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# The Linguistic and Message Features Driving Information Diffusion on Twitter: The Case of #RevolutionNow in Nigeria

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Employing the diffusion of innovations theory, this study investigates how linguistic and message features of tweets drive information diffusion on Twitter in the case of #RevolutionNow, a 2019 Nigerian political activism event. Information diffusion was studied in terms of the number of favorites, replies, and retweets. Linguistic Inquiry and Word Count and inferential statistical analyses revealed that word choice, otherwise called linguistic categories (e.g., *work, quantifiers*), increased the diffusion of #RevolutionNow. Surprisingly, lengthy messages were found to be mostly positively correlated with the diffusion of tweets, whereas mentions and URLs mostly impeded favorites, replies, and retweets. Implications of these findings for innovation attributes (e.g., *relative advantage, compatibility, complexity*) and the diffusion of political activism on Twitter are discussed.

*Keywords: Twitter, political activism, hashtag revolution, information diffusion, diffusion of innovations, social media, social movements, LIWC*

On August 3, 2019, Omoyele Sowore, a human rights activist in Nigeria, was arrested by a Nigerian government security agency, Department of State and Services. Sowore's arrest came after he used Twitter to call for a protest against bad government in Nigeria. He tagged the protest #RevolutionNow (RN). Sowore's call for revolution sparked attention and was tweeted on Twitter. He said, "We don't want war. We want a very clean, quick, succinct revolutionary process, surgical. That we put an end to the shenanigans of government, that we put an end to oppression, the corruption of government" (SaharaTV, 2019). Despite Sowore's arrest, protests took place in four states, including Osun, Ogun, Lagos, Cross River, and Abuja,

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Nigeria's capital, on August 5 (Vanguard, 2019a, 2019b). The government had limited the protest demonstrations by imposing lockdowns and arresting protesters.

Although "RevolutionNow" (RN) has since quieted, a demonstration tagged "National Day of Action" (Vanguard, 2020, para 1) was held in major cities in Nigeria on August 5, 2020, to commemorate the #RevolutionNow protest. Furthermore, social media's (SM) role in galvanizing the protest remains significant, as individuals proceeded to protest, despite their leader's arrest. Such protest mobilization on SM (e.g., Twitter and Facebook) is not new to Nigeria. Much research also emphasizes the power of SM, in convening thousands of protesters, aiding the expression of dissent, and more. However, understanding strategies, factors, and particularly, message characteristics that enhance the massive dissemination or diffusion of such protests, is relatively new. This knowledge becomes important to developing societies where voices of dissent are increasingly depending on SM for expression.

## Theoretical Framework: Diffusion of Innovations

Studies (e.g., Hoang & Mothe, 2018; Kafeza, Kanavos, Makris, & Vikatos, 2014; Liang & Kee, 2018) have explained that this organic spread of information on SM is based on the principle of diffusion of innovations (DOI) posited by Rogers (2003). DOI theory describes, explains, and predicts the spread of new ideas, technologies, behaviors, and more, in social systems through communication channels over time (Rogers, 2003). DOI also suggests that the adoption and systemic diffusion of an innovation is determined by five innovation attributes: *relative advantage*, *compatibility*, *complexity*, *trialability*, and *observability* (Rogers, 2003). All attributes are positive predictors of diffusion, except *perceived complexity*. This study elaborates the concepts of the five attributes in message and linguistic features that contributed to the diffusion of #RN on Twitter.

## Background of #RevolutionNow

Sowore, owner of Sahara reporters, an online news agency, has been a known critic of bad government since his college days. He suffered arrests and harassment, especially by the police, because of his activism roles (*The Guardian*, 2018). However, the February 2019 election was Sowore's first time of contesting for a political seat. Sowore contested under his newly created party, the African Action Congress, but lost to President Muhammadu Buhari who returned as Nigeria's president for the second time. Buhari's reelection bid in 2019, sparked criticism among Nigerians, including Sowore. Buhari's party, all progressive congress allegedly bought votes to win his reelection.

The criticisms of Buhari and his party's corruption continued until July 2019, when #RN tweets appeared on Twitter. The hashtag was used by Sowore to clamor for five demands: an economy that works for the masses, an effective and democratic end to insecurity, an end to systemic corruption and for total system change, immediate implementation of the N30,000 minimum wage for Nigerian workers, and a free and quality education for all (Review of African Political Economy [ROAPE], 2019). Unfortunately, the meaning of "Revolution" was debated and contested by journalists, politicians, and government officials and was believed to be one of the reasons that the protest was short lived.

