in fake news leverages humans' fear of the future. Fear evolved as a mechanism to protect against predators. As the future entails uncertainties, preparing for an uncertainty-laden future has helped humans survive (Sherlock, 2015). Thus, "fear of the future" exemplifies a psychological trait. Fear of the future will lead to more instinctive response to any message focused on the future relative to messages focused on the present or past—even if the message is

[4] Twitter previously had a 140 character limit, which was increased to 280 characters in November 2017 (https://blog.twitter.com/en_us/topics/product/2017/tweetingmadeeasier.html). Hence, older tweets may have less text compared to tweets after November 2017.

fake news. In addition to fear, humans experience anxiety, which is conceptualized as the cognitive association between basic emotions like fear with events, meaning, and responses (Hofmann et al., 2002; Izard, 1992). Hence, while fear is an emotion, anxiety is its association with a response. How humans respond to fear is quite heterogeneous and the response can be physiological and/or behavioral (Thrasher & LoBue, 2016). Information sharing may be a coping mechanism when an individual experiences fear and anxiety (Fang, 2017). For the majority of human history, information sharing has only been possible through interactions in a physical setting or exchanged physical communication like letters. However, modern technology—especially social media—has enabled humans to exchange ideas at a previously unimaginable scale.

Thus, sharing a fake news item on a platform like Twitter exemplifies task performance in which fear of the future, as a psychological trait, plays an essential role. The modern task environment (i.e., the environment surrounding humans while performing a task—here, the sharing of fake news) includes aspects such as the credibility of the person generating the fake news that influences the relationship between the fear of the future in the message and sharing. Here, we adopt ideas from EP to develop four distinct hypotheses that relate temporal orientation to fake news sharing. Fear of the future (temporal orientation), which could lead to anxiety, and fake news retweets form the two essential pillars of our research model. Retweets are tweets shared publicly by individuals on Twitter and exemplify fake news sharing. Likes are an endorsement of a tweet and are assumed to reflect appreciation for a tweet's content. When a tweet is frequently retweeted, it is described as going "viral" (widely shared).

2.2 Hypotheses

Our first hypothesis speaks to the increasing literature on what characterizes fake news. Fake news mimics news media content but lacks credible information (Lazer et al., 2018). It also lacks the two journalistic norms of objectivity (solely factual reporting) and balance (presenting all sides of a story without undue preference for one side over the other). Fake news is often used as a propaganda tool (Lazer et al., 2018). Propagandists seek to create fake news items that lack objectivity and balance yet are still challenging to distinguish from real news characterized by objectivity and balance. Temporal orientation, or how time is emphasized, can make fake news difficult to distinguish. FTO, i.e., a relative emphasis on the future (Park et al., 2017) can make it particularly difficult for readers to differentiate fake news from real news. There is a strong rationale for expecting this relationship. Time is a socially constructed variable (Liang et al., 2018) in that the present exists in relation to the past and future. Language plays an essential role in perceiving and interpreting time. As language influences cognitive processes (Liang et al., 2018), the expression of FTO in fake news may also influence cognition. Specifically, FTO may shift an individual's focus to the multiple possibilities offered by the future. However, since an individual cannot be certain what possibilities will translate into reality, the future can be envisioned in multiple manners. FTO may thus trigger humans' innate fear of the future owing to their evolutionary history. By directly appealing to this inherited instinct, FTO can cloud the ability to distinguish between fake news and real news. Consider two example tweets: The first is a tweet of true news titled "Families Facing Tax Increases Under Trump's Tax Plan." This news is based on a study examining the implications of Trump's tax plan (2016) for low and middle-income families. Another news item circulating in the same year was titled "WE <u>WILL</u> RIOT! Michelle Obama's Mom <u>Will</u> Receive $160k Every Year out of Taxpayers' Pockets!" This is an example of a fake news tweet. In this example, one can observe the use of the future tense (will). While true news also has implications that could materialize in the future, true news does not emphasize the future akin to fake news, as its aim is not to exploit human fear. The fake news seems to strongly emphasize the future to appeal to humans' innate fear—in this case, fear that a privileged person will benefit at the expense of taxpayers—which may make it difficult for a person to accurately judge its authenticity. Hence, we hypothesize:

H1: Fake news is more likely to have an FTO than real news.

Prior studies have identified several reasons why individuals share fake news. Talwar et al. (2019) found that self-disclosure (the need for popularity), fear of missing out, and social media fatigue were positively associated with sharing fake news. A recent study found that individuals share fake news despite their preference for accuracy due to attentional constraints (Pennycook & Rand, 2020). Alternatively, the uncertainty inherent in FTO may evoke fear and anxiety and lead to sharing. Fear of the unknown, such as the future, has been built into the human psyche over millions of years of evolution (Nikolsky et al., 2019). Several studies across disciplines have examined fear of the unknown. Individuals respond to fear of the unknown in diverse ways, including physiological to physical responses (Adolphs, 2013). In the context of uncertainty associated with future-oriented fake news, anxious individuals may like and share such items more on social media to achieve a sense of belonging (Hall, 2014). Increased communication may also help individuals manage their anxiety (Loerzel, 2020). Hence, some individuals might like and share future-oriented fake news to manage their anxiety, whereas others might like future-oriented fake news to express their anxiety and show a sense of solidarity. In general, news with an FTO is shared more as it triggers humans' fear of the future. However, as noted in H1, fake news is more likely to exhibit FTO because fake news propagandists leverage FTO to trigger humans' innate fear of the future, leading to disproportionate sharing. Between fake news items with and without FTO, those with FTO are more likely to be shared because of the mechanisms discussed above. Hence, we hypothesize:

H2: Future-oriented fake news is shared more than non-future-oriented fake news.

The following two hypotheses relate to FTO in different parts of fake news. Fake news on Twitter comprises two parts: the title and main content. For example, "Melissa McCarthy on Why She 'Roots for' Online Trolls" illustrates a fake news title. The accompanying text includes a detailed report on Melissa McCarthy's views on online trolls.[5] Twitter limits the amount of content that can be shared, currently restricting tweets to 280 characters (roughly 60 words[6]). Many other platforms, such as Snapchat, impose similar limits. The limit associated with the technological platform constitutes another aspect of the modern task environment. This limit may contribute to the centrality of FTO in fake news titles in increasing user engagement because individuals tend to focus on titles. Support for this line of reasoning comes from prior studies such as Sidoff (2018), who found that 97% of readers read the title and spend an average of 2.9 seconds doing so, whereas a significantly lower percentage read the other content (62.9% of young readers and 54.5% of older readers viewed the entire article). Thus, we argue that the inherent FTO in fake news titles plays a more significant role relative to the FTO in the accompanying text in increasing user engagement by evoking anxiety and subsequent response mechanisms. Hence, we expect a difference in the FTO of the fake news titles and accompanying text. As fake news propagandists leverage a platform's characteristics to their benefit, we predict that titles show more FTO to enhance user engagement. Moreover, achieving higher FTO in fake news titles is more effective and efficient than focusing on the accompanying text, which comprises more words and thus requires more effort. Hence, we hypothesize:

H3: The FTO of fake news titles is significantly greater than that of the accompanying text.

The hypothesized difference in FTO between fake news titles and the accompanying text leads to an interesting question: How does this difference influence user engagement? We expect the relationship between fake news sharing and the difference in FTO between the title and accompanying text to be nonlinear. Specifically, we predict an inverted U-shaped relationship: Initially, as the difference increases, fake news sharing will increase. The increase in the difference arises from a higher increase in FTO in fake news titles relative to the accompanying text. As our studied platform imposes a constraint on shared content, fake news titles showing higher FTO will receive more attention from individuals. Less attention will be paid to the relatively weaker FTO of the accompanying text. Nevertheless, higher attention to fake news titles would be expected to lead to increased fake news sharing to manage heightened anxiety due to high FTO in fake news titles.

Larger differences in sentiment or experiences can lead to stronger reactions from users (disconfirmation effect) (Guo & Zhou, 2016; Ho et al., 2017; Jha & Shah, 2019; Qazi et al., 2017). However, we posit that a larger difference in FTO between the tweet text and news titles will elicit a different response: Once the difference reaches a certain threshold, fake news sharing will decrease. This could be because very high FTO in fake news titles, paired with relatively milder FTO in the accompanying text, might alert individuals to the possibility that the news is not true. This difference could be construed as a sign of inconsistency and, subsequently, a lack of credibility. Hence, we hypothesize:

H4: The relationship between fake news sharing and the difference in FTO between the fake news title and accompanying text has an inverted U-shape. Fake news sharing will initially increase with an increasing difference and then decline once the difference reaches a certain threshold.

Our hypotheses and their rationale are summarized in Table 2.

3 Methods

3.1 Data Collection

This study is based on analysis of a fake news dataset identified and made available through the FakeNewsNet project (Shu et al., 2020). The FakeNewsNet project provides a list of curated PolitiFact links and the required Python code. We downloaded the complete data and adapted the original code. The overall data collection and preparation process is depicted in Figure 2.

[5] "An individual who posts false accusations or inflammatory remarks on social media to promote a cause or to harass someone" (https://www.pcmag.com/encyclopedia/term/internet-troll) accessed February 9, 2022.

[6] An average word is 4.79 letters long (http://norvig.com/mayzner.html). Thus, 280 characters translate to 58.46 words.

Table 2. Hypotheses and Their Logic

Hypotheses	Logic
H1: Fake news is more likely to have a future temporal orientation than real news	Fake news propagandists will leverage fear of the future, which is a psychological trait ingrained in humans due to their evolutionary history.
H2: Future-oriented fake news is shared more than non-future-oriented fake news	Future-oriented fake news will be shared more due to heightened anxiety and sharing as a coping mechanism to manage this resulting anxiety.
H3: The future temporal orientation of the fake news title is significantly more than the future temporal orientation of the accompanying user text	Achieving higher FTO in fake news titles is more effective and efficient than focusing on the accompanying text, which comprises more words and thus requires more effort.
H4: The relationship between fake news sharing and the difference in the future temporal orientation of the fake news title and accompanying user text has an inverted U-shape: fake news sharing will initially increase with the difference, followed by a decline once the difference reaches a high threshold value	Differences in future temporal orientation initially lead to higher fake news sharing due to higher attention to fake news titles, but later lower fake news sharing due to inconsistency.

