2021

An Analysis of People's Reasoning for Sharing Real and Fake News

Anu Shrestha
Boise State University

Francesca Spezzano
Boise State University

An Analysis of People's Reasoning for Sharing Real and Fake News

Anu Shrestha and Francesca Spezzano

Computer Science Department
Boise State University
anushrestha@u.boisestate.edu
francescaspezzano@boisestate.edu

Abstract. The problem of the increase in the volume of fake news and its widespread over social media has gained massive attention as most of the population seeks social media for daily news diet. Humans are equally responsible for the surge of fake news spread. Thus, it is imperative to understand people's behavior when they decide to share real and fake news items on social media. In an attempt to do so, we performed an analysis on data collected through a survey where participants (n= 363) were asked whether they were willing to share the given news item on their social media and explain the reasoning for their decision. The results show that the analysis presents several commonalities with previous studies. Moreover, we also addressed the problem of predicting whether a person will share a given news item or not. For this, we used intrinsic features from participants' open-ended responses and demographics attributes. We found that the perceived emotions triggered by the news item show a strong influence on the user's decision to share news items on social media.

Keywords: Fake News · News Sharing · Emotion · Misinformation · Social Media.

1 Introduction

Social media has emerged as popular information source people rely on for events, breaking news, and emergencies. Indeed, it has become a source of daily news diet for the increasingly large population. Statistics show that majority of the population (71% of American adults) ever get news through social media in 2020 [24] which was increased by 3% since 2018 [23]. The landscape of news consumption and information flow has drastically changed with the popularity of social media. It has transformed how news content is created, how people engage with news items, and share information, blurring the journalists' boundary

 Presented at the MISINFO 2021 Workshop, held in conjunction with the 30th ACM The Web Conference, 2021, in Ljubljana, Slovenia.

in traditional media that is first verifying and then disseminating only the accurate news items [25]. Moreover, users in social media (both organizations and individuals) actively participate in creating and sharing news items with friends, families, and other readers due to its ease of use, lower cost, and convenience of further sharing [2, 29]. This shift of news paradigm has led to an unprecedented transformation in both news quality and quantity that users encounter in social media, increasing the probability of potential encounters and the spread of fake news, fostering social media as a fertile ground for the production and propagation of fake news.

The sheer volume of fake news being observed in social media has recently become an obvious cause of concern. Many studies have highlighted the characteristics of fake news through linguistic and psychological attributes [11, 20, 21, 27], writing styles [3, 11, 13], network-based attributes [7] and hybrid attributes considering both linguistic and network [29].

Despite several studies illustrating cues to identify fake news and mitigate its spread, there is a worrisome amount of fake news widely spreading over social media. Fake news has been identified as more likely to go viral than real news, spreading faster and wider [35]. Additionally, an analysis of news about the 2016 election conducted by BuzzFeed, also found more engagement with fake news than real news [32]. Earlier studies analyzed the potential reason behind this rapid diffusion of news in social media, focusing on various factors, including polarized communities of users with common belief (echo-chambers) [4], epidemiological models [12]. Some studies highlighted the actors responsible for spreading fake news, including bots and cyborgs [6]. Although bots are equally responsible for spreading real and fake news, the considerable spread of fake news is caused by human activity [30, 35] as people are generally not able to accurately identify which news item is fake and which is real [34]. Thus, it is crucial to understand the people's sharing behavior of fake and real news on social media to minimize fake news diffusion.

In this context, this study seeks to better understand how people reason when they decide to share real news and fake news. In particular, we surveyed 363 undergraduate students where we asked participants to report and explain their willingness to share given news item (with headline and image) on their social media. We also leveraged the demographic attributes of participants like gender and political orientation in our study. We performed a comprehensive data analysis to investigate the pattern of news sharing behavior, the role of demographics in news sharing decisions, and why people share real and fake news. Furthermore, we addressed the problem of predicting whether a person will share a given news item or not according to emotion, psychological, and demographics features as a binary classification task.

Our experiments show several commonalities with previous findings regarding news sharing behavior.

- News sharing is rare as only a small percentage (19.2% to 28.2%) of users expressed the willingness to share news in social media, regardless of news veracity.

