Stylistic Features Usage: Similarities and Differences Using Multiple Social Networks

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Abstract. User engagement on social networks is essential for news outlets where they often distribute online content. News outlets simultaneously leverage multiple social media platforms to reach their overall audience and to increase marketshare. In this research, we analyze ten common stylistic features indicative of user engagement for news postings on multiple social media platforms. We display the stylistic features usage differences of news posts from various news sources. Results show that there are differences in the usage of stylistic features across social media platforms (Facebook, Instagram, Twitter, and YouTube). Online news outlets can benefit from these findings in building guidelines for content editors and creators to create more users engaging postings.

Keywords: Stylistic features · User engagement · News outlets

1 Introduction

Social networks are important dissemination channels for news outlets producing digital content [18]. More than half of news readers get at least part of their news from social networks [19], with most news outlets having an online presence on multiple social networks [20]. High user engagement on social networks is an indicator of news outlet success, where employees are trained to produce more engaging content [9]. Some typical user engagement metrics are likes, comments, shares, and views [2]. One commonly studied topic concerning user engagement is stylistic features (e.g., using question marks and emojis) in social media posts [3,5,6,15]. Stylistic features of online content have been used for a variety of tasks [23] and are effective in many domains [21]. However, there is a lack of studies using both multiple social networks and numerous news outlets. The largest social networks used by news outlets are Facebook, Twitter,

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Instagram, and YouTube [20]. Given that news outlets use multiple social platforms, and news readers are also using multiple platforms for getting their news, there are some open questions. *Does user engagement differ across platforms? Are there different audience behaviors for a news outlet on different platforms?*. Those questions motivate our research. For addressing a portion of these questions, we focus on understanding the similarities and differences of employed stylistic features in news postings of multiple news outlets. Also, we focus on four social platforms, which are Facebook (FB), Twitter (TW), Instagram (IG), and YouTube(YT).

Our objective is to understand what are the similarities and differences in styles in news social media posts affecting user engagement across social media platforms. Our results can assist news outlets when using multiple social media platforms for distributing their content. Through, focusing on the stylistic aspects of the content, we formulate the following research question (RQ): *Is user engagement on different social media platforms affected by content stylistic factors?* To answer our research question, we select two media type features: image and video, and eight common stylistic features for social networks content from the literature which are: emojis, question mark, exclamation mark, sentiment, hashtags, post length, URLs, and mentions. For simplicity, we call all ten features stylistics features, as most of them are related to the style of the post content.

2 Related Work

User Engagement on Facebook: Banhawi and Ali [3] report that posts with images, exclamation marks receive more likes and number of comments, question marks have no effect, and length of a post has a generally negative effect. Similarly, Cvijik and Michahelles [16] reported a significant relationship between media type and post topic on user engagement (likes, comments, and shares). Yu et al. [24] reported that status and photo posts trigger more likes than links and video.

User Engagement on Instagram: Manikonda et al. [14] report that users of Instagram and Twitter are fundamentally different (or users use these platforms differently) with Twitter being more of an information platform, resulting in differences in linguistic, topical and visual aspects of posts. Researching the visual content of images and emojis, Jaakonmäki et al. [11] report that these features impact the number of likes and comments. Burney [5] found that using question marks or hashtags in Instagram posts increase the number of likes and comments; however, using an exclamation mark reduces them.

User Engagement on Twitter: Naveed et al. [15] report that tweets with hashtags, usernames, and URLs are more likely to be retweeted; exclamation marks have a negative effect; question marks have a positive impact. Hua et al. [8] claim that topic influences audience interaction, and Lotan et al. [13] report that the probability of a user clicking on social media postings can also vary by topic. Brems et al. [4] report that journalists struggle with being factual or opinionated, being personal or professional, and how to balance broadcasting their message with engagement. Hong et al. [7] report that there is a network effect of the news media and user-generated content. Tweets with negative sentiment have a positive correlation with user engagement [22].

User Engagement on YouTube: Sayre et al. [17] find that the social media posts content reflects mainstream news and also influences professional media coverage. An et al. [1] show that audience segments are clustered around video topics. Hoiles et al. [6] state that title, description, and hashtags have positive effects on videos popularity if optimized.