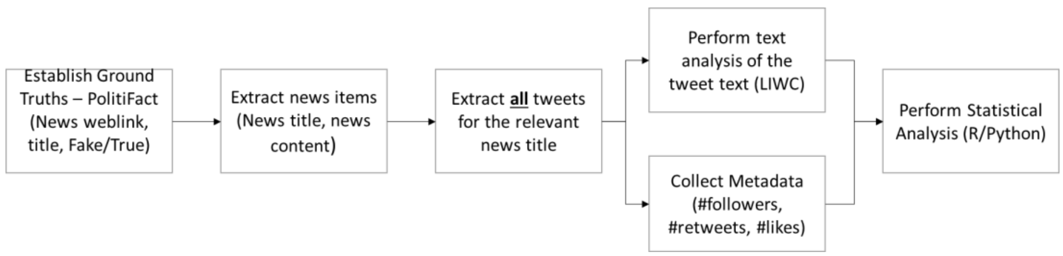


Figure 2. Data Collection Process

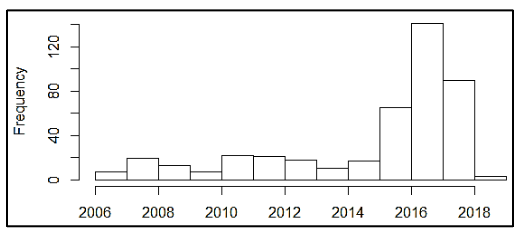


Figure 3. Histogram of News Content by Year (for News Items with Dated Content)

The first step in any study on fake news is to establish the ground truth, i.e., what news items are to be treated as true versus false. The dataset made available through the FakeNewsNet project relies on PolitiFact to establish ground truths. PolitiFact, an independent journalism website that assesses and publishes the authenticity of news items, has verified the authenticity of these items and tagged them as fake or real (Nash, 2012). These news items were published in various media outlets ranging from mainstream outlets like CNN, Bloomberg, and Fox to modern online-only outlets like BuzzFeed. PolitiFact creates a repository of the most popular news items shared on social media platforms and verifies their authenticity (Farnsworth & Lichter, 2016). After establishing the use of PolitiFact as the basis for adjudicating true and fake news, we extracted the required information from the PolitiFact website using a Python-based script. The extracted information included the news title, news link (i.e., webpage/source where the news was originally published), and the news story's verified status (true/false). The dataset consisted of 971 news items (565 fake and 406 real). Data collection was performed in December 2019. The tweets belong to the period 2015-2019, with the tweets sometimes describing old news items.

In the dataset used here, the earliest news item described events from 2006. Many news items came from websites and sources without explicit mention of the publication date. Figure 3 depicts a histogram of the publication dates of the news items, while Table 3 presents the major sources[7] along with the number of true and fake news items published by each source.

[7] The category "Others" in Table 2 includes news items from old websites accessed through web archives.

Table 3. Sources of Analyzed News Items

News source	True news count	Fake news count
YOUTUBE	49	1
NYTIMES	29	1
ABCNEWS	24	0
POLITIFACT	22	2
CNN	22	3
WHITEHOUSE	17	0
CQ	17	0
MSNBC	14	0
WASHINGTON POST	12	4
MEDIUM	9	1
TWITTER	8	1
BLS	8	0
SENATE	7	0
CBSNEWS	6	0
FRWEBGATE.ACCESS.GPO	5	0
THOMAS	5	0
POLITICO	5	2
FOX NEWS	4	2
TIME	4	1
CDC	4	0
POLITICALADARCHIVE	4	0
NBCNEWS	4	2
C-SPAN	3	0
DESMOINESREGISTER	3	0
KFF	3	0
GOVTRAC	2	0
POLLINGREPORT	2	0
THEHILL	2	4
CBO	2	0
FACEBOOK	2	6
CENSUS	2	0
GPO	2	0
COLBERTNATION	2	0
UNHCR	2	0
BEA	2	0
TAXPOLICYCENTER	2	0
EIA	2	0
ILGA	2	0
THEGATEWAYPUNDIT	0	5
YOURNEWSWIRE	0	4
TRENDOLIZER	0	4
REACT365	0	4
WORLDNEWSDAILYREPORT	0	4
USATODAY	0	3
BREITBART	0	3
ME.ME	0	3
USACARRY	0	3
NEONNETTLE	0	3
BREAKINGNEWS365	0	3
OUR.	0	3
DISASTER.TRENDOLIZER	0	2
RIP.TRENDOLIZER	0	2
NYPOST	0	2
BBC	0	2
OBAMA.TRENDOLIZER	0	2
BABYLONBEE	0	2
EMPIRENEWS	0	2
CONSERVATIVEDAILYPOST	0	2
POLITICONO	0	2
BREAKINGNEWS247	0	2
NYEVENINGNEWS	0	2
PUPPETSTRINGNEWS	0	2
NOTALLOWEDTO	0	2
NEWSLO	0	2
OTHERS	250	306

Note: The category "Others" includes sources with 1 news item each in the database.

While there have been some concerns about PolitiFact's overall tone and potential biases against certain political ideologies (Shin & Thorson, 2017), our sample includes news items from 322 outlets to minimize any such bias. The dataset used here is of a reasonable size to enable statistical analysis. The distribution of news items by outlet (Table 3) shows that most outlets are biased toward true or fake news, with only a few outlets publishing both. We account for bias of the news source later in the analysis. In the second step (Figure 2), we downloaded the complete news items, i.e., the full content from the original publisher's website whose link we retrieved from PolitiFact in Step 1.

In Step 3 (Figure 2), the titles of the news articles were used as search terms on Twitter's application programming interface (API) to download all communication about each news item. Twitter provides its own API, which is utilized with a Python-based script, to download data from its platform for research and education purposes. To ensure that only tweets related to the news item were retrieved, the search was performed including all words from the original news title. This method prevents bias in the downloaded social media data since all possible communications about the specified news items are downloaded and included in the analysis. The news items were then mapped to their respective tweets. We downloaded information about the user who tweeted the specific news item (userid, number of followers, verified status, etc.) and the tweet (number of likes, number of retweets, etc.). All of the above-mentioned data are included in Twitter's API data guidelines for fair use.[8] A total of 465519 tweets were downloaded and analyzed as part of this study.

Through these steps, we created a combined database of tweets, details of the users that posted the tweets, tweet user engagement (retweets), and complete news content data of the link shared in the tweets. Each data point in our dataset consists of three segments. The first segment is the news content exclusively hosted on the news provider's website; the reader must click on the link shared by the Twitter user to access the full content. In this news content, the title is visible (second segment) and accompanies the tweet text (third segment). There are some instances where a user simply tweets a link to a news item without any accompanying text. We excluded such cases from our dataset to ensure analysis of a balanced sample and the ability to examine the impact of differences between user tweets (user commentary) and news titles. As shown in Figure 1, the tweet text and news title are prominently visible in each tweet. The title is an integral part of the news and the central unit of analysis in this study.

In Step 4, we used LIWC 2015 software to perform linguistic analysis of the text of the tweets and news content. LIWC is a widely used tool in social sciences and management that enables researchers to compute linguistic metrics for textual data (Tausczik & Pennebaker, 2010) and psychological and grammatical properties (Pennebaker et al., 2003). We used LIWC to compute the word count, temporality, and tone of the news content and tweets. LIWC measures word count as the total number of words separated by spaces in the text. Temporality is measured as the percentage of words in the text denoting a future orientation (Pennebaker et al., 2015), which could be through grammatical content like "may" or "will" or future-oriented words like "tomorrow." For example, the future orientation for the fake news item titled "WE WILL RIOT! Michelle Obama's Mom Will Receive $160k Every Year out of Taxpayers' Pockets!" was 16.67 (2/12, when multi-word phrases counted as one word) and that for the item titled "Donald Trump Protester Speaks Out:" I Was Paid $3500 to Protest Trump's Rally!" was 0.00 (no future-oriented words).

The internal consistency for LIWC's future orientation was assessed using the Spearman-Brown prophecy formula. The corrected alpha value was 0.68,[9] which is considered good consistency (Pennebaker et al., 2015). "Tone" represents the sentiment/mood of the text and is measured by LIWC on a scale of 1 to 100, with a higher number denoting a more positive and upbeat style (Pennebaker et al., 2015). The metrics computed using LIWC were then merged with the tweets' metadata, i.e., number of followers, number of likes, retweets, etc., to create a unified dataset.

Several controls were also used, including sentiment (the emotions inherent in communication—Stieglitz & Dang-Xuan, 2013), operationalized as tone in the LIWC analysis), and the verified status (blue tick) of the person posting the tweet. The first control was included because prior studies (Stieglitz & Dang-Xuan, 2013) have found that tweets high on sentiment receive higher engagement (sharing and liking) than neutral tweets. Negative sentiment is particularly likely to go viral (Tsugawa & Ohsaki, 2015). The use of verified status as a control was motivated by past studies such as Turcotte et al. (2015), who reported that opinion leaders are central to user engagement. At the time of this study, Twitter provided a blue verified badge as part of the verified account program to inform the public that a user account is authentic. A blue verified badge required identity confirmation,

[8] https://developer.twitter.com/en/docs/ads/general/overview/guidelines

[9] The detailed methodology and dictionary of LIWC software can be accessed through the LIWC manual (Pennebaker et al., 2015).

notability, and an active account.[10] Such badges were commonly given to users associated with music, acting, fashion, government, politics, religion, journalism, media, sports, business, and other key interest areas. These controls can be considered conceptually meaningful control variables in the context of fake news (Becker et al., 2016). In Step 5, we performed statistical analysis of this unified dataset. Table 4 provides the definitions and sources of the various constructs used in our study. Table 5 presents the descriptive statistics and correlation coefficients of the variables.