To Buhari's administration, "revolution" meant a plan to unseat president Buhari, and therefore, represented treason against the government (*Premium Times*, 2019). However, to some Nigerians, revolution meant a harmless agitation for change from bad governance and corruption to a better government. The argument of what revolution connotes explains why a few states observed a one-year anniversary of the #RN protest but abandoned the #RevolutionNow tag in favor of a more benign name, "National Day of Action" (Vanguard, 2020, para. 1). This suggests that messages must be cautiously and strategically created to drive diffusion, especially for democracies that are not very supportive of dissent.

## Social Media and Protests

Since 2008, an SM post with engagement, such as likes, shares, and replies, has been instrumental for mobilizing dispersed strangers to achieve social (Shirky, 2008) and political justice (Jowett & O'Donnel, 2015; Wolfsfeld, Segev, & Sheafer, 2013). Twitter and Facebook especially, helped to covey thousands of protesters during the Arab Spring revolution in 2010. This revolution led to the overthrow of Tunisia's long-time president, Zine El Abidine Ben Ali, and spurred other Arab countries (e.g., Egypt, Libya, and Yemen) to join the revolution. Arab Spring represents a pivotal point in the powerful role that Twitter and other SM play in fostering political activism and influencing political power (Christensen & Christensen, 2013; Jowett & O'Donnel, 2015).

Within Africa, SM, especially Twitter, has become even more useful for organizing protests. For example, Brobbery, Da-Costa, and Apeakoran (2021) captured how Ghanaian youths criticized their government in the protest #FixTheCountry during the COVID-19 pandemic. Although this protest was interrupted by the Ghanaian government, #FixTheCountry tweets "resonated with young Ghanaians on Twitter and resulted in a coordinated effort to organize a protest in the capital Accra" (Global Voices, 2021, para. 6).

Similarly, Twitter has become the site for launching protests in Nigeria, where there is a growing hub of 21.3 million Twitter users as well as a dense youth population (NOIPolls, 2019). For example, in January 2012, Nigerians formed the theme, #OccupyNigeria, to protest the federal government's decision under President Goodluck Jonathan. Jonathan had announced the removal of fuel subsidy, a decision that expedited inflation on costs of living. Hence, Nigerians in all 36 states of the country protested that the government rescinded its decision. Two weeks into #OccupyNigeria protests, the federal government succumbed.

#OccupyNigeria witnessed the highest number of participants, particularly workers and youths, in the history of protests. This turnout was attributed to Facebook and Twitter, which enabled Nigerians, particularly young people, to cover and report offline marches, popularize the protest, show solidarity to protesters, frame the protest issue from their perspective, and altogether galvanize individuals and different groups to participate in the protest (Egbunike & Olorunisola, 2015). Similarly, in April 2014, Nigerians formed #BBOG (BringBackOurGirls) on Twitter to galvanize protests, both nationwide and globally, pressuring the federal government to rescue girls who were abducted from the northern part of Nigeria, by an Islamic sect, Boko Haram (Ofori-Parku & Moscato, 2018; Olson, 2016).

Most recently, in October 2020, Twitter was used to mobilize nationwide and global protests, against police brutality by a Special Anti-Robbery Squad (SARS). A few days after the protests, the federal government dissolved SARS. Given the continued use of SM to galvanize protests and its potential influence in bringing about real-world change and justice, it becomes important to understand the message structures that may enhance protest mobilization on SM in Nigeria.

Factors contributing to the mass diffusion of each protest is diverse. They include salience of the topic (Zhang, Moe, & Schweidel, 2017), and in Nigeria's case, a failure of the mainstream press (i.e., TV, radio, newspaper) to express agitated voices (Amusa, Yahya, & Balogun, 2016). However, information diffusion studies argue that message composition is an important factor that may determine the mass diffusion of messages (Jalali & Papatla, 2019; Malhotra, Malhotra, & See, 2012). Consequently, this study examines how messaging, specifically, linguistic categories, message length, and linking mechanisms (i.e., #, @, URL) contribute to the diffusion of such protests.

## Information Diffusion on Twitter

In the context of SM, information diffusion has been operationalized as "retweeting"—sharing or forwarding information that was created by another user (help.twitter.com). However, literature has found that all acts that contribute to the exposure of any message indicate diffusion (Chung, Han, & Koo, 2015; Liang & Kee, 2018). SM communication involves both giving and taking. Giving implies the act of creating messages and posting (tweeting), and the taking involves any act of engagement done to receive or adopt that message (e.g., liking, replying, commenting, and forwarding; Chung et al., 2015). Similarly, viewing is seen as a diffusion outcome as much as liking and replying, since they all show that the information or idea has been exposed to another individual and as such disseminated (Liang & Kee, 2018). Consequently, the current study measures diffusion on Twitter in terms of the following diffusion outcomes:

- ***Favorites***. Favorites are counted as the number of times users showed positive interest in a post by clicking the "favorite" icon. They are also known as "likes" in other SM platforms.
- ***Replies***. Replies are counted as the number of times that users commented on a tweet by using the "reply" icon. They are also indicated as comments in other SM platforms and could be done privately or publicly.
- ***Retweets***. Retweets are counted as the number of times that users forwarded a tweet by using the "retweet" icon. They are also known as shares in other SM platforms.