- Female participants are prone to share more news than male participants regardless of news veracity.
- Left-leaning participants tend to share real news more than fake news, independently of the news source's political orientation, and right-leaning participants were instead more prone to share news items from sources with the same political-leaning, independently of news veracity.
- The prominent themes illustrated by the approaches used by participants to make their sharing decisions falls under subjectivity and the focus on others interest or disinterest in news topic.
- Emotion features are more effective in predicting people's willingness to share a given news item.

2 Related Work

Several studies have been conducted to understand the characteristics of users that are likely to contribute to spreading fake news on social networks. Vosoughi et al. [35] revealed that the fake news spreaders had, on average, significantly fewer followers, followed significantly fewer people, and were significantly less active on Twitter. Moreover, bots tend to spread both real and fake news, and the considerable spread of fake news on Twitter is caused by human activity. Shrestha and Spezzano showed that social network properties help in identifying active fake news spreaders [26]. Shu et al. [30] analyzed user profiles to understand the characteristics of users that are likely to trust/distrust fake news. They found that, on average, users who share fake news tend to be registered for a shorter time than the ones who share real news and that bots are more likely to post a piece of fake news than a real one, even though users who spread fake news are still more likely to be humans than bots. They also show that real news spreaders are more likely to be more popular and that older people and females are more likely to spread fake news. Guess et al. [9] also analyzed user demographics as predictors of fake news sharing on Facebook and found out political-orientation, age, and social media usage to be the most relevant. Specifically, people are more likely to share articles they agree with (e.g., right-leaning people tended to share more fake news because the majority of the fake news considered in the study were from 2016 and pro-Trump), seniors tend to share more fake news probably because they lack digital media literacy skills that are necessary to assess online news truthfulness, and the more people post in social media, the less they are likely to share fake news, most likely because they are familiar with the platform and they know what they share.

Shrestha et al. [28] analyzed the linguistic patterns used by a user in their tweets and personality traits as a predictor for identifying users who tend to share fake news on Twitter data [22, 28]. Likewise, Giachanou et al. [8] proposed an approach based on a convolutional neural network to process the user Twitter feed in combination with features representing user personality traits and linguistic patterns used in their tweets to address the problem of discriminating between fake news spreaders and fact-checkers.

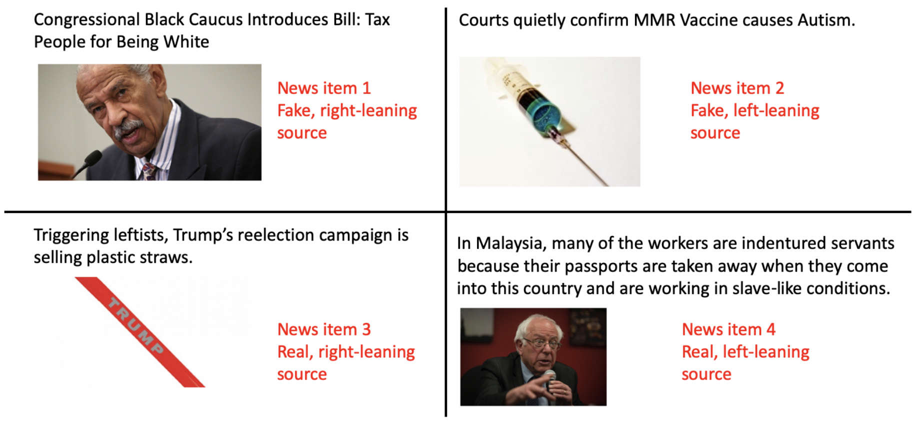


Fig. 1: News items used in our survey instrument.

Ma et al. [15] went beyond the user and news characteristics and analyzed the characteristics of diffusion networks to explain users' news sharing behavior. They found opinion leadership, news preference, and tie strength to be the most important factors at predicting news sharing, while homophily hampered news sharing in users' local networks. Also, people driven by gratifications of information seeking, socializing, and status-seeking were more likely to share news on social media platforms [14].

3 Data Collection

We conducted an online survey delivered via Qualtrics. Through this online survey, participants were given four news headlines and accompanying images. For each news item, participants were asked whether they were willing to share the given news item on their social media and write an explanation of the reasoning for their decision. We considered the four news items shown in Figure 1 and gathered from `politifact.com`. In this news set, two are real news items, and two are fake news items, as fact-checked by `politifact.com`. Both real and fake news items are one from a left-leaning source and one from a right-leaning source. News source political-leaning has been gathered from `mediabiasfactcheck.com`.