Table 4. Variable Definitions and Sources

Construct	Variable	Definition	Source
Dependent variable			
User engagement	Retweets	The number of times a tweet is retweeted after being posted	Extracted from Twitter dataset
Independent variable (variables of interest)			
Temporal	Title future focus	Percentage of future-focused orientation words in the title of the news text	Computed using LIWC
	Tweet future focus	Percentage of future-focused orientation words in the user-written tweet accompanying the shared news article	Computed using LIWC
	Content future focus	Percentage of future-focused orientation words in the content of the news text	Computed using LIWC
News status	Fake news	Dummy variable with 1 indicating that the news item is fake and 0 otherwise	PolitiFact
Control variables			
Sentiment	Title tone	Sentiment of the title of the news, with a higher score denoting positive and a lower score denoting negative	Computed using LIWC
	Tweet tone	Sentiment of the tweet, with a higher score denoting positive and a lower score denoting negative	Computed using LIWC
	Content tone	Sentiment of the news content, with a higher score denoting positive and a lower score denoting negative	Computed using LIWC
User characteristic	Verified status	Presence of a verified symbol on the user's account	Extracted from Twitter dataset
	Follower count	Number of followers of a particular user account	Extracted from Twitter dataset

Table 5. Two-Tailed Pearson Correlation Coefficients

	Mean	***SD***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Retweets	3.95	102.428		-.008** (0.00)	.091** (0.00)	.008** (0.00)	0.001 (0.403)	.004** (0.002)	.007** (0.00)	0.00 (0.863)	-0.001 (0.706)	0.001 (0.63)
Followers (log)	6.4993	2.48829	-.008** (0.00)		-.057** (0.00)	-.038** (0.00)	-.114** (0.00)	-.046** (0.00)	-.086** (0.00)	.161** (0.00)	-.141** (0)	.038** (0.00)
Fake	0.27	0.446	.091** (0.00)	-.057** (0.00)		-.006** (0.00)	.004* (0.011)	-0.001 (0.728)	.032** (0.00)	-.030** (0.00)	.005** (0.00)	.023** (0.00)
Tweet word count	30.52	24.88	.008** (0.00)	-.038** (0.00)	-.006** (0.00)		.003* (0.039)	.010** (0.00)	.005** (0.00)	-.041** (0.00)	-.058** (0.00)	.031** (0.00)
Tweet tone	36.9185	33.04056	0.001 (0.403)	-.114** (0.00)	.004* (0.011)	.003* (0.039)		.058** (0.00)	.212** (0.00)	-.026** (0.00)	.050** (0)	-0.002 (0.292)
Tweet future focus	0.5885	1.63395	.004** (0.002)	-.046** (0.00)	-0.001 (0.728)	.010** (0.00)	.058** (0.00)		-.009** (0.00)	.244** (0.00)	0.003 (0.065)	.024** (0.00)
Title tone	30.0274	22.79597	.007** (0.00)	-.086** (0.00)	.032** (0.00)	.005** (0.00)	.212** (0.00)	-.009** (0.00)		-.016** (0.00)	.215** (0.00)	.071** (0.00)
Title future focus	0.112	1.04953	0.00 (0.863)	.161** (0.00)	-.030** (0.00)	-.041** (0.00)	-.026** (0.00)	.244** (0.00)	-.016** (0.00)		-.088** (0.00)	.060** (0.00)
Content tone	47.8299	29.51451	-0.001 (0.706)	-.141** (0.00)	.005** (0.00)	-.058** (0.00)	.050** (0.00)	0.003 (0.065)	.215** (0.00)	-.088** (0.00)		-.063** (0.00)
Content future focus	0.8288	1.03878	0.001 (0.63)	.038** (0.00)	.023** (0.00)	.031** (0.00)	-0.002 (0.292)	.024** (0.00)	.071** (0.00)	.060** (0.00)	-.063** (0.00)	

Note: Values in brackets represent the p-values ** $p < 0.01$ level (2-tailed), * $p < 0.05$ level (2-tailed).

[10] https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts (accessed February 5, 2022).

4 Analysis and Results

As shown in Table 5, none of the correlation coefficients exceeded 0.25, indicating that multicollinearity is not expected to be an issue.[11] We used the natural logarithm of the follower count, as it was a long-tailed variable. We performed three sets of analyses to test our hypotheses. The first set of analyses tested the presence of temporality in fake news (H1). The next two sets of analyses corresponded to testing the factors that drive user engagement (H2-H4). Although both likes and retweets indicate user engagement, retweets—by their fundamental nature—indicate greater user engagement, as the user accepts the proposition being shared and then reshares it as their own view (Mustafaraj & Metaxas, 2011). As such, past studies using Twitter data have considered retweets as a proxy for user engagement (Ibrahim et al., 2017; Mustafaraj & Metaxas, 2011). As noted by Mustafaraj and Metaxas (2011, p. 38), "Twitter itself uses the number of retweets as a way to rank relevant tweets shown in search results." Hence, in line with previous research practices, we treat retweets as a construct to measure user engagement. Thus, there is empirical justification for our focus on sharing.

We performed two analyses to test the presence of temporality in fake news. First, we used analysis of variance (ANOVA) to examine the differences between the FTO of fake and true news. Second, we built a probit model to estimate the relationship of the text's linguistic features with its status (true/fake). The model for the probit analysis included the *tweet word count*, *tweet tone* (sentiment), *title tone* (sentiment), *content tone* (sentiment), *title future focus* (fake news title), *tweet future focus* (accompanying text), and *content future focus* (shared news content) as explanatory variables. As argued in the theoretical sections, we believe that fake news is written to be more future oriented—particularly the title. Hence, we argue that the likelihood of news being fake increases with increasing FTO.

The ANOVA results indicate a statistically significant difference between the future focus of real and fake news titles (Table 6). The mean FTO of fake news titles is approximately 48-fold that of true news. The results of the probit analysis (Table 7) indicate that the probability of news being fake is significantly higher for news with future-focused titles ($\beta = 0.256$, $p < 0.001$) and for news with future-focused content ($\beta = 0.037$, $p < 0.001$). Together, the results shown in Tables 6 and 7 support H1.

The second set of analyses tested our hypotheses regarding fake news sharing. The results in Table 8 show the impact of linguistic characteristics on retweets. Besides the variables of interest discussed above, we also controlled for news sources using dummy variables. This approach is consistent with the use of dummy variables to control for different sources of variation, such as year, industry, etc. (Karafiath, 1988). Given the high number of dummy variables (>200) due to the many different news sources, we ran an additional analysis treating the news source as a nominal factor variable. The results remained similar.[12] To ensure the robustness of the results and provide a comparable baseline, we analyzed both real and fake news.

Models 1 and 3 present the results for real news, while Models 2 and 4 present the results for fake news. All models include *title future focus, tweet future focus, content future focus, title tone, tweet tone, content tone*, and *verified status* (blue badge) as variables of interest. Models 3 and 4 also include interaction terms (*Verified status* × *Title future focus, Title tone* × *Title future focus*) and linear and quadratic terms of the difference between the title and accompanying text (*sentiment difference, sentiment difference squared, future orientation difference*, and *future orientation difference squared*). The rationale for including the interaction term of a control variable with the variable of interest and square term of a control variable is that verified status and title tone could influence the relationship of title future focus with fake news sharing and, akin to FTO, sentiment differences could influence sharing of fake news nonlinearly. Furthermore, the models include *follower count (log), news source dummy*, and *tweet word count* to control for other factors that may influence sharing.

Table 6. ANOVA Results Comparing Title Future Focus between Fake and True News

	Count	Mean	Std. Dev.
True news	338174	0.00813	0.29
Fake news	127345	0.388	1.92
ANOVA results			
	df.	**Sum of squares**	***F*-value**
Fake	1	309127	33201****
Residuals	465518	4334284	

[11] We report the VIF values alongside the regression analysis to provide additional robustness.

[12] To maintain parsimony, these results are not provided here. However, they can be requested from the authors.

Table 7. Probit Analysis Results for a News Item Being Fake

	Coefficient
Tweet word count	-0.002*** (0.001)
Tweet tone	-0.0038*** (0.001)
Tweet future focus	-0.083*** (0.001)
Title tone	-0.0028*** (0.001)
Title future focus	0.256*** (0.003)
Content tone	-0.005*** (0.001)
Content future focus	0.037*** (0.002)
Intercept	-0.0984*** (0.005)
AIC	517046
Log likelihood	-258515.1****
Note: Fake news is a dummy variable where a value of 1 indicates that a news item is fake. **** $p < 0.001$, *** $p < 0.01$, ** $p < 0.05$. Numbers in brackets indicate standard errors.	

Table 8. Regression Coefficients for Retweets as the Dependent Variable

	Model 1 Real news	Model 2 Fake news	Model 3 Real news	Model 4 Fake news
Tweet word count	0.052*** (0.008)	0.002 (0.007)	0.051*** (0.008)	-0.001 (0.007)
Tweet tone	-0.002 (0.005)	0.004 (0.008)	-0.001 (0.006)	0.006 (0.017)
Tweet future focus	0.236* (0.113)	-0.038 (0.169)	0.438* (0.202)	0.047 (0.265)
Title tone	0.013 (0.008)	0.031* (0.012)	0.007 (0.008)	0.033* (0.014)
Title future focus	-0.467 (0.653)	0.268** (0.122)	-0.398 (1.132)	0.863** (0.289)
Content tone	-0.002 (0.007)	0.062** (0.008)	-0.001 (0.006)	0.037** (0.013)
Content future focus	-0.453* (0.17)	0.217 (0.229)	-0.423* (0.179)	0.3497 (0.457)
Verified status × Title future focus			-3.45 (2.822)	-4.987*** (1.266)
Title tone × Title future focus			0.004 (0.022)	-0.0178** (0.070)
Sentiment difference			-0.02*** (0.001)	-0.02*** (<0.001)
Sentiment diff squared			0.0002** (<0.001)	0.0002*** (<0.001)
Future orientation diff			0.032 (0.073)	0.017** (<0.001)
Future orientation diff squared			-0.028 (0.022)	-0.0011** (<0.001)
Follower count (log)	2.57*** (0.08)	1.74*** (0.095)	2.574*** (0.086)	1.724*** (0.095)
Verified status	32.55*** (0.872)	47.69*** (1.701)	32.56*** (0.873)	49.81*** (1.643)
News source dummy	Included	Included	Included	Included
Intercept	-16.14** (0.842)	-11.85*** (0.948)	-16.02*** (0.844)	-11.22** (0.951)
AIC	4139470	1461810	4139467	1462000
Log likelihood	-2069723***	-730892.9***	-2069717***	-730879.9***
Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Numbers in brackets indicate standard errors				

We also computed variance inflation factors (VIF) for all predictors in the models. The maximum VIF of all models was below 3.4 (range of 1.2–3.3), which is significantly below the acceptable threshold of 10 and the more conservative threshold of 5 (Lin et al., 2019). The computed VIF values and low correlation values (< 0.25) eliminate the possibility of bias due to multicollinearity (Hair et al., 2014).

Separate analyses were performed for fake and real news tweets to observe any differences in the effects. The results indicate that future-oriented fake news receives significantly more retweets. The coefficient for FTO in Model 2 is positive and statistically significant ($\beta = 0.268$, $p < 0.01$), implying that a 1% increase in future focus in a fake news title leads to 26.8 additional retweets. Hence, there is strong support for H2. In contrast, when we look at the results of Model 1 for real news, the coefficient for FTO of real news titles is not positive and statistically significant ($\beta = 0.268$, $p < 0.01$).

As the rationale for H2, we argued that individuals share future-oriented fake news more often as a coping mechanism to manage anxiety due to uncertainty about the future. Hence, we used LIWC to measure and compare the anxiety expressed in the accompanying text. The mean value was 0.15 for real news and 0.17 for fake news ($p < 0.001$). We also computed the correlation between anxiety and FTO. For true news, the correlation between anxiety and FTO was -0.006 ($p > 0.05$, not significant); in contrast, for fake news, the correlation was 0.023 ($p < 0.001$, statistically significant). The significantly higher anxiety and significant correlation between anxiety and FTO in the context of fake news support our principal argument that individuals share future-oriented fake news more often as a coping mechanism to manage anxiety due to uncertainty about the future.