Following the principles of Rogers (2003), such indications of information diffusion (i.e., favoriting/liking, replying/commenting, viewing, sharing/retweeting), are determined by five attributes: (1) *relative advantage*—perceived superiority to its predecessor and/or other options; (2) *perceived compatibility*—perceived conformity with existing attitudes, values, beliefs, and/or norms; (3) *perceived complexity*—difficulty experienced by potential adopters in understanding the innovation; (4) *trialability*—availability for potential adopters to test out the innovation before adoption; and (5) *observability*—visibility of an innovation to potential adopters. These attributes can influence adopters to accept or reject, and subsequently (dis)continue adoption (Kee, 2017; Rogers, 2003).

In the context of social movements, the relative advantage could be interpreted as new ideas or messages that may be perceived as offering or promising a benefit compared to what is status quo. Stieglitz and Dang-Xuan's (2012) analysis showed that wordings of SM messages reflecting *positive* and *negative emotion* with *affective processes* (e.g., happy, cried) attract retweets of political matters, finding that messages reflecting *positive emotion* attracted a higher number of retweets compared to *negative emotion*. The tweets that reflected positive emotion contained names of popular politicians and political parties, suggesting that retweets may be driven by perceived relative advantage (i.e., inclusion of popular politicians who, perhaps, are known for their favorable policies or political ideologies; Amusa et al., 2016; Stieglitz & Dang-Xuan, 2012).

The second attribute that an innovation must have is *perceived compatibility* with existing needs, beliefs, and culture. Implicitly, messages must be composed in a way that resonates with readers, viewers, or users. Using a software that captures linguistic categories of texts, known as the linguistic inquiry and word count (LIWC), Liang and Kee (2018) found that wordings of a university blog post that related to *achievement* (e.g., hero, win) and *function* (I, you, he/she, a, an, the) contributed to a higher number of views; wordings related to *insight* (e.g., think, know) contributed to a higher number of comments, and short sentences seemed to contribute to a higher number of shares. Testing this same category of words in an experiment showed that users were more likely to like, comment on, and share messages in the same word categories (*achievement*, *function*, and *insight*). Similarly, Xu and Zhang's (2018) analysis of tweets during the disappearance of the March 8, 2014, Malaysian Airlines flight (#MH370), showed that wordings of SM messages reflecting *positive emotion* (e.g., nice, love) attracted diffusion in terms of a higher number of retweets compared to *negative emotion* (e.g., hurt, nasty). The authors explain that the diffusion achieved in a crisis context is connected to people's tendency to share hope rather than negative messages that may aggravate crisis reactions. In agreement with the latter, Pope and Griffith's (2016) analysis revealed that wordings of messages reflecting *negative emotion* described tweets and retweets around the refugee crisis in Europe across French and German languages, especially two days after the crisis occurred. Perhaps the tweets contained breaking news, and news is associated with negativity (Hansen, Arvidsson, Nielsen, Colleoni, & Etter, 2011). Implicitly, a tweet may attract retweets because it is newsworthy or perceived as compatible with the need for news. Such need for news, social, emotional, social support, and solidarity are not uncommon during protests (Jost et al., 2018). Hence, linguistic categories that express these needs may contribute to diffusion during protests. However, since there is scarce examination of protest messaging that contributes to diffusion, the first question is posed:

*RQ1: What linguistic categories predicted information diffusion on Twitter during #RevolutionNow?*

The third attribute, *perceived complexity*, is the only innovation attribute that should be avoided to drive diffusion. It implies that a new message must be easy to read and understand. Scholars have identified lengthy messages and use of many punctuations as part of the complexities that may inhibit diffusion on SM. Longer sentences and indicators of longer sentences such as the use of colon (i.e., ":"), were found to impede diffusion on a university blogging site (Liang & Kee, 2018). Such sentences may require more time for an average reader to comprehend and consequently decrease the likelihood of fully reading such messages, hence resulting in fewer views. Contrastingly, Wang, Wang, Bu, Chen, and Zhang (2013) argued that message length can increase information diffusion on Twitter. They argued that the former limit of 140 characters on Twitter was a major limitation to the diffusion of messages, limiting the number of words and names that could be included in a tweet. However, since Twitter has increased the character limit from 140 to 280 in 2017 (Tsukayama, 2017), perhaps an increase in word limit can be a relative advantage to users in the diffusion of protests. Given the mixed review above, this study advanced the second research question:

*RQ2: Is message length of tweets correlated with information diffusion on Twitter?*

The last two attributes are *trialability* and *observability*. In the sense of information diffusion, it implies that a message can be tested or observed. Scholars have suggested that the use of linking mechanisms, such as hashtags (#), mentions (@), and URLs (Web address) brings about perceived importance and visibility of a message and therefore contribute to diffusion in terms of a higher number of likes, replies, and retweets (Suh, Hong, Pirolli, & Chi, 2010; van de Velde, Meijer, & Homburg, 2014). Hashtags in particular make a message visible and easy for users to understand happenings around a topic or issue (Blevins, Lee, McCabe, & Edgerton, 2019); mentions (@) can give clue on new events; and URLs provide external information for users. Together, the three (#, @, and URL) showcase a message and give users the opportunity to observe and decide whether they want to like, reply, or retweet.

Primarily, Suh et al. (2010) found that the presence of hashtags and URLs in tweets were strongly correlated with the average number of retweets. Although Suh and colleagues' analysis does not lead one to make a solid assumption on hashtags and URLs, some studies (e.g., Tanaka, Sakamonto, & Honda, 2014) agreed that users showed a higher intention to share a tweet about rumors around the great East Japan earthquake when it contained URLs, compared to when it did not. Kafeza et al. (2014) added that the presence of URLs in a tweet indicated that people exhibit the need for information and news and perhaps community mobilization during a crisis. While such needs are common during protests, limited studies have examined URLs' role in the diffusion of protests or any form of politics. However, examining "stickiness" (i.e., the tendency for users to stick to the use of one hashtag over others), Romero, Meeder, and Klienberg (2011) found that the spread of political hashtags depends on the follower network of a Twitter user. In essence, if a user tweets a particular hashtag often, his or her network of followers is more likely to adopt and diffuse that hashtag, suggesting that tweets with a widely adopted hashtag have higher probability of attracting retweets and replies.

Although there are scarce studies examining the role of mentions in information diffusion, a study found that the function is useful for attracting followers of popular users (Wang et al., 2013). Indicated by @ followed by a user's name, mentions can attract followers and admirers to the tweet. In essence, popular users can drive diffusion by retweeting or by replying to a tweet that mentions them. Taken together, linking mechanisms (i.e., hashtags, mentions, and URLs) are triable by users and enhance the visibility of tweets. Hence, they drive information diffusion because of two innovation attributes: *trialability* and *observability*. The final research question, therefore, advances the literature above:

*RQ3: Does information diffusion vary between tweets with and without the use of linking mechanisms such as (a) hashtags, (b) mentions, and (c) URLs?*

## Methodology

This study investigates the linguistic features, message length, and linking mechanisms of tweets as message design strategies for information diffusion on Twitter during #RN in Nigeria.

### *Research Study Site*

Twitter, the second-largest microblogging site in the world, allows registered users to share messages, or tweets, within 280 characters. This study analyzed tweets from Nigerian Twitter Sphere, particularly, looking at the indices of engagement such as favoriting, replying, and retweeting. Although retweeting is a powerful feature for diffusion enabling users to share tweets with audiences across the globe (Stieglitz & Dang-Xuan, 2012), the current study extended the literature by investigating diffusion not only in terms of retweets, but also favorites and replies.

### *Linguistic Inquiry and Word Count (LIWC) Variables*

The LIWC software (www.liwc.net) is a computational tool that reveals the linguistic, psychological, and emotional nature of texts. LIWC was designed in 1993 by social psychologist James Pennebaker to reveal individuals' psychological traits, such as fears, thinking patterns, beliefs, relationships, and personalities through word use. The most recent version of LIWC (as at the time of writing this paper) "captures, on average, over 86% of the words that people use in writing and speech" (Pennebaker, Boyd, Jordan, & Blackburn, 2015, p. 11).