We recruited undergraduate students ($n = 363$) from a volunteer pool in general education social science courses (Psychology 101) to participate in our survey (258 F, 101 M, 4 Other; mean age 19.7, SD = 4.25). The research was approved by the university IRB. Participants were compensated with course credit (volunteering for studies being one option for a research experience requirement). Participants received no training.

	Percentage of Sharing
News Item 1 (Fake)	19.2%
News Item 2 (Fake)	22.9%
News Item 3 (Real)	20.0%
News Item 4 (Real)	28.2%

Table 1: News Sharing Behavior.

4 Data Analysis

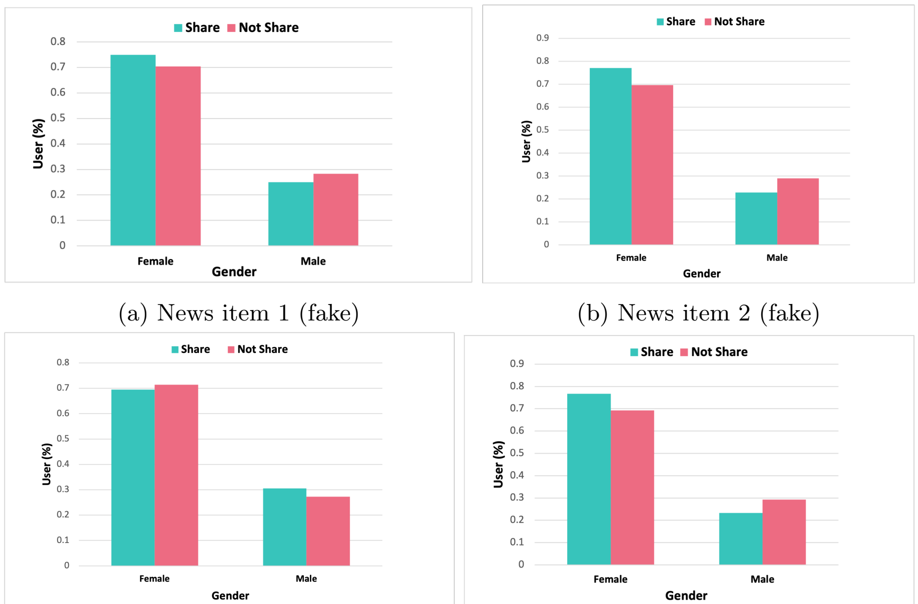
News sharing is rare. We start the analysis of our data by observing that only a small percentage of users expressed the willingness to share news in social media, independently of the veracity of the news. As shown in Table 1, this percentage ranges between 19.2% and 28.2% among the news considered in our survey. Previous research [10] has shown that sharing news articles from fake news domains on Facebook was a rare activity during the 2016 U.S. presidential campaign. Our data on fake news sharing is aligned with this result, but our respondents also showed some preliminary evidence that this pattern may be true for real news sharing as well.

The role of demographics in news sharing. We collected demographic data from our survey participants, including gender, political orientation, and age. As most participants are in the same age range (18-25), we did not consider age in our analysis.

When looking at differences in sharing behavior according to gender (see Figure 2), we observe that the female participants were more prone to share both the fake news items considered than male participants who were more skeptical about the same news items. Shu et al. [31] in his studies have shown a similar result where female users tend to trust fake news more than male users. In general, females were more prone to share more news items than males (three vs. one).

Regarding participants political orientation, we see two interesting patterns as reported in Figure 3: (1) left-leaning participants were more prone to share real news than fake news, independently of the political orientation of the news source; (2) right-leaning participants were instead more prone to share news items from sources with the same political-leaning (news items 1 and 3), independently of news veracity. Similarly, Guess et al. [10] have shown that, in 2016, conservatives were more likely to share articles from pro-Trump fake news domains than liberals or moderates.