To assess H3, we refer to the means of all variables of interest (Table 6). The mean future focus values of fake news titles and tweets (accompanying text) are 0.388 and 0.214, respectively. This statistically significant difference ($t = 11.389$, $p < 0.001$) indicates support for H3. In comparison, the future focus mean values of real news titles and tweets (accompanying text) are 0.00813 and 0.729, respectively. This finding alludes to the need felt by users who tweet true news items to add uncertainty to the accompanying text to achieve greater user engagement. Comparing Models 1 and 2 (Table 8), we note that the coefficient for *tweet future focus* is statistically significant for real news, but not for fake news. This may indicate that while fake news titles are inherently future-focused and target the emotions of fear and anxiety to be more engaging, users sharing these fake news items use less future-focused supporting text to legitimize the content, whereas the opposite pattern is observed for real news items.

Next, we examined Model 4 (Table 8) to understand the implications of the difference in FTO of fake news titles and user tweets (accompanying text). Both the linear and squared terms are statistically significant. Specifically, the coefficient for the squared term is negative and statistically significant ($\beta = -0.0011$, $p < 0.001$). By plotting the relationship between user engagement (retweet count) and the difference in FTO between fake news titles and user tweets (accompanying text) (Figure 4), we observe an inverted U-shaped relationship. Hence, our findings support H4. Although the effect of these relationships is small (a difference of 1% in future focus leads to approximately 2 additional retweets), this may still generate a large negative impact due to the sheer number of individuals using Twitter and the ability of social media platforms to spread any message because of the network effect.

Some interesting patterns are observed for the additional terms in our model. The coefficient for the interaction term (*Title future orientation* × *Title tone*) is negative and statistically significant ($\beta = -0.0178$, $p < 0.01$). The interaction effect is plotted in Figure 5 and shows that for negative sentiment news (represented by a dashed line), sharing (retweets) increases as FTO increases; in contrast, for positive sentiment news, retweets decrease as FTO increases. The slope for positive and negative sentiment lines are significantly different, as the coefficient of the interaction effect in Model 4 is significant. Comparing these results with those for real news in Model 3, the effect is statistically insignificant. The results thus suggest that future orientation strengthens the relationship between negative sentiment and retweets, but this effect is specific to fake news.

Notably, the coefficient for the interaction term of FTO and verified users is negative and statistically significant ($\beta = -4.987$, $p < 0.001$). Figure 6 illustrates this relationship and shows that having a verified badge moderates the relationship of FTO with retweets. For verified users, retweets decrease as the percentage of future focus in fake news titles increases; in contrast, for unverified users, retweets increase as the percentage of future focus in fake news titles increases. Models 1 and 2 provide further nuanced insights. Verified users always have more retweets. Tweets from accounts with blue verified badges have more retweets irrespective of the type of news being shared, although retweets are still significantly higher for fake news (Model 1, $\beta = 32.55$, $p < 0.001$; Model 2, $\beta = 47.69$, $p < 0.001$). In other words, when verified users tweet fake news, it is retweeted more than real news, indicating the strong role of FTO in fostering engagement with fake news. In terms of the effect size, one additional share of a fake news item by a verified user leads to approximately 48 additional retweets.

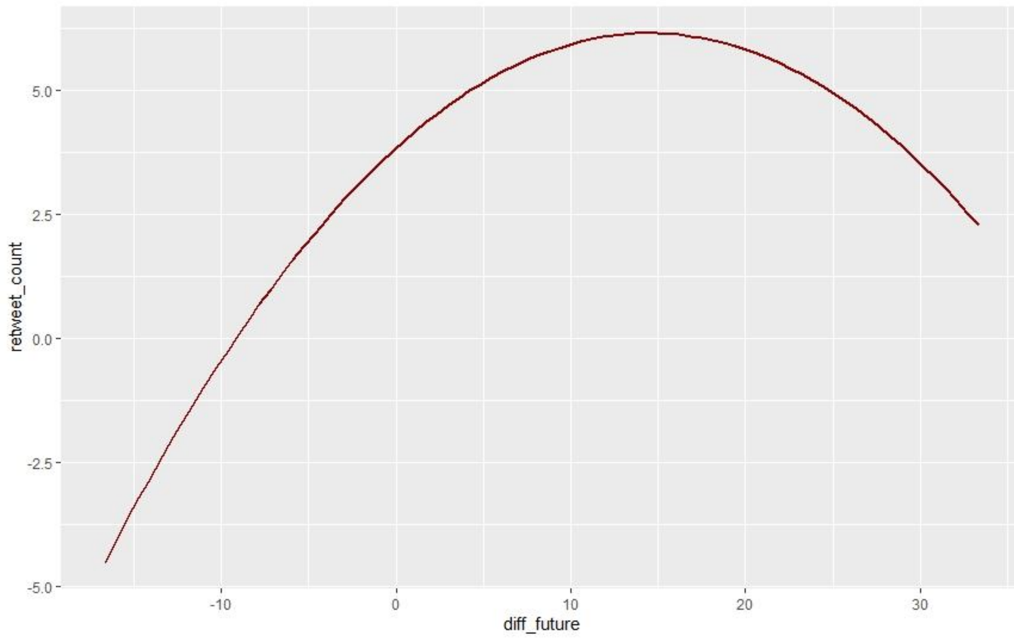
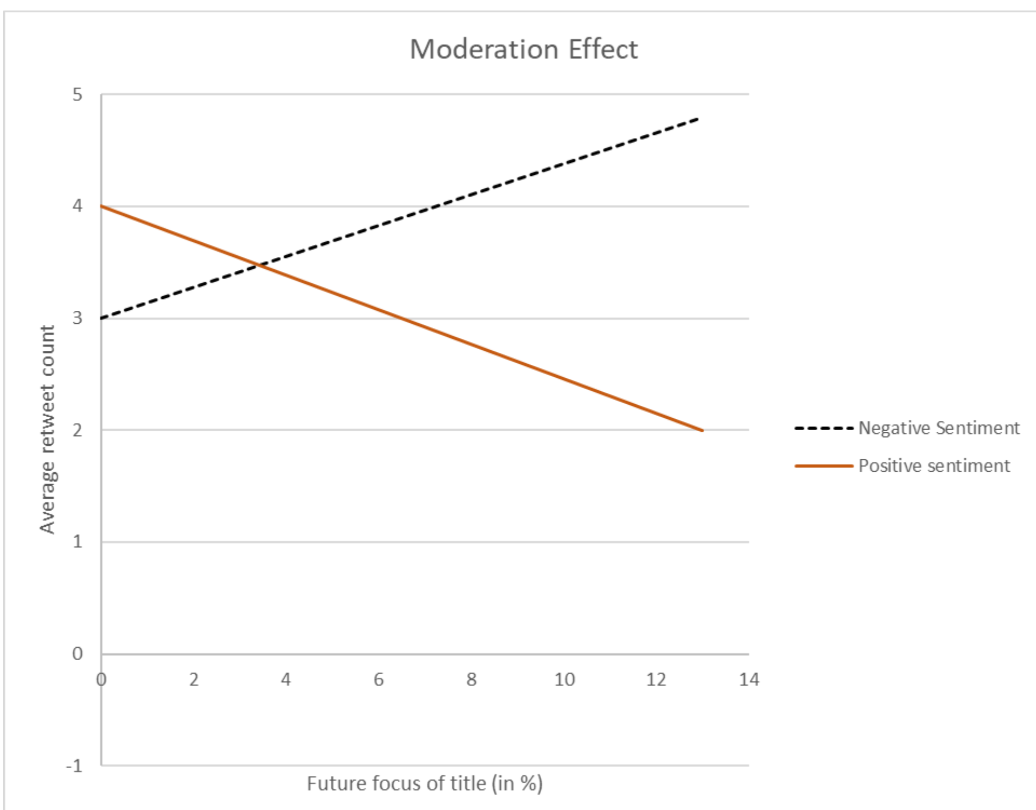


Figure 4. Relationship Between User Engagement (Retweet Count) and the Difference Between Future Orientation of the User Tweet and News Title



Note: Figure 5 shows a smooth line to eliminate outliers and aid interpretation.

Figure 5. Moderation Effect of the Future Focus of a News Title on the Relationship Between Sentiment and Retweet Count

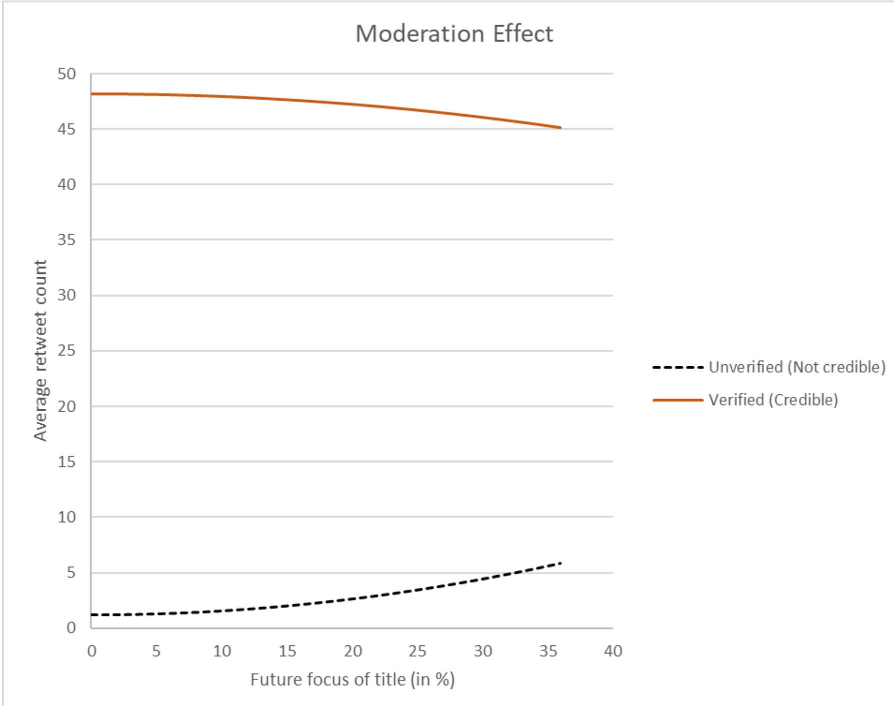


Figure 6. Moderation Effect of Account Verification on the Relationship Between the Future Focus of the News Title and Number of Retweets

4.1 Robustness Checks

4.1.1 Data Robustness: Is FTO Only Relevant to Political News? Are the Findings Generalizable?

One potential critique of this study is the use of a dataset limited to political news that could be polarizing and emotionally charged (Farkas & Schou, 2019). Thus, to ensure the robustness of the results, we collected and analyzed data for an alternate fake news phenomenon, namely fake news related to COVID-19. Multiple studies have highlighted the ill effects and mass spread of fake news items related to the pandemic ("The COVID-19 Infodemic," 2020; Laato et al., 2020). For this robustness check, we utilized a COVID-19 rumor dataset (Cheng et al., 2021) that has been widely used in extant research, with all tweets validated against technical sources like the World Health Organization (WHO) website. We utilized the same principles depicted in Figure 1 to use LIWC to create the variables. As shown in Table 9a, the ANOVA results again indicate that the mean future focus value of real news is significantly lower than that of fake news. This finding further supports our argument that fake news is more likely to have an FTO.