Specifically, LIWC 2015 can quantitatively analyze written or spoken texts into different linguistic categories. For example, the linguistic category *affiliation* reflects relationships with and/or reference to others. An LIWC output of 0.2 under *affiliation* category means that 0.2% of the words used in an analyzed tweet referred to others (e.g., ally, friend). Similarly, the category *power* reflects status, dominance, or social hierarchy. An LIWC output of 20 under *power* category means that 20% of words used in the analyzed tweet reflected status, dominance, or social hierarchy (e.g., superior, bullying). Furthermore, LIWC analyzes "netspeak" language—an abbreviation of words commonly used on SM, SMS (short message service/text messaging), and SMS-like modes of communication (e.g., Snapchat, instant messaging). For example, "b4," despite the abbreviation, is still coded as "before" (Pennebaker et al., 2015).

LIWC is increasingly a potent tool for analyzing texts on SM. Studies found that LIWC shows a very high correlation (.75) with human language use, attesting to the technique's robustness for analyzing linguistic SM data (Windsor, Cupit, & Windsor, 2019; Young & Soroka, 2012). Therefore, the current study measured linguistic categories for RQ1, using the default LIWC categories. Similarly, for RQ2, message length is operationalized into the following variables: (a) word count (WC), (b) words per sentence (WPS), and (c) words with more than six letters (Sixltr). As outlined in RQ3, this study measured linking mechanisms of a tweet using (a) hashtags, (b) mentions, and (c) URLs.

## Data Collection

This study analyzed individual tweets created and posted between July 31, 2019 (when Sowore posted a video to announce #RN), and August 29, 2019 (the month of Sowore's arrest). This period of 29 days represents pivotal moments (e.g., the arrest of Sowore and killing of some protesters) in the #RN protest (*The Cable*, 2019; Vanguard, 2019b). Since Sowore tagged the protest #RevolutionNow, data in the form of tweets with the keywords "RevolutionNow" (42,636 tweets) and "Sowore" (14,349 tweets) were captured on June 7, 2020. This process yielded a total of 56,985 tweets. Analysis was then limited to tweets with the keywords, "RevolutionNow" and "Sowore," posted during the specified period. Although each capture of tweets is a unique effort, at times excluding some because of the capture technique, the data set was the most complete available.

The Twitter Intelligent Tool, also known as TWINT, was used to collect tweets. TWINT is a software application written in Python that allows users to capture tweets from Twitter without using Twitter's application programming interface (i.e., API—a software that allows two applications to interact with Twitter contents such as tweets, usernames, retweets, date and time a tweet was created and posted).

## Data Processing and Preparation Procedure

To prepare the data comprising tweets for analyses on the LIWC software, the captured tweets were: (1) saved in CSV formats, (2) organized and sorted according to their dates, corresponding hashtags, mentions, URLs, the number of favorites, replies, retweets, and so on, (3) assigned an identification (ID) number, (4) saved into a new CSV file, (5) and uploaded into and analyzed on LIWC. LIWC output included the software's pregenerated linguistic categories of each tweet and its corresponding WC, WPS, and Sixltr (words with more than six letters) score.

For the statistical analyses on the statistical package for the social sciences (SPSS), (1) LIWC output and other tweet features were merged into the same CSV file, (2) tweets were dummy coded for use/and nonuse of hashtags, mentions, and URLs, and (3) the full data comprising steps 1 and 2 were uploaded on SPSS. An analysis of the frequency distribution of diffusion outcome variables (the number/raw counts of favorites, replies, and retweets) was conducted on SPSS. Each of these appeared to follow an exponential decay function. Therefore, to avoid violating statistical assumptions in linear regression, the three diffusion outcomes were subjected to log transformation.

## Results

### *Research Question 1: Linguistic Categories and Diffusion Outcomes*

To answer RQ1 (1) a series of Pearson correlations were conducted with variables, including linguistic categories, message length (i.e., WC, WPS, and Sixltr), and diffusion outcomes (i.e., log transformed numbers of favorites, replies, and retweets), (2) linguistic categories that did not produce statistically significant correlations were removed, and (3) a series of multiple regression tests were then run with the significant linguistic categories as the independent variables and the three diffusion outcomes as the dependent variables. Although the multiple regression results for each diffusion outcome were statistically significant, each overall model (as seen in the $R^2$ and $R^2_{adjusted}$ values below) was poorly fitted.