3 Methodology

Data Collection: For addressing our research question, we used the API of the four social networks for collecting the news posting of 53 English news outlets that have active posting activities in the four networks. We collected the news postings from 1^{st} of January 2017 until 31^{st} of August 2017. The total collected posts are 27,117 (Facebook), 35,289 (Instagram), 571,270 (Twitter), 43,103 (YouTube). Some of the news outlets are CNN, BBC, New York Times, Vice, Bleacher Report, Aljazeera, The Guardian, The Washington Post, Fox News, The Wall Street Journal, MSNBC, Chicago Tribune, CNBC, and TIME (see appendix for complete listing).

Engagement Metrics: The number of likes and comments are common across the four selected social media platforms, so we use both to measure the effect of the usage of the stylistic feature in improving them. For overcoming the sparsity issue of many posts with zero engagement values, we use the log-normalized values for the number of likes and comments. We call the normalized values likes ratio (LR) and comments ratio (CR) throughout the rest of the paper. The normalization function used for LR is $LR_i = \log_2(\frac{L_i+1}{T_i+M_i})$, where L_i is the number of likes of the post i, T_i is the number of days from the posting day of the post i till the collection day, inclusive, and M_i is the maximum number of likes for the news outlet that posted the content. The same function used to calculate the CR using the number of comments.

Feature Extraction: *Media Type* features are video or image contained in the post. Media-type features do not apply to YouTube since all posts are videos; however, Facebook, Instagram, and Twitter posts can have a video or an image. *Emojis* are symbols used in posts to express emotions, feelings, ideas, activities, or objects within the digital text. To extract emojis from posts, we use a Python library called “emoji”, which is part of the MIT licensed library. *Sentiment* of digital content can be one of three conditions: positive, neutral, or negative. For extracting sentiment for the posts, we use VADER (Valence Aware Dictionary and sEntiment Reasoner), as it is tuned to work specifically within social networks context [10]. VADER provides a compound score representing sentiment metrics for a given post. *URLs* We extract URLs from all posts and use URLs count as the URL feature. *Other* We count the question marks (?), exclamation marks (!), mentions (@), and hashtags (#) within each post. Also, we calculate the post length using the number of characters.

3.1 Prediction Model for User Engagement

We use stylistic features to build a model that predicts user engagement. Using 2-classes prediction model, we predict whether a given post will have high or low engagement on a social network. For building a model for each social network posts and each engagement metric, we use the LR and CR to separate the posts with the top 33% of engagement value posts labeled 1 (high engagement). The bottom 33% of posts with 0 (low engagement), while 0.5 is the random baseline of our model. For each news outlet, we separate the high and low engagement posts based on engagement level, as different numbers of followers are recorded for individual news outlets. We use all news outlets posts as one input to each model and add the news outlet as a categorical feature to address the effect of the actual news outlet. In total, we have 53 features representing the news outlets vector and ten stylistic features as input to the model. It is essential to highlight that we have used only suggestive stylistic features, and one can build on top of that using other features. For measuring the performance of the prediction models, we use F1-score using 10-fold cross-validation. Other measures (Precision, Recall, and Area Under the Curve) are positively correlated with F1-score as the dataset is balanced. We test four classification algorithms: AdaBoost, Decision Tree, Logistic Regression, and Random Forest. We report results only of Logistic Regression, as it performed better than other algorithms.

4 Results and Discussion

4.1 Individual Feature Analysis

To understand how individual features are associated with user engagement, we first analyze the coefficients of those features in the Logistic Regression model, shown in Table 1. Appendix A shows a visual illustration of the logistic regression coefficients values for individual features.

Table 1. Logistic regression coefficients and P-value significance

		FB	IG	TW	YT
Intercept	LR	–0.28***	0.00	–0.22***	–0.03***
	CR	–0.47***	0.09***	0.12***	–0.06***
[H1] Has Video	LR	0.68***	–0.48***	0.99***	N/A
	CR	0.68***	0.13***	0.43***	N/A
[H2] Has Image	LR	0.61***	0.48***	0.28***	N/A
	CR	–0.09	–0.04**	0.6***	N/A
[H3] Has Emoji	LR	0.76***	0.12***	0.26***	1.16*
	CR	0.49***	–0.07*	–0.11***	0.58
[H4] Has (?)	LR	–43***	–0.15**	–0.53***	0.07*
	CR	0.11*	0.48***	0.31***	0.07*
[H5] Has (!)	LR	0.07	–0.25***	–0.07**	0.05
	CR	–0.27**	–0.35***	–0.26***	0.04
[H6] Sentiment	LR	0.28***	0.29***	0.29***	–0.01***
	CR	–0.19***	–0.25***	–0.26***	–0.39***
[H7] # Count	LR	–0.34***	0.02***	–0.05***	0.0
	CR	–0.35***	0.0	–0.34***	0.0*
[H8] characters	LR	0.0*	–0.0***	0.01***	0**
	CR	0.0*	0.0*	0.01***	0.0***
[H9] URL count	LR	–0.203***	–0.22***	–0.41***	0.0
	CR	–0.37***	0.12**	–0.79***	–0.02***
[H10] @ Count	LR	–1.57***	0.05***	–0.30***	0.02
	CR	–0.84*	–0.11***	–0.11***	0.14