To further generalize these findings, we studied the misinformation context along with fake news context. Note that fake news and misinformation are often used synonymously in studies and popular parlance. However, we differentiated between these terms to develop nuances about different kinds of malicious content on social media. We used the follwing definitions: Fake news is news initiated by a news outlet, whereas misinformation is wrong or misleading information shared online by any individual (Zeynep, 2018). The primary difference in this context is the presence of a website URL (uniform resource locator or web address) that connects the shared piece of information to a news outlet. Figure A2 provides an example misinformation tweet for comparison with the fake news tweet in Figure 1. A social media post lacking a URL would be classified as misinformation because it is spread without any reference to the news outlet. Such posts are commonly an opinion or morphed image/video designed to cause panic or spread lies (Cerf, 2016).

To collect data about misinformation we used the context of COVID-19, as a tremendous amount of fake news and misinformation has been shared (Loomba et al., 2021). The dataset was built upon the AntiVax misinformation dataset (Hayawi et al., 2022). The dataset provides Twitter IDs for misinformation tweets that have been verified against information released by the WHO and other major international bodies.[13] We downloaded the dataset using custom Python code and analyzed it in a similar fashion as the main dataset. We utilized the same principles depicted

[13] Full information on truth checking of the dataset and other parameters are available at https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8648668/

in Figure 1, using LIWC to create the variables. As shown in Table 9b, the ANOVA results again indicate that the mean future focus value of true tweets is significantly lower than that of misinformation. These findings further support that our results are robust to different kinds of news and rumors present on social media.

4.1.2 Methodological Robustness: Are the Findings Robust to Unbalanced Characteristics of the Dataset?

As our dataset comprised 72.64% true news tweets and 27.36% fake news tweets, the imbalanced nature may raise concerns about our findings. Hence, we employed the propensity score matching (PSM) technique (Rosenbaum & Rubin, 1983) to confirm the robustness of our results. To do so, we created matched samples of true and fake news tweets, resulting in control and treatment groups of equal sizes and properties. This method is commonly used in IS research to test the robustness of the results of studies involving an imbalanced number of cases, as it controls for potential endogeneity concerns (Haislip et al., 2021; Pu et al., 2020).

We created matched samples using three approaches. In the first approach, we matched tweeters (users posting tweets) according to their verified status and follower count. This created an equal and comparable dataset with a similar proportion of verified users and a similar level of followers, with the distinguishing feature of the two groups being their sharing of true or fake news. In the second approach, we matched the samples based on tweet style, i.e., word count and tone. This created an equal and comparable dataset with similar writing styles for fake and true news tweets. In the third approach, we matched the samples based on the news source. While we included the news source as a control variable in our main analysis, the imbalanced nature of the dataset warrants this analysis to ensure the robustness of the results. This approach created an equal and comparable dataset. Table A2 in the Appendix presents the distributions of the datasets for the unmatched and matched sample approaches. Since the fake news tweets dataset was smaller, all fake news tweets were matched to the nearest true news tweets using either user characteristics or tweet style characteristics. As shown, the post-matching samples for true and fake news tweets are closer in their characteristics; hence, any causal conclusions will be more robust. An interesting insight from Table A2 is that the two groups differ in terms of word count and tone, even after matching the tweets based on writing style. This finding suggests a difference in how fake and true news tweets are written, with fake news tweets tending to have a lower word count and a more negative tone. Tables A3 and A4 show the results of the regression analyses. The results are consistent with the primary findings reported in the preceding section. Notably, the regression results for the two matching approaches are identical up to three decimal places.

4.1.3 Model Robustness: Are the Findings Robust to Additional Variables in the Model, e.g., Videos and Images in Fake News?

One concern raised about the virality or sharing of posts on social media is composition, i.e., the use of images, videos, etc. Such audio-visual components have higher appeal on social media compared to plain text and, hence, attract more user interactions (Berger & Milkman, 2012). In a recent study on misinformation, Wang et al. (2022) found that inclusion of video significantly impacted how people react to online posts. Specifically, they found that inclusion of video increases the probability of misinformation being reported.

Table 9a. ANOVA Results of the COVID-19 Fake News Future Focus Analysis

	Count	**Mean**	***SD***
True news	1878	0.761	2.01
Fake news	5301	0.989	1.68
	ANOVA Results		
	df.	**Sum of squares**	***F*-value**
Fake	1	22.72	9.865***
Residuals	7177	46289.58	
Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$			

Table 9b. ANOVA Results of the AntiVax Misinformation Future Focus Analysis

	Count	**Mean**	***SD***
True news	8141	0.556	1.91
Fake news	4169	0.957	2.36
ANOVA results			
	df.	**Sum of squares**	***F*-value**
Fake	1	447	103.8***
Residuals	12308	53024	
Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$			

Given the design of our study, this finding presents a unique conundrum. As previously stated, we used a strict definition of fake news. Our data points consisted entirely of news items originating from a news source with a web address shared in the Twitter post. As per the Twitter user interface, when a web address is shared, a preview of the website/news item is provided (Figure 1). Even if an image is not attached to the tweet, the image from the news item is displayed. Hence, all posts have images attached to them.[14] Thus, the differential impact of including images cannot be ascertained as all posts in the main dataset have images (either directly attached or from the underlying news item).

However, the AntiVax misinformation dataset used for the robustness tests (Section 4.1.1) enabled us to test the impact of including videos and images on misinformation virality. This analysis thus aimed to isolate the impact of FTO from that of images and videos on a Tweet's virality. The results are presented in Table A5 of the Appendix. The analysis did not include variables for news title or content, as this misinformation dataset was not linked to a larger news source. As shown, the inclusion of images leads to higher retweets for misinformation and the effect of FTO remains significant. In the context of fake news, we can infer that, while FTO is a significant predictor of retweeting behavior, including images in fake news tweets magnifies the retweeting behavior of users who see them.

4.1.4 Analytical Robustness: Are the Findings Robust to Different Analytical Techniques?

Consistent with previous studies (Stieglitz & Dang-Xuan, 2013), this work utilized a large sample of tweets. However, a large sample may cause insignificant results to appear significant (Faber & Fonseca, 2014). Thus, we verified the robustness of our findings using a machine learning (ML)[15] model designed for large datasets. To do so, we applied two distinct approaches: First, we tested what factors have the highest predictive power for predicting fake news using gradient-boosted trees (used for regression and classification). Consistent with the Probit model (Table 7), a future focus supports the prediction of a news item being fake.

We also used a generalized linear model (GLM) grounded in ML logic, which provides estimates like our probit model (the probit model is also a GLM model), to help us compare and ascertain the robustness of the findings. The difference between the GLM approach used here and the standard GLM statistical approach is that, for the ML approach, the sample is split into training and testing datasets and focuses on prediction, whereas a conventional GLM utilizes the full sample to compute a coefficient to help understand relationships. The results obtained (Table 10) are similar to those of the probit model. Notably, no data balancing strategy was used in this model as the imbalanced nature reflects the real-world setting where a significantly large proportion of news is still true (Table 6).

It is still possible that unbalanced data can lead to biased models. Thus, we also used a balancing approach in which records were duplicated in the dataset. In the original dataset, real news and fake news existed at a 2.66:1 ratio; thus, fake news records were duplicated to ensure a balanced sample. The results of this analysis (Figure A1) again suggest that title FTO is the most important predictor of fake news.[16]

Table 10. GLM Model Coefficients with Fake News as the Dependent Variable

Attribute	Coefficient	Standardized coefficient	*SE*	*z*-value	*p*-value
Tweet word count	-0.001	-0.017	0.000	-26.459	<0.001
Tweet tone	-0.001	-0.040	0.000	-61.630	<0.001
Tweet future focus	-0.022	-0.036	0.000	-55.378	<0.001
Title tone	-0.001	-0.019	0.000	-28.716	<0.001
Title future focus	0.072	0.073	0.001	111.740	<0.001
Content tone	-0.002	-0.05	0.000	-77.143	<0.001
Content future focus	0.011	0.011	0.001	18.606	<0.001

[14] For more details on how Twitter handles embedded links and previews, please see https://support.sendible.com/hc/en-us/articles/115000159366-How-are-link-previews-handled-by-the-different-social-sites- (accessed June 2021)

[15] We used Rapidmodeler 9.7.0 automodeler

[16] We used IBM SPSS Modeler 18.2 for this analysis.

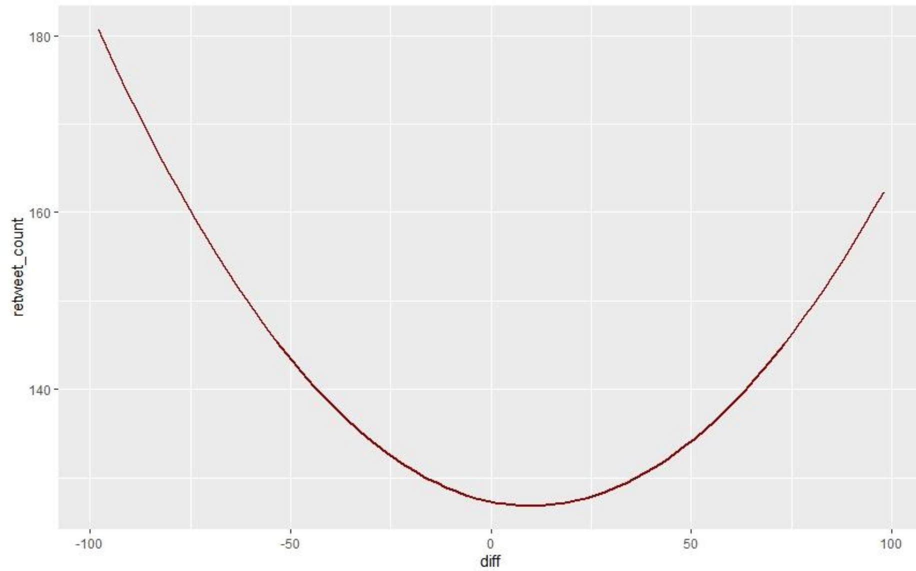


Figure 7. Relationship Between User Engagement (Retweet Count) and the Difference Between the Sentiment of the User Tweet and the News Title

4.1.5 Construct Robustness: Additional Statistical Analyses

We performed additional statistical analyses to assess the robustness of our empirical analysis. The first was an analysis of construct robustness. While retweets have been previously used as a proxy for user engagement on Twitter, another metric is "likes," which indicate how many users have responded positively to a specific tweet. Although less expressive and personal than retweeting content, likes nevertheless represent a form of user engagement. Likes also enable a post to rank higher in Twitter's algorithm of top posts and become more visible on users' timelines.[17] Thus, we also tested our hypothesis using likes as a proxy for user engagement. As presented in Table A5 (in the Appendix), Model 1 shows the results for real news tweets, while Model 2 shows the results for fake news tweets. The results are qualitatively the same as those of the main analysis but slightly weaker. This effect is consistent with previous studies demonstrating that retweets are more expressive and hence a stronger metric for user engagement on Twitter compared to likes (Mustafaraj & Metaxas, 2011).