Why people share real and fake news? Yaqub et al. [36] analyzed open-ended responses of participants in the study where they explained the reason behind their intention to share true, false, and satire headlines. In their study, the most frequent rationales behind sharing/not sharing news were (1) the interest/non-interest towards the news, (2) the potential of generating discussion among the



(a) News item 1 (fake)

(b) News item 2 (fake)

(c) News item 3 (real)

(d) News item 4 (real)

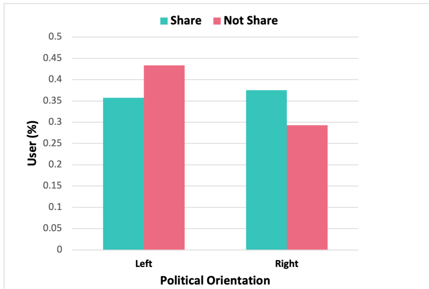
Fig. 2: Distribution of participant's gender.

friends, (3) the fact that the news is not relevant to the user's life, and (4) the perceived news credibility, especially as a motivation for not sharing news.

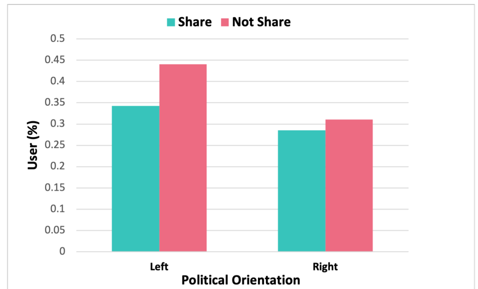
We conducted a similar analysis on a sample of our data (n=25). Specifically, we conducted a thematic analysis to identify the prominent themes that illustrated the approaches used by participants to make their sharing decisions. We followed an inductive approach to generating codes [5]. We found out the principal codes to be focused on potential others ("My friends would/would not be interested in this"), interest or disinterest in the news topic, and subjectivity/the self ("I would/wouldn't share this because...", "I would call that fake/real") and are mostly aligned with the finding by Yaqub et al. [36].

Regarding performing credibility assessment before making the sharing decision, we also found in our sample data that this was performed more often for fake news (28% of the times for news item 1 and 56% for news item 2) than for real news (24% of the times for news item 3 and 16% for news item 4). Moreover, when performed, the credibility assessment was much more correct in the case of fake news (100% of the times for news item 1 and 93% for news item 2) than real news (67% of the times for news item 3 and 25% for news item 4).

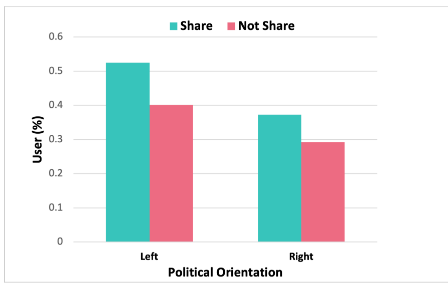
Overall, the data analysis performed in this section shows that our collected data presents several commonalities with previous studies, ensuring we have quality data suitable for further investigations.



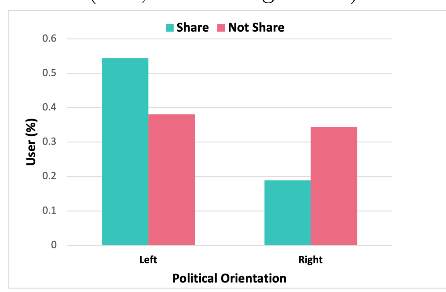
(a) News item 1
(fake, right-leaning source)



(b) News item 2
(fake, left-leaning source)



(c) News item 3
(real, right-leaning source)



(d) News item 4
(real, left-leaning source)

Fig. 3: Distribution of participant's self-identified political orientation.

5 Predicting News Sharing

In this section, we address the problem of predicting whether a person will share or not a news item according to emotion and psychological features generated when they consider a news item and demographics (gender and political orientation) as well. We modeled the problem as a binary classification task where we computed emotion and psychological features from participants' open-ended responses to the survey question asking for an explanation of their decision to share or not the given news item.

5.1 Textual Features Extraction

Emotion Features (Emotion) In order to compute a vector of scores quantifying participants' emotions when deciding whether or not to share a news item, we considered their open-ended survey responses and proceeded as follows. We started by cleaning responses' text by expanding contraction words, correcting misspellings and grammatical mistakes using LanguageTool[1] and replacing negated words with their WordNet antonym. Next, we extracted emo-

[1] https://pypi.org/project/language-tool-python/

tions from the text by using the Emotion Intensity Lexicon (NRC-EIL) [18] and EmoLex [33]. Emotion features computed via NRC-EIL include anger, joy, sadness, fear, disgust, anticipation, surprise, and trust, while Emolex[2] features include happy, sad, angry, don't care, inspired, afraid, amused, and annoyed. Feature vectors have been computed by using the approaches proposed in [16,17]. In addition, we also considered emotion-related features as computed by the 2015 Linguistic Inquiry and Word Count (LIWC) [19] tool, which includes effective processes like anxiety, anger, positive and negative emotion.