***Table 1. The Statistically Significant LIWC Predictors of the Number of Favorites.***

| Diffusion Outcomes | LIWC Categories | Standardized β | Example of Words |
|---|---|---|---|
| Favorites | *See* | 0.08** | View, see |
| ($R^2$ = .07, | *Colon* | 0.07** | : |
| $R^2$ $_{adjusted}$ = .07) | *Quantifiers* | 0.05** | Few, many |
| | *Quotation marks* | 0.04** | “ ” |
| | *Shehe* | 0.03* | Her, him |
| | *Work* | 0.03* | Job, majors |
| | *Anger* | 0.02* | Hate, kill |
| | *Past focus* | 0.02* | Ago, talked |
| | *Reward* | −0.02** | Prize, benefit |
| | *Swear words* | −0.02* | Fuck, damn |
| | *You* | −0.03** | You, your |
| | *Article* | −0.03* | An, the |
| | *Number* | −0.03* | Thousand, twenty |
| | *Cognitive processes* | −0.03* | Cause, ought |
| | *Money* | −0.03** | Audit, Cash |
| | *Other punctuations* | −0.14* | #, @, /, & |

*Note.* $p$ < *0.05 ** $p$ < 0.01 significant.
LIWC: Linguistic Inquiry and Word Count.
Negative values indicate that the increase in the LIWC category predicted a decrease in the number of favorites.

As seen in Table 1, multiple regression results indicated a collective significant effect between 16 linguistic categories and the number of favorites a tweet received, $F(76, 23{,}692) = 23.82$, $p < .001$, $R^2 = .07$, $R^2_{adjusted} = .07$. Thus, only 7% of the variance in favorites can be explained by linguistic categories. Linguistic categories that uniquely contributed to the number of favorites were *see*, *colon*, *quantifiers*, *quotation marks*, *she/he*, *work*, *anger*, *past focus*, *reward*, *swear words*, *you*, *article*, *number*, *cognitive processes*, *money*, and *other punctuations* (#, @, /, &; Pennebaker, Francis, & Booth, 1999). Standardized beta coefficients show that the use of *see* words ($\beta_{\text{standardized}} = 0.08$) attracted the greatest unique increase in the number of favorites a tweet received, while the use of *other punctuations* ($\beta_{\text{standardized}} = -0.14$) led to the greatest unique decrease in the number of favorites a tweet received.

***Table 2. The Statistically Significant LIWC Predictors of the Number of Replies.***

| Diffusion Outcomes | LIWC Categories | Standardized $\beta$ | Example of Words |
|---|---|---|---|
| Replies | *Colon* | 0.12 | : |
| ($R^2$ = .08, | *Verb* | 0.06 | Carry, come |
| $R^2_{adjusted}$ =.08) | *Quantifiers* | 0.06 | Few, many |
| | *Quotation marks* | 0.06 | " " |
| | *Differentiation* | 0.05 | Hasn't, but |
| | *Dash* | 0.05 | - |
| | *Work* | 0.03 | Job, majors |
| | *Reward* | −0.02 | Prize, benefit |
| | *Death* | −0.02 | Bury, kill |
| | *Article* | −0.03 | An, the |
| | *Tentative* | −0.03 | Maybe, perhaps |
| | *Conjunction* | −0.04 | And, but |

*Note*. LIWC: Linguistic Inquiry and Word Count.
Negative values indicate that the increase in the LIWC category predicted a decrease in the number of replies.

Similarly, Table 2 shows the results of a multiple regression that indicated a collective significant effect between 12 linguistic categories and the number of replies a tweet received, $F(67, 10{,}189) = 13.74$, $p < .001$, $R^2 = .08$, $R^2_{adjusted} = .08$. Linguistic categories that uniquely contributed to the number of replies were *colon*, *verb*, *quantifiers*, *quotation marks*, *differentiation*, *dash*, *work*, *reward*, *death*, *article*, *tentative*, and *conjunction*. Standardized beta coefficients show using a *colon* ($\beta_{\text{standardized}} = 0.12$) attracted the greatest unique increase in the number of replies a tweet received, while *conjunctions* ($\beta_{\text{standardized}} = -0.04$) led to the greatest unique decrease in the number of replies a tweet received.

***Table 3. The Statistically Significant LIWC Predictors of the Number of Retweets.***

| Diffusion Outcomes | LIWC Categories | Standardized $\beta$ | Example of Words |
|---|---|---|---|
| Retweets | *See* | 0.11 | View, see |
| ($R^2$ = .08, $R^2_{adjusted}$ = .07) | *Drives* | 0.07 | Words in the categories: *affiliation*, *achievement*, *power*, *reward*, *risk* |
| | *Quantifiers* | 0.06 | Few, many |
| | *Colon* | 0.06 | : |
| | *Quotation marks* | 0.04 | " " |
| | *Anger* | 0.03 | Hate, kill |
| | *Past focus* | 0.03 | Ago, talked |
| | *Work* | 0.02 | Job, majors |
| | *Tentative* | −0.02 | Maybe, perhaps |
| | *Swear words* | −0.02 | Fuck, damn |
| | *You* | −0.03 | You, your |
| | *Conjunction* | −0.03 | And, but |
| | *Number* | −0.03 | Thousand, twenty |
| | *Power* | −0.05 | Superior, bully |
| | *Reward* | −0.05 | Prize, benefit |
| | *Other punctuations* | −0.08 | #, @, /, & |

*Note.* LIWC: Linguistic Inquiry and Word Count.
Negative values indicate that the increase in the LIWC category predicted a decrease in the number of retweets.