4.2 Extreme Value Analysis

We performed a subset analysis by removing tweets with extreme numbers of retweets. This was done because retweets can have extreme values, with some tweets going "viral" and receiving intense attraction. The dynamics of platforms like Twitter further promote such tweets, resulting in a cycle that makes such tweets even more viral (Anderson et al., 2012). To evaluate our hypothesis in less extreme situations, we limited the dataset to tweets with more than one but less than 50 retweets. This reduced the dataset to 42340 tweets. As shown by Model 3 in Table A5, the results remain qualitatively the same using this outlier-free dataset. Although the squared difference of future focus on user engagement is marginally insignificant, the coefficient is still significant at $p < 0.1$.

4.3 Post Hoc Analysis

We plotted the relationship of retweets with the difference in sentiment between fake news titles and accompanying text, finding it to be U-shaped (Figure 7). The trough for the plotted relationship is around 0, indicating that the posts with the lowest user engagement were those with no difference in sentiment; any increase in this difference led to higher user engagement.

5 Discussion

Our findings that FTO tends to be associated with fake news (H1) extend existing research demonstrating that fake news and real news differ in terms of linguistic style. For example, through analysis of a relatively small dataset, Horne and Adali (2017) found that fake news titles have significantly more past-oriented words for political news items, e.g., "A quick trip down memory lane causes a stumble over this gem from Obama. He was gearing up for his first run at the office of President and was spewing lies all over the American public."

[17] https://blog.hootsuite.com/twitter-algorithm/

However, this trend was not observed for the election and satire datasets. In contrast, our analysis of a large corpus of tweets shows that that fake news and its sharing is associated with FTO on this social media platform (Twitter). Our findings suggest that FTO is central to fake news, irrespective of context. In contexts such as COVID-19 and misinformation, we found that future-oriented fake news receives higher engagement in terms of retweets, even after controlling for factors like the use of images and videos. A plausible reason for the salience of FTO in our study's context is that uncertainty associated with the future is a potent reason for sharing; Fake news with a strong past orientation may be used to discredit political leaders but will elicit less uncertainty.

The observed support for H2 that users are more likely to engage with future-oriented fake news confirms that fear of the unknown is ingrained in the human psyche. In particular, the follow-up analysis for H2 supports this argument. Through this analysis, we extend work such as Karami et al.'s (2021) study focusing on the characteristics of fake news spreaders and the factors that motivate them. Through their *t*-test analysis, Karami et al. found that fake news spreaders exhibit significantly less lack of control measured through the use of future-oriented words in political news and a higher lack of control measured through the use of future-oriented words in gossip. Our study focused on fake news itself as the primary analysis unit. Through econometric analysis, we demonstrated that fake news with higher FTO has a greater appeal to the human psyche, resulting in higher engagement. Thus, fake news spreaders might exhibit less lack of control, but fake news must exhibit a higher FTO.

Our analyses revealed several other interesting insights. While FTO in fake news titles is positively associated with sharing, FTO in real news titles is not significantly associated with sharing. This finding contradicts our prediction grounded in EP that FTO, in general, will lead to the sharing of any news. A plausible explanation is that FTO in fake news titles evokes anxiety and leads to sharing as a coping mechanism. Fake news propagandists leverage FTO when crafting fake news titles to evoke anxiety. Hence, we observed a positive relationship between FTO in fake news titles and in the sharing of fake news. As true news is grounded in facts, true news titles are not intentionally constructed with high FTO to evoke anxiety. This difference leads to considerable variation in FTO, retweets, and insignificant relationships. Nevertheless, our findings provide nuances to studies examining different contents' characteristics by leveraging linguistic theories or theories related to text organization, such as rhetorical structure theory (e.g., Beisecker et al., 2024; Horne & Adali, 2017).

The findings for H3 support our argument that fake news propagandists view fake news titles as a less time-consuming method for leveraging anxieties associated with FTO. Lastly, the support for H4 suggests that when it exceeds a certain threshold, the difference in FTO between fake news titles and accompanying text can backfire and actually reduce retweets.

Overall, our findings suggest that the FTO of fake news titles contributes to anxiety arising from negative sentiment. Notably, fake news sharing (retweets) does not increase with FTO when the tweets are from authentic accounts. It appears that verified users speculate less about the future than average users who tweet more interesting future-focused fake news. Alternatively, readers may become cynical or skeptical when a verified user engages in such speculation. This finding could be attributed to complex dynamics where authentic accounts are more prudent in sharing tweets with high or very high FTO; it is also possible that fake news titles tweeted by authentic accounts make readers skeptical.

Taken together, these results provide several nuanced insights into users' motivations for engaging with fake news. We show that fake news items typically have higher negative sentiment across their tweets, titles, and content (Table 7). This pattern is consistent with existing research demonstrating that negative sentiment leads users to engage more deeply and that negative or fear-inducing fake news stories receive much higher traction with end users. Positive emotions could also drive people to share future-oriented fake news. For example, a fake news story on an increased supply of COVID-19 vaccines may be shared out of fear, joy, or relief. However, our finding that fake news often has higher negative sentiment suggests that fake news propagandists view negative emotions as more powerful for attracting readers. Consistent with this notion, in their work on epidemic news, Klemm et al. (2019) found that emotion- and sentiment-driven news led to more fear and received higher traction than fact-based news.

5.1 Theoretical Contributions

The primary theoretical contribution of this study is its examination of the role of FTO in propagating fake news through an EP perspective. Most prior research has focused on emotions and sentiment as the cause of sharing fake news on social media, refraining from exploring temporal orientation as a cause of such emotions and sentiment. This lack of focus on temporal orientation is not surprising, as it has only recently become a subject of inquiry in management research (DesJardine & Bansal, 2019). The exclusion of temporal orientation in prior analyses has resulted in a theoretical gap: Because time is inherent to our subjective reality, it is therefore central to emotions and sentiment. Focusing on FTO, we utilized EP to understand responses to fear of the future. In doing so, we respond to two distinct calls: (1) incorporating temporal orientation when examining a phenomenon (DesJardine & Bansal, 2019) and (2) further theorizing based on EP (Kock, 2009). Two key implications emerge from our findings.[18] First, people respond to future-oriented, anxiety-inducing tweets (an aspect relatively unexplored in prior studies). Second, detecting FTO may be an effective approach to identify—and then curb—the spread of fake news.

Our finding that the salience of FTO illuminates how fake news propagandists utilize factors that evoke emotions and sentiment empirically contributes to research on the nature of fake news (e.g., Kim & Dennis, 2019; Kim et al., 2019). It also addresses the question "How does fake news spread?" by demonstrating that appealing to instincts that are the product of our evolutionary history is an effective mechanism to spread fake news. Social media platforms provide an easy technological tool to leverage these instincts. By adopting an EP perspective, our study also provides an explanation of why fake news spreads. Future studies can build upon this work to explore other factors that may be exploited to evoke emotions and sentiment, especially those linked to human evolutionary history. Recent black swan events, such as the COVID-19 pandemic, have enabled researchers to address previously unexplored issues. For instance, recent epidemics have increased conspiracy theories targeting governments and prevailing governance systems (Spinney, 2019). Future studies could examine if these experiences are now woven into our institutional memory. Moreover, is it possible that experiences related to pandemics have been transferred through generations and could be misused to spread propaganda in modern contexts? Recent experiences have shown that the pandemic has exacerbated racism and reduced trust and social cohesion. Future studies could explore how these events contribute to fake news and if our evolutionary history is salient to individuals' responses to fake news during a pandemic. Our robustness checks using different datasets provide a glimpse into how FTO is salient to individuals' responses to fake news and misinformation in the context of a pandemic.

The finding related to the squared difference between the future focus (Figure 4) and sentiment (Figure 7) of fake news titles and accompanying tweets indicates that disconfirmation can simultaneously influence fake news propagation in two distinct ways. For future orientation, the inverse U-shaped relationship supports the contrast between the news title and tweet content, followed by cognitive dissonance (Nishant et al., 2019). However, for sentiment, the U-shaped relationship supports cognitive dissonance, followed by support for the contrast between the news title and tweet content. These findings suggest that multiple psychological mechanisms grounded in our evolutionary past influence complex human behavioral responses, highlighting the need for an in-depth examination of such behaviors in different contexts.

Our finding that, for negative sentiment news, a higher future focus leads to higher user engagement (retweets) sheds light on the factors that define the boundaries of such relationships. This result highlights the need to explore other factors that form such boundary conditions. For example, existing IS research emphasizes sentiment as key to user engagement (Alibakhshi & Srivastava, 2019). Increased focus on the boundary conditions for sentiment and temporal orientation will enrich our understanding of their respective roles.

Our findings regarding temporal orientation offer insights for future studies aiming to manage and control fake news. Research in the computer science domain has focused on tools and platforms that use advanced approaches, such as deep transfer learning, to identify fake news (Ghayoomi & Mousavian, 2022). Another measure to control fake news sharing is content moderation. However, identifying problematic content is complex and leads to allegations of bias and censorship (Stewart, 2021). Carrasco-Farré (2022) found that the cognitive effort needed to process fake news is low and that fake news is more emotion-laden. Current tools used to control fake news utilize natural language processing (NLP) and focus extensively on sentiment and emotions (Parikh & Atrey, 2018). However, the limitations of such tools necessitate new approaches to manage the fake news menace(Gupta et al., 2022). Our findings suggest that FTO is an underlying mechanism in fake news that evokes negative sentiment and can influence users' judgment when distinguishing fake news from true news. Thus, the inclusion of temporal cues in tools aimed to control fake news could improve their effectiveness. Content moderators could specifically focus on FTO to identify fake news. Fake news detection tools offer a unique opportunity to extend design science research (an existing paradigm focused on designing, developing, and deploying IT artifacts (March & Storey, 2008) by exploring tools rooted in linguistics and human behavior. Studies focused on controlling and managing fake news also emphasize policy responses and interventions, such as critical media literacy (Tambini, 2017). Searching for and critically evaluating temporal cues in news items could be an integral part of a media literacy program.

[18] We would like to express our sincere gratitude to the anonymous reviewers and the SE for guiding us on this line of thought.