Significant level codes: * $p<0.05$,** $p<0.01$, *** $p<0.001$

Videos on FB and TW posts significantly increase both LR and CR. Videos in IG posts significantly increase CR but decreased LR. Media type features do not apply to YT because all posts are video type. **Images** significantly increase LR for FB, IG, and TW posts, as well as increasing CR for TW posts. In contrast, images significantly decrease CR engagement with FB and IG posts. This media type feature does not apply to YT. **Emojis** increase LR for the four platforms and increase the CR for FB. There is no significant effect on CR on YT and negative effect on CR on both IG and TW. **Question marks** in YT posts increase both LR and CR engagement, and they increase CR on the other three platforms (FB, IG, TW). However, question marks decrease the LR for FB, IG, and TW posts. **Exclamation marks** harm the engagement of three platforms. Exclamation marks significantly reduce both LR and CR engagement for IG and TW posts, and CR for Facebook posts. However, they do not affect the engagement of YT posts or LR for FB posts. **Post sentiment** significantly affects user engagement on all four social networks; although, the effect differed based on the type of engagement. Regarding LR, positive sentiment does increase the LR for FB, IG, and TW posts, but it decreases LR for YT posts. On the other hand, negative sentiment increases CR for all platforms. **Hashtags** have a weak but significant positive effect on LR on IG and CR for YT posts; however, hashtags have a significant negative impact on both LR and CR in FB and TW posts. The **number of characters** has a weak but significant positive effect on both LR and CR on FB, TW, and YT. With IG, the number of characters has a slight negative but significant impact on LR and a weak, positive effect on CR. The use of a **URL** within posts has a negative correlation with engagement on FB and TW. URL use decreases both LR and CR on FB and TW, LR on IG, and CR on YT posts. **Mentions** also decreases engagement on FB and TW. The use of mentions decreases CR but increases LR on IG.

Examining the results in Table 1, the takeaways are that there are some general trends across platforms, such as (a) commonality between Facebook and Twitter and also Instagram and YouTube, (b) some features can increase both LR and CR or at least one of these metrics, and (c) there are some features to avoid when attempting to increase engagement. The stylistic features have varied impact on likes and comments with some having a positive and others a negative impact. This indicates that the audience base likely varies among platforms and that likes and comments report different forms or levels of user engagement. This context complicates user engagement efforts by news outlets, as the environment is multifaceted with no simple rules or straightforward trends.

In comparing our findings to prior work, there are similarities. For Facebook, having a video in a post increases both LR and CR engagement [16]. For Instagram, emojis increase LR engagement [11]. For Twitter, exclamation marks decrease engagement [15]. On the other hand, there are differences between our findings and prior work. The number of characters was reported to affect user engagement on Facebook negatively [3]; however, our findings show a marginal but positive correlation on CR and LR. Also, negative sentiment was reported to increase user engagement on Twitter [22]; however, our findings show that negative sentiment has a positive correlation with CR but not for LR. For Facebook, having a URL in a post reportedly increases both LR and CR engagement [24]; however, our findings show a negative correlation. Our conjecture that this difference is the result of our controlled domain of news (avoiding domain differences), a large number of news outlets (avoiding news outlets differences), and the use of multiple platforms (controlling for content differences across platforms).

As such, we believe our results are an inspiration for further and more detailed research in this area by (1) providing a holistic view of media and stylistic features across the four platforms for the news domain and (2) showing what features are commonly used across different platforms within this domain. Also, we emphasize that the stylistic differences across platforms could be a result of the network (e.g., facilities and character) or because of the content and people on that network.