Finally, Table 3 shows the results of a multiple regression that indicated a collective significant effect between 16 linguistic categories and the number of retweets a tweet received, $F(53, 15{,}090) = 23.32$, $p < .001$, $R^2 = .08$, $R^2_{adjusted} = .07$. Linguistic categories that uniquely contributed to the number of retweets are *see*, *drives*, *quantifiers*, *colon*, *quotation marks*, *anger*, *past focus*, *work*, *tentative*, *swear words*, *you*, *conjunction*, *number*, *power*, *reward*, and *other punctuations* (#, @, /, &). Standardized beta coefficients show that the use of *see* words ($\beta_{\text{standardized}} = 0.11$) attracted the greatest unique increase in the number of retweets a tweet received, while the use of *other punctuations* ($\beta_{\text{standardized}} = -0.08$) led to the greatest unique decrease in the number of retweets a tweet received.

### ***Research Question 2: Message Length and Diffusion Outcomes***

RQ2 asks if the length of tweets (i.e., WC, WPS, and Sixltr) is correlated with the three diffusion outcomes on Twitter. To test the predicted relationships, a series of multiple regression was conducted and showed that the length of tweets significantly predicted diffusion of tweets in terms of the number of favorites, $F(2, 23{,}766) = 322.23$, $p < .001$, $R^2 = .03$, $R^2_{adjusted} = .03$; replies, $F(3, 10{,}253) = 61.15$, $p < .001$, $R^2 = .02$, $R^2_{adjusted} = .02$; and retweets $F(2, 15{,}141) = 322.23$, $p < .001$, $R^2 = .03$, $R^2_{adjusted} = .03$, although the overall regression models were poor.

***Table 4. Standardized β Results Showing Tweet Length Dimensions Predicting the Number of Favorites, Replies, and Retweets.***

| Diffusion Outcomes | WC | WPS | Sixltr | *n* |
|---|---|---|---|---|
| Favorites | .18** | | .04** | 23, 766 |
| Replies | .08** | .05** | .1** | 10, 253 |
| Retweets | .2** | | .09* | 15,141 |

*Note.* $p$ < *0.05 ** $p$ < 0.01 significant.

Furthermore, the Standardized $\beta$ results on Table 4 showed that WC ($\beta_{\text{standardized}}$ = .18) predicted the higher unique increase to the number of favorites compared to Sixltr ($\beta_{\text{standardized}}$ = .04), while WPS was not a predictor. Similarly, Table 4 showed that Sixltr ($\beta_{\text{standardized}}$ = .1) predicted the highest unique increase in the number of replies, compared to WC ($\beta_{\text{standardized}}$ = .08) and WPS ($\beta_{\text{standardized}}$ = .05), and finally, the Table showed that WC ($\beta_{\text{standardized}}$ = .2) predicted the higher unique increase in the number of retweets compared to Sixltr ($\beta_{\text{standardized}}$ = .09). In other words, WPS was not a predictor for the number of favorites and retweets.

### *Research Question 3: Linking Mechanisms and Diffusion Outcomes*

RQ3 examines if the three diffusion outcomes vary between tweets with and without the use of (a) hashtags, (b) mentions, and (c) URLs. A series of independent sample *t*-tests were conducted where independent variables were the presence or absence of the three linking mechanisms and dependent variables were the three diffusion outcomes previously defined.

***Table 5. Results of a Series of Independent Sample T-Tests Examining Relationship Between the Use of Hashtag (#) and Diffusion Outcomes.***

| | Hashtags | | | | *t* | df | *p* | Cohen's *d* |
|---|---|---|---|---|---|---|---|---|
| Diffusion Outcomes | | | | | | | | |
| | With # | | Without # | | | | | |
| | *M* | *SD* | *M* | *SD* | | | | |
| Favorites | 0.47 | 0.57 | 0.48 | 0.58 | 1.29 | 5,536.48 | 0.2 | 0.02 |
| Replies | 0.23 | 0.41 | 0.21 | 0.37 | 2.01 | 4,340.47 | 0.05 | 0.05 |
| Retweets | 0.45 | 0.56 | 0.44 | 0.56 | 0.23 | 15,142 | 0.82 | 0.02 |

As seen in Table 5, results show that there were no statistically significant differences in the number of favorites and retweets as a function of whether tweets contained hashtags or not. However, findings did show a statistically significant increase in the number of replies when tweets contained hashtags compared to when they did not. The effect size was negligible, as it fails to meet the minimum value of 0.2 to be considered a small effect size (Lakens, 2013). This suggests that the presence of hashtags in tweets is associated with a negligible increase in replies.