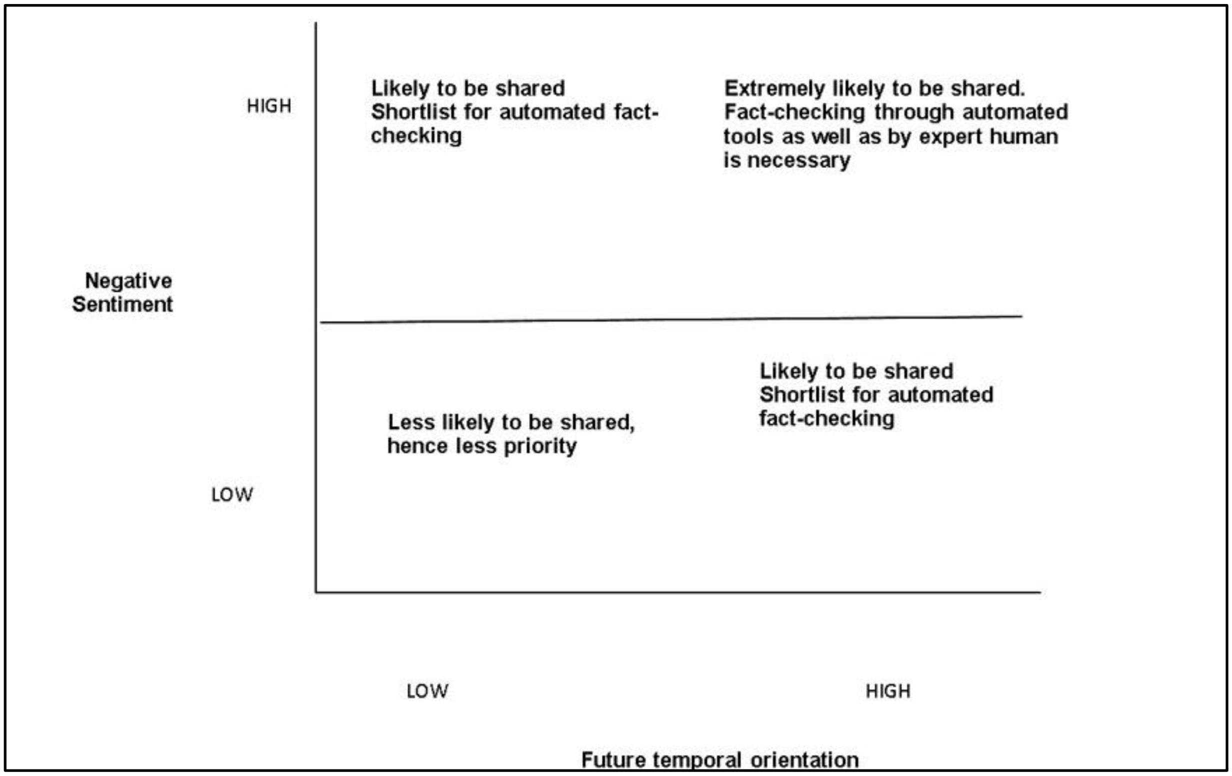


Figure 8. Proposed 2×2 Matrix for Fake News Identification and Management

5.2 Practical Implications

In a world where fake news and disinformation campaigns are considered modern warfare mechanisms, governments and corporations must identify and tackle such campaigns (Coppins, 2020). Adopting an EP narrative, this study identifies individuals' motivations for engaging with potentially fake news that may help quell their inherent fear of the future or uncertainty. Policymakers and corporations could also use this approach to take action to stop—or at least minimize—the spread of fake news.

The on-going COVID-19 pandemic and widespread transmission of fake news has put many human lives at risk. The BBC (2020) reported that social media firms have been unable to stop the spread of COVID-19-related fake news. According to Solon (2020), it is extremely complicated—if not impossible—for social media platforms like Facebook to identify and stop fake news after it has started to circulate on individuals' social media feeds.

On social media platforms, fake news items that reach larger populations are more dangerous. Social media companies need a strategy to identify potential fake news items among billions of posts. Our study provides a mechanism for community managers of such platforms to identify a subset of potentially misleading posts, thereby reducing the workload of identifying and acting on possible fake news. We use these findings to propose a 2 × 2 matrix to identify and manage fake news (Figure 8). Negative sentiment and FTO in news items can be analyzed using tools such as LIWC. If negative sentiment and FTO are low, then such news items are less likely to go viral and can be considered low priority for fake news identification tools. In contrast, if either negative sentiment or FTO is high, the news items are a relatively higher priority for automated fact-checking. Given their likelihood of going viral, news items high in negative sentiment and FTO should be the top priority for automated fact-checking and expert human judgment to ensure veracity. It is worth noting that the menace of fake news is expected to become even more severe with increasing internet penetration. Our proposed 2 × 2 matrix provides a simple yet powerful heuristic grounded in an aspect wired into the human psyche due to our evolutionary history that may help curb this menace.

The proposed 2 × 2 matrix can also be made more nuanced. Recent advances in NLP can help identify individual writing styles (Benzebouchi et al., 2019). Using such advances, our work can support governments and social media platforms in developing algorithms and policies to quickly identify fake new content as well as the individuals spreading fake news (by their tendency to write uncertain or future-oriented posts).

From the policymaker perspective, there is a significant need for mechanisms to identify how antisocial elements create fake news content that targets vulnerable individuals on matters of national security and pandemic-related health. Advances that enable policymakers to recognize social media posts that prey on survival instincts are essential to form policy on communication styles and policy notes that are less amenable to distortion. Since many fake news items that appeal to end users are based on distorting and falsifying certain aspects of real news (McBeth & Clemons, 2011), it would benefit policymakers to design their communications to eliminate such possibilities.

6 Limitations

Our study is subject to the following limitations, which offer opportunities for future research to extend the work on fake news. First, our primary analysis is based on tweets covering political news only. Recent events like the COVID-19 pandemic have demonstrated that fake news can become widespread in various contexts. Second, our tweets are restricted to US political news and our analysis is based on English-language tweets only. Future work could explore fake news phenomena in different languages, countries, and contexts. The limitations of the tools used to assess temporal focus should also be acknowledged. As writing styles vary from person to person—especially on social media platforms with limited writing space—the elicitation of temporal focus may be limited. Future studies could use different mechanisms to evaluate the temporality of texts to accommodate the writing styles prevalent on different social media platforms. Future studies could also leverage different methods, such as experiments or surveys, to measure the fear that future temporal orientation evokes.

7 Conclusion

This study has extended the discourse on fake news by applying the EP lens to understand people's motivation to share fake news items. Specifically, we aimed to increase understanding of the role of FTO in fake news propagation. We found that FTO characterizes fake news and plays a significant role in user engagement. Given this finding, it is imperative that (1) future research on user engagement with fake news considers temporal orientation and (2) tools and content moderation approaches designed to control the spread of fake news incorporate FTO.

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Appendix

Table A1. A Nonexhaustive Snapshot of the Relevant Literature and its Findings in the Domain of Misinformation and Fake News.

Paper	Data and method	Theoretical view	Major finding
Oh et al. (2013)	Econometric analysis of Twitter data	Rumor theory and information ambiguity	Anxiety, personal involvement, and absence of source were leading causes of spread of rumors.
Zhang et al. (2016)	Data mining on online product reviews	N/A	Fake review detection model. Nonverbal cues are significant predictors of fake review detection.
Shu et al. (2017)	Data mining on Twitter and news content data	N/A	Compared different methods of identifying and detecting fake news by mining various aspects of news and social media users.
Bakir & McStay (2018)	Text analysis of verified fake news	N/A	Fake news uses personal and emotionally charged content on social media.
Ginting et al. (2018)	Social network analysis on Twitter data	N/A	Identify fake news through its source and centroids of such spread.
Jang & Kim (2018)	Online surveys	Third person perception (TPP)	Personality and news factors lead to TPP and belief that others would be more affected by fake news.
Shin et al. (2018)	Text analysis of Twitter content	Information diffusion	Periodic recurrence of misinformation from lesser-known sources leads to higher credibility and hence sharing on social media.
Vosoughi et al. (2018)	Twitter data-based statistical analysis	N/A	Bots are not central in the spread of fake news and false news spreads deeper and faster.
Grinberg et al. (2019)	Network analysis and econometrics on Twitter data	N/A	More propensity to share fake news in right-wing supporters of higher age group.
Kim & Dennis (2019)	Lab experiments	Nudge theory	The presentation format of the news in terms of who wrote the news has an impact on forcing readers to think whether it is fake.
Kim et al. (2019)	Lab experiments	Source reputation/ confirmation bias	Source ratings can be used to create a mechanism that enables social media users to identify fake news from real news.
Visentin et al. (2019)	Lab experiment	N/A	Fake news affects people's perception of a brand.
Effron & Raj (2020)	Lab experiment	N/A	Repeated encounters with fake news makes people share it even when they know it is fake.
Pennycook & Rand (2020)	Online surveys	N/A	"Reflexive open-mindedness" leads an individual to be more accepting of fake news.
Gimpel et al. (2021)	Lab experiment	Social psychology	Fake news reporting behavior can be increased by highlighting specific and desired social norms.

Table A2. Comparison of Matched and Unmatched Sample Properties

	Real news	**Fake news**	***p***	**Real news**	**Fake news**	***p***	**Real news**	**Fake news**	***p***	**Real news**	**Fake news**	***p***
	Unmatched sample			*Matched with user features*			*Matched with the writing style*			*Matched with the news source*		
n	338175	127345		127345	127345		127345	127345		127345	127345	
Tweet word count	31.11 (22.21)	28.97 (30.81)	<0.001	30.68 (19.78)	28.97 (30.81)	<0.001	30.67 (19.84)	28.97 (30.81)	>0.01	29.14 (16.92)	28.97 (30.81)	0.076
Tweet tone	39.22 (33.67)	30.80 (30.48)	<0.001	39.66 (34.29)	30.80 (30.48)	<0.001	38.69 (32.48)	30.80 (30.48)	>0.01	39.50 (33.17)	30.80 (30.48)	<0.001
Verified users count	22464 (6.6)	2427 (1.9)	<0.001	2427 (1.9)	2427 (1.9)	1	2427 (1.9)	2427 (1.9)	1	8654 (6.8)	2427 (1.9)	<0.001
Average followers count (x10^4)	8.85 (128.69)	2.01 (56.65)	<0.001	2.01 (56.80)	2.01 (56.65)	0.993	2.01 (56.80)	2.01 (56.65)	0.993	9.92 (147.01)	2.01 (56.65)	<0.001

Note: Values in parentheses represent the standard deviation.