4.2 Predicting User Engagement

We now explore to what extent stylistic features can predict user engagement in the news domain on each of the individual platforms. As explained in the methods section, we first predict the level of user engagement given a post for each platform. Through 10-fold cross-validation using logistic regression on each platform, stylistic features perform better than random, with the F1 scores range 0.57–0.59, inclusively; hence, stylistic features work approximately the same across all platforms. Using FB (IG) posts the F1-scores are 0.58 and 0.57 (0.59 and 0.58) for LR and CR, respectively. Moreover, using TW posts stylistic features, the model predicts LR (CR) with F1-score 0.59 (0.57) while using YT posts, the F1-score is 0.58 for both LR and CR.

5 Conclusions and Future Research

In our research, we use ten common stylistic features to understand their usage similarities and differences for a large number of news outlets and across four social networks. We compared our findings with the patchwork of different studies concerning the effect of stylistic features on user engagement. In future work, other features [12] can be studied, including the volume of the posts per news outlet and the post type (e.g., breaking news, exclusive report, opinion). The 53 news outlet considered in this study are targeting an English-speaking audience, and most news outlets are US-based. This means that our results might not be generalizable for news media with other languages. It would be interesting to conduct a similar study for news media outlets in other countries in their mother tongues to see whether the patterns we found are consistent across different cultures.

A The Logistic Regression Coefficients graphs

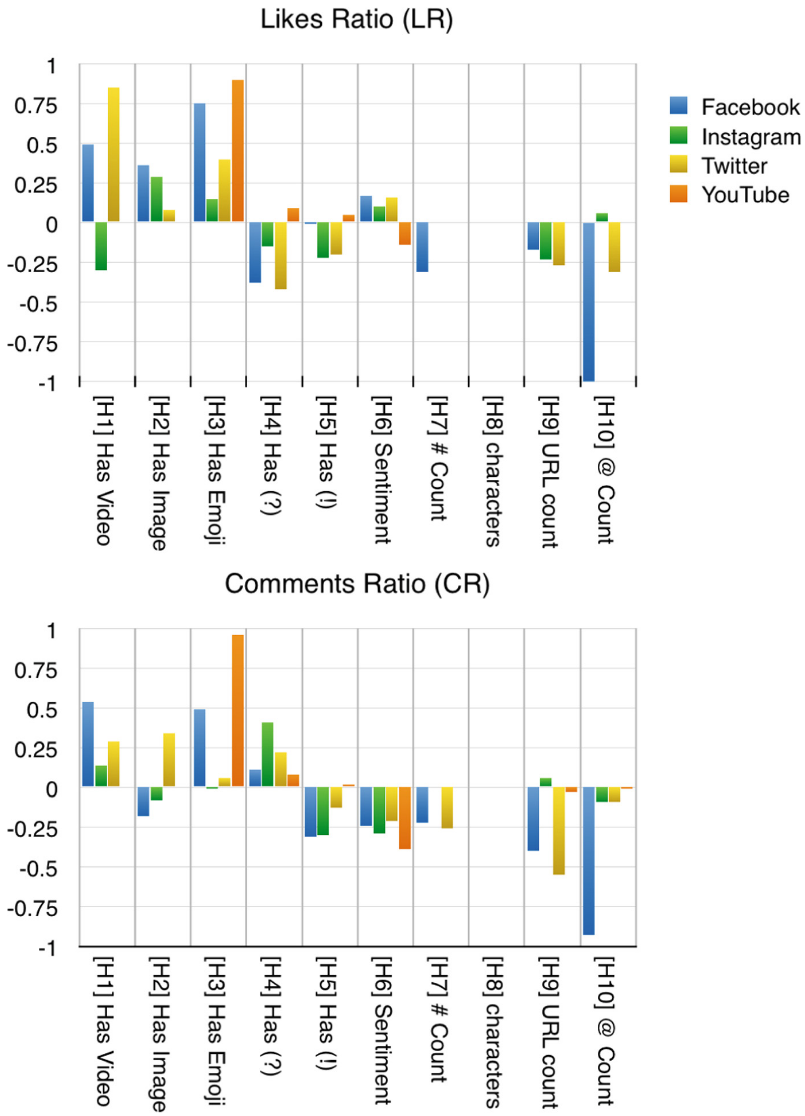

Fig. 1. The logistic regression coefficients for each stylistic feature and for each platforms

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