Psycho-linguistic Features (LIWC) To understand the relationship between psychological states and the participants' decision-making, we considered the set of psycho-linguistic features computed by the Linguistic Inquiry and Word Count (LIWC) tool [19]. LIWC is a transparent text analysis tool that counts words in psychologically meaningful categories. Specifically, we considered psychological processes that include social processes (e.g., family, friends), cognitive processes (e.g., think, cause, perhaps), perceptual processes (e.g., see, heard, felt), biological processes (e.g., eat, pain, love), relativity (e.g., area, move, day) and personal concerns (e.g., work, leisure, achieve, home, money, religion, death).

Demographics (Demog) As explicit features, we used participants' self-identified gender and political orientation to understand if the demographic attributes provide potential cues in predicting users' sharing decisions.

5.2 Experimental Setting and Results

We used each group of features described in the previous section as input to a random forest classifier to compute the performance of these features in predicting whether a reader of a news item (a participant of our survey) is willing to share or not the given news item on their social networks. We also tried other classifiers such as Support Vector Machine (SVM) and logistic regression, but random forest achieved the best results. Hence, in the paper, we report the results of random forest only. We used class weighting to deal with the class imbalance and performed 5-fold cross-validation.

The results are reported in Table 2 according to the area under the ROC curve (AUROC), average precision (AvgP), and F1-measure (F1). As can be seen, when each feature group is considered separately, emotion features are the best performing features compared to LIWC features and demographics with 72% vs. 61% and 52% AUROC and 40% vs. 25% and 20% average precision for news item 1, 71% vs. 61% and 57% AUROC and 42% vs. 31% and 25% average precision for news item 2, 77% vs. 59% and 62% AUROC and 58% vs. 31% and 26% average precision for news item 3 and 78% vs. 61% and 59% AUROC and 56% vs. 40% and 42% average precision for news item 4 (bold in Table 2). We further considered a combination of all feature groups to see

[2] https://sites.google.com/site/emolexdata/

	Features	AUROC	AvgP	F1
News Item 1 (Fake)	LIWC	0.611	0.247	0.166
	Demog	0.518	0.207	**0.228**
	Emotion	**0.720**	**0.403**	**0.228**
	All	**0.722**	0.382	0.129
News Item 2 (Fake)	LIWC	0.608	0.307	0.175
	Demog	0.565	0.250	**0.325**
	Emotion	**0.706**	**0.416**	0.162
	All	**0.707**	**0.421**	0.122
News Item 3 (Real)	LIWC	0.586	0.310	0.257
	Demog	0.617	0.258	0.300
	Emotion	**0.771**	**0.578**	**0.477**
	All	**0.796**	**0.585**	0.439
News Item 4 (Real)	LIWC	0.611	0.397	0.302
	Demog	0.590	0.317	0.356
	Emotion	**0.784**	**0.564**	**0.423**
	All	**0.786**	0.562	0.359

Table 2: Comparison of emotion, psycho-linguistic, and demographic features to predict whether a news item will be shared or not. We used a random forest classifier. Best results among feature groups considered separately are in bold. Best overall results are shaded.

if combining demographics, psychological and emotional features can provide complementary information that can help improve the prediction. We observed that when the combination of all feature groups is considered, the performance remained more or less the same if not improved according to AUROC (shaded in Table 2). This demonstrates that emotion features are more effective than other groups of features considered in our study for predicting people's sharing behavior. Hence, one of the motivations for potential news-sharing behavior in social media could be emotional persuasion. It will not be inaccurate to say that being persuaded by strong emotions like anger, fear, surprise, joy, etc., triggered by news content, people tend to get involved and share more news on social media. This finding aligns with the previous research by Berger et al. [1] which also states that emotional arousal tends to increases the likelihood of sharing news on social media.

6 Conclusion and Future Work

To sum up, this paper presents findings from studying people's reasoning when they decide to share real and fake news items provided with headlines and images. This paper investigates the correlation between the user's sharing decision and explicit attributes provided by participants like demographics and political orientation. Furthermore, we addressed the problem of predicting whether a person will share a given news item or not using intrinsic features like psychological and emotion from participants' open-ended responses explaining their willingness to share given news item along with demographics attributes.