Table A3. Probit Analysis Results for a News Item Being Fake

	Coefficient Matched with user features	Coefficient Matched with writing style	Coefficient Matched with news source
Tweet word count	-0.001*** (<0.001)	-0.001*** (<0.001)	0.001*** (<0.001)
Tweet tone	-0.004*** (0.001)	-0.004*** (0.001)	-0.002*** (<0.001)
Tweet future focus	-0.085*** (0.001)	-0.085*** (0.001)	-0.071*** (0.002)
Title tone	-0.001*** (<0.001)	-0.001*** (<0.001)	-0.011*** (0.001)
Title future focus	0.283*** (0.006)	0.283*** (0.006)	0.204*** (0.004)
Content tone	-0.009*** (<0.001)	-0.009*** (<0.001)	-0.012*** (<0.001)
Content future focus	-0.064*** (0.002)	-0.064*** (0.002)	-0.171*** (0.003)
Intercept	0.743*** (0.007)	0.743*** (0.007)	1.213*** (0.008)
AIC	327203	327203	305318
Log likelihood	-163593.6***	-163593.6***	-1743312.5***
Note: p < 0.001 ***, p < 0.01 **, p < 0.05 *. Numbers in brackets indicate standard errors. Fake news is defined as a dummy variable with a value of 1 for news being fake.			

Table A4. Regression Coefficients for Retweets as Dependent Variable

	Model 1 Real news	Model 2 Fake news (fake = 1)	Model 1 Real news	Model 2 Fake news (fake = 1)
	Matched with user features		*Matched with writing style*	
Tweet word count	0.032*** (0.005)	-0.0009 (0.006)	0.032*** (0.005)	-0.0009 (0.006)
Tweet tone	0.001 (0.003)	0.011 (0.012)	0.001 (0.003)	0.011 (0.012)
Tweet future focus	0.321* (0.102)	-0.081 (0.188)	0.321* (0.102)	-0.081 (0.188)
Title tone	0.007 (0.005)	0.035* (0.014)	0.007 (0.005)	0.035* (0.014)
Title future focus	-0.453 (1.041)	0.843*** (0.217)	-0.453 (1.041)	0.843*** (0.217)
Content tone	0.001 (0.004)	0.004 (.007)	0.001 (0.004)	0.004 (.007)
Content future focus	-0.111 (0.079)	0.197 (0.223)	-0.111 (0.079)	0.197 (0.223)
Verified status × Title future focus	-1.34 (2.255)	-5.14*** (1.259)	-1.34 (2.255)	-5.14*** (1.259)
Title tone ×Title future focus	0.004 (0.013)	-1.91** (0.006)	0.004 (0.013)	-1.91** (0.006)
Sentiment difference	-0.01*** (<0.001)	-0.02*** (<0.001)	-0.01*** (<0.001)	-0.02*** (<0.001)
Sentiment diff squared	0.0003*** (<0.001)	0.0008*** (<0.001)	0.0003*** (<0.001)	0.0008*** (<0.001)
Future orientation diff	0.014 (0.107)	0.013*** (0.0001)	0.014 (0.107)	0.013*** (<0.001)
Future orientation diff squared	-0.012 (0.011)	-0.0025*** (0.0000)	-0.012 (0.011)	-0.0025*** (<0.001)
Followers count (log)	1.10*** (0.044)	1.73*** (0.009)	1.10*** (0.044)	1.73*** (0.009)
Verified status	21.26*** (0.759)	48.41*** (1.62)	21.26*** (0.759)	48.41*** (1.62)
News source dummy	Included	Included	Included	Included
Intercept	-6.73*** (0.452)	-10.79*** (0.771)	-6.73*** (0.452)	-10.79*** (0.771)
AIC	1271187	1461794	1271187	1461794
Log likelihood	-132703***	-730882.2***	-132703***	-730882.2***
Note: p < 0.001 ***, p < 0.01 **, p < 0.05 *; Numbers in brackets indicate standard errors				

Table A4. Regression Coefficients for Retweets as Dependent Variable

	Model 1 Real news	Model 2 Fake news (fake=1)
	Matched with news source	
Tweet word count	0.032*** (0.005)	-0.001 (0.006)
Tweet tone	0.001 (0.003)	0.011 (0.012)
Tweet future focus	0.321* (0.102)	-0.081 (0.188)
Title tone	0.007 (0.005)	0.034* (0.014)
Title future focus	-0.453 (1.041)	0.843*** (0.217)
Content tone	0.001 (0.004)	0.004 (0.007)
Content future focus	-0.111 (0.079)	0.197 (0.229)
Verified status × Title future focus	-1.34 (2.255)	-5.14*** (1.259)
Title tone ×Title future focus	0.004 (0.013)	-1.91** (0.006)
Sentiment difference	-0.01*** (0.0001)	-0.02*** (<0.001)
Sentiment diff squared	0.0003*** (0.000)	0.0008*** (0.00)
Future orientation diff	0.014 (0.107)	0.013*** (<0.001)
Future orientation diff squared	-0.012 (0.011)	-0.0025*** (<0.001)
Followers count (log)	1.10*** (0.044)	1.737* (0.093)
Verified status	21.26*** (0.759)	48.41* (1.62)
News source dummy	Included	Included
Intercept	-6.73*** (0.452)	-10.79*** (0.817)
AIC	1271187	1461794
Log likelihood	-132703***	-730882.2***
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *; Numbers in brackets indicate standard errors		

Table A5. Additional Robustness Tests' Regression Coefficients

	Model 1, DV= No. of likes Real news	Model 2, DV = No. of likes Fake news	Model 3, DV= No. of retweets All news
Fake news			0.614** (0.35)
Followers count (log)	2.463*** (0.113)	3.058*** (0.2261)	2.333*** (0.067)
Verified status	63.581*** (1.943)	122.4*** (4.099)	34.83*** (0.744)
News source dummy	Included	Included	Included
Tweet word count	0.061*** (0.013)	0.001 (0.017)	0.032*** (0.006)
Tweet tone	-0.005 (0.009)	-0.011 (0.02)	-0.008 (0.0056)
Tweet future focus	0.476* (0.262)	0.336 (0.417)	0.192** (0.094)
Title tone	0.002 (0.012)	0.056* (0.031)	0.016** (0.007)
Title future focus	-1.332 (2.676)	1.269** (0.52)	-0.229 (0.149)
Content tone	0.009 (0.009)	0.038** (0.018)	-0.0033 (0.005)
Content future focus	-0.258 (0.202)	0.419 (0.556)	-0.309** (0.145)
Verified status × Title future focus	-6.954 (6.426)	11.45*** (2.605)	3.135* (1.945)
Title tone × Title future focus	0.013 (0.033)	-0.003* (0.002)	-0.0058* (0.003)
Sentiment difference squared	0.0003* (<0.001)	0.002*** (<0.001)	0.0002** (<0.001)

Future focus difference squared	-0.043 (0.028)	-0.0086* (0.0345)	-0.0011** (0.0001)
Intercept	-14.57*** (1.158)	-20.01*** (1.884)	-0.144 (0.711)
AIC	1510596	1687993	5624945
Log likelihood	-755282.8***	-843984.4***	-2812459***
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *; Numbers in brackets indicate standard errors			

Table A5. Robustness Tests with Antivax Misinformation Dataset

	Model 1, DV = No. of retweets Factual tweets	**Model 2, DV = No. of retweets Misinformation**
Tweet word count	0.221 (0.268)	0.31 (0.238)
Tweet tone	2.29 (1.949)	1.37 (1.30)
Tweet future focus	-0.116 (0.696)	0.602* (0.217)
Images	5.721 (5.071)	21.078*** (6.13)
Videos	2.561 (3.11)	2.45 (3.40)
Followers count (log)	6.813*** (0.223)	7.653*** (0.422)
Verified status	48.581*** (1.976)	34.193** (2.099)
Intercept	-2.255 (4.193)	-3.41 (4.99)
AIC	100975	165981
Log likelihood	-50480.66***	-32391.79***
Note: $p < 0.001$ ***, $p < 0.01$ **, $p < 0.05$ *; Numbers in brackets indicate standard errors		

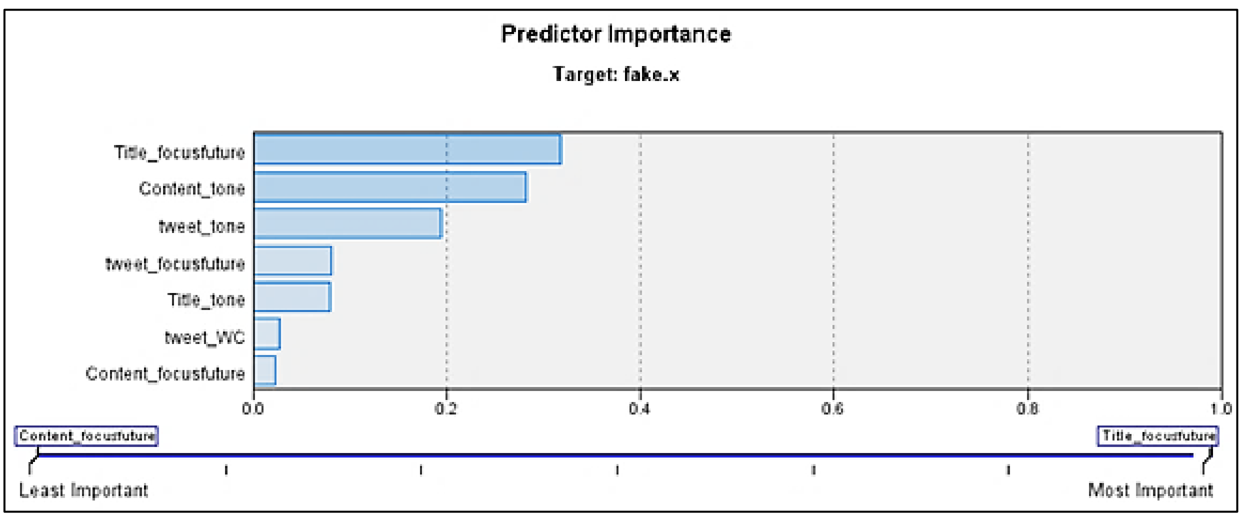

Figure A1. Predictor Importance for Balanced Sample

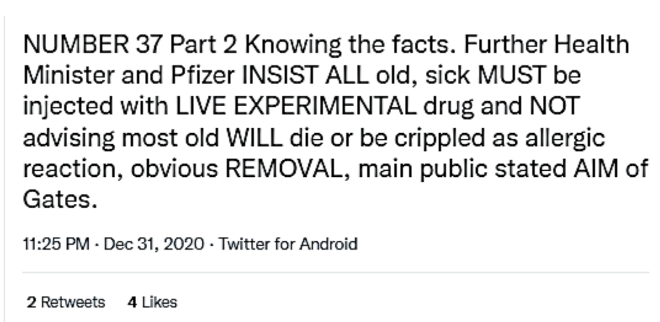

Figure A2. An Example of Misinformation

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