The results show that news sharing is rare, and among the participants expressing willingness to share, females are prone to share more news in general. Participants' political orientation exerts a significant pattern on news sharing behavior that is left-leaning participants' news sharing behavior is motivated by news veracity rather than political orientation. In contrast, it is the other way around for right-leaning participants. Likewise, it shows the possibility of users sharing news items depends on the perceived relevance of news interest among friends and families. Moreover, this paper also highlights that the perceived emotions triggered by the news item show a strong influence on user's news sharing behavior in social media.

One potential limitation of our study is that we have considered only four news of each political leaning (2 fake and 2 real). Considering a bigger set of news items could have shown significant patterns and support to our findings. Furthermore, this work focuses on a younger sample of the limited range of age, due to which we did not consider age in demographic attributes. It could have added some more insights regarding news sharing behavior among different age groups if we could consider participants of a wide range of ages (from younger to older population). We will address these limitations in our future work.

Acknowledgements

This work has been supported by the National Science Foundation under Award no. 1943370. We thank Brian Stone for facilitating the data collection and Ashlee Milton and Maria Soledad Pera for providing us with the code used in their papers [16, 17] to compute emotional features.

References

1. Berger, J.: Arousal increases social transmission of information. Psychological science **22**(7), 891–893 (2011)
2. Bruns, A., Highfield, T., Lind, R.A.: Blogs, twitter, and breaking news: The produsage of citizen journalism. Produsing theory in a digital world: The intersection of audiences and production in contemporary theory **80**(2012), 15–32 (2012)
3. Castillo, C., Mendoza, M., Poblete, B.: Information credibility on twitter. In: Proceedings of the 20th international conference on World wide web. pp. 675–684 (2011)
4. Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H.E., Quattrociocchi, W.: The spreading of misinformation online. Proceedings of the National Academy of Sciences **113**(3), 554–559 (2016)
5. DNSc, J., Strauss, A.: Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory. SAGE Publications, Inc, Los Angeles, fourth edition edn. (Dec 2014)

6. Ferrara, E., Varol, O., Davis, C., Menczer, F., Flammini, A.: The rise of social bots. Communications of the ACM **59**(7), 96–104 (2016)
7. Gayo-Avello, D., Metaxas, P.T., Mustafaraj, E., Strohmaier, M., Schoen, H., Gloor, P., Castillo, C., Mendoza, M., Poblete, B.: Predicting information credibility in time-sensitive social media. Internet Research (2013)
8. Giachanou, A., Rissola, E.A., Ghanem, B., Crestani, F., Rosso, P.: The role of personality and linguistic patterns in discriminating between fake news spreaders and fact checkers. In: Natural Language Processing and Information Systems: 25th International Conference on Applications of Natural Language to Information Systems, NLDB 2020. p. 181. Springer Nature
9. Guess, A., Nagler, J., Tucker, J.: Less than you think: Prevalence and predictors of fake news dissemination on facebook. Science advances **5**(1), eaau4586 (2019)
10. Guess, A., Nagler, J., Tucker, J.: Less than you think: Prevalence and predictors of fake news dissemination on facebook. Science Advances **5**(1) (2019)
11. Horne, B.D., Adali, S.: This just in: Fake news packs a lot in title, uses simpler, repetitive content in text body, more similar to satire than real news. In: The 2nd International Workshop on News and Public Opinion at ICWSM (2017)
12. Jin, F., Dougherty, E., Saraf, P., Cao, Y., Ramakrishnan, N.: Epidemiological modeling of news and rumors on twitter. In: Proceedings of the 7th workshop on social network mining and analysis. pp. 1–9 (2013)
13. Jin, Z., Cao, J., Zhang, Y., Luo, J.: News verification by exploiting conflicting social viewpoints in microblogs. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 30 (2016)
14. Lee, C.S., Ma, L.: News sharing in social media: The effect of gratifications and prior experience. Computers in human behavior **28**(2), 331–339 (2012)
15. Ma, L., Lee, C.S., Goh, D.H.: Understanding news sharing in social media from the diffusion of innovations perspective. In: 2013 IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing. pp. 1013–1020. IEEE (2013)
16. Milton, A., Batista, L., Allen, G., Gao, S., Ng, Y., Pera, M.S.: "don't judge a book by its cover": Exploring book traits children favor. In: RecSys 2020: Fourteenth ACM Conference on Recommender Systems, Virtual Event, Brazil, September 22-26, 2020. pp. 669–674. ACM (2020)
17. Milton, A., Pera, M.S.: What snippets feel: Depression, search, and snippets. In: Cantador, I., Chevalier, M., Melucci, M., Mothe, J. (eds.) Proceedings of the Joint Conference of the Information Retrieval Communities in Europe (CIRCLE 2020), Samatan, Gers, France, July 6-9, 2020. CEUR Workshop Proceedings, vol. 2621 (2020)
18. Mohammad, S.: Word affect intensities. In: Proceedings of the Eleventh International Conference on Language Resources and Evaluation, LREC 2018, Miyazaki, Japan, May 7-12, 2018. European Language Resources Association (ELRA) (2018)
19. Pennebaker, J.W., Boyd, R.L., Jordan, K., Blackburn, K.: The development and psychometric properties of liwc2015. Tech. rep. (2015)
20. Pérez-Rosas, V., Kleinberg, B., Lefevre, A., Mihalcea, R.: Automatic detection of fake news. In: Proceedings of the 27th International Conference on Computational Linguistics. pp. 3391–3401 (2018)
21. Potthast, M., Kiesel, J., Reinartz, K., Bevendorff, J., Stein, B.: A stylometric inquiry into hyperpartisan and fake news. In: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). pp. 231–240 (2018)

22. Rangel, F., Giachanou, A., Ghanem, B., Rosso, P.: Overview of the 8th author profiling task at pan 2020: Profiling fake news spreaders on twitter. In: CLEF (2020)
23. Shearer, E., Matsa, K.E.: News use across social media platforms 2018. Pew Research Center (2018)
24. Shearer, E., Mitchell, A.: News use across social media platforms in 2020. Pew Research Center (2020)
25. Shoemaker, P.J., Vos, T.P., Reese, S.D.: Journalists as gatekeepers. The handbook of journalism studies **73** (2009)
26. Shrestha, A., Spezzano, F.: Online misinformation: from the deceiver to the victim. In: ASONAM '19: International Conference on Advances in Social Networks Analysis and Mining. pp. 847–850. ACM (2019)
27. Shrestha, A., Spezzano, F.: Textual characteristics of news title and body to detect fake news: A reproducibility study. In: Advances in Information Retrieval - 43rd European Conference on IR Research, ECIR 2021, Proceedings, Part II. Lecture Notes in Computer Science, vol. 12657, pp. 120–133. Springer (2021)
28. Shrestha, A., Spezzano, F., Joy, A.: Detecting fake news spreaders in social networks via linguistic and personality features. In: CLEF (2020)
29. Shu, K., Sliva, A., Wang, S., Tang, J., Liu, H.: Fake news detection on social media: A data mining perspective. ACM SIGKDD explorations newsletter **19**(1), 22–36 (2017)
30. Shu, K., Wang, S., Liu, H.: Understanding user profiles on social media for fake news detection. In: 1st IEEE International Workshop on Fake MultiMedia (FakeMM 2018) (2018)
31. Shu, K., Wang, S., Liu, H.: Understanding user profiles on social media for fake news detection. In: 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR). pp. 430–435. IEEE (2018)
32. Silverman, C.: This analysis shows how viral fake election news stories outperformed real news on facebook. BuzzFeed News **16** (2016)
33. Song, K., Gao, W., Chen, L., Feng, S., Wang, D., Zhang, C.: Build emotion lexicon from the mood of crowd via topic-assisted joint non-negative matrix factorization. In: Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval, SIGIR 2016. pp. 773–776. ACM (2016)
34. Spezzano, F., Shrestha, A., Fails, J.A., Stone, B.W.: That's fake news! investigating how readers identify the reliability of news when provided title, image, source bias, and full articles. Proceedings of the ACM on Human Computer Interaction journal **5**(CSCW1, Article 109) (2021)
35. Vosoughi, S., Roy, D., Aral, S.: The spread of true and false news online. Science **359**(6380), 1146–1151 (2018)
36. Yaqub, W., Kakhidze, O., Brockman, M.L., Memon, N., Patil, S.: Effects of credibility indicators on social media news sharing intent. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. p. 1–14. CHI '20 (2020)