***Table 6. Relationship Between the Use of Mentions (@) and Diffusion Outcomes.***

| | Mentions | | | | *t* | df | *p* | Cohen's *d* |
|---|---|---|---|---|---|---|---|---|
| Diffusion Outcomes | | | | | | | | |
| | With @ | | Without @ | | | | | |
| | *M* | *SD* | *M* | *SD* | | | | |
| Favorites | 0.45 | 0.54 | 0.49 | 0.59 | 5.97 | 22,186.26 | 0.001 | 0.07 |
| Replies | 0.18 | 0.35 | 0.27 | 0.44 | 11.92 | 9,601.45 | 0.001 | 0.23 |
| Retweets | 0.41 | 0.56 | 0.46 | 0.56 | 5.72 | 11,705.60 | 0.001 | 0.09 |

In Table 6, a series of independent sample *t*-tests reveal that there was a statistically significant decrease in the three diffusion outcomes when tweets contained mentions (@), compared to when they did not. However, the effect sizes of mentions in the number of favorites and retweets were negligible and small in the number of replies, suggesting that the presence of mentions in tweets led to (1) a negligible practical decrease in diffusion in terms of favorites and retweets, and (2) a small decrease in diffusion in terms of replies.

***Table 7. Relationship Between the Use of URLs and Diffusion Outcomes.***

| | URLs | | | | *t* | df | *p* | Cohen's *d* |
|---|---|---|---|---|---|---|---|---|
| Diffusion Outcomes | | | | | | | | |
| | With URLs | | Without URLs | | | | | |
| | *M* | *SD* | *M* | *SD* | | | | |
| Favorites | 0.44 | 0.56 | 0.48 | 0.57 | 4.7 | 19,290 | 0.001 | 0.07 |
| Replies | 0.31 | 0.46 | 0.21 | 0.4 | 8.47 | 2,274.75 | 0.001 | 0.23 |
| Retweets | 0.41 | 0.52 | 0.46 | 0.59 | 4.77 | 9,911.49 | 0.001 | 0.09 |

Table 7 shows the results of a series of independent sample *t*-tests demonstrating that there was a statistically significant increase in the number of replies when tweets contained URLs, compared to when they did not, whereas a statistically significant decrease in the number of favorites and retweets when tweets contained URLs compared to when they did not. As in the case of mentions, the effect size of URLs impact on replies was small and negligible on favorites and retweets, suggesting that the presence of URLs in tweets led to (1) a small increase in diffusion in terms of replies, and (2) statistically significant decrease but a negligible practical decrease in diffusion in terms of favorites and retweets.

**Discussion**

This study examined how linguistic and features of tweets around the political activism, #RevolutionNow, in Nigeria drove information diffusion. Overall, to increase the number of favorites, the data suggest increasing word count, words with six or more letters, and using words in these linguistic categories: *see* (e.g., view, see*)*, *colon* (i.e., :), *quantifiers* (e.g., few, many), *quotation marks* (i.e., " "), *she/he* (e.g., him, her), *work* (e.g., job, major), *anger* (e.g., hate, kill), and *past focus* (e.g., ago, talked).

To increase the number of replies, the data suggest using words relating to the linguistic categories: *colon* (i.e., :), *verb* (e.g., come, carry), *quantifiers* (e.g., few, many), *quotation marks* (i.e., " "), *differentiation* (e.g., hasn't, but), dash (i.e., -), and *work* (e.g., job, majors). The data also suggest that WC, WPS, Sixltr, #hashtags, and URLs can increase replies, although the effect size of hashtag is practically negligible.

Finally, to increase the number of retweets, the data suggest increasing word count and words with six or more letters and using words relating to the linguistic categories: *see* (e.g., view, see), *drives* (words relating to *affiliation*, *achievement*, *power*, *reward*, *risk*), *quantifiers* (few, many), *colon* (i.e., :)*, quotation marks* (i.e., " "), *anger* (e.g., hate, kill), *past focus* (e.g., ago, talked), and *work* (job, majors). Summarily, the statistically significant linguistic categories positively driving all three diffusion outcomes are *work* (e.g., job, major), *quantifiers* (e.g., few, many), *quotation marks* (i.e., " "), and *colon* (i.e., :).

Given the context of this study, the finding that *work*, *quantifiers*—related words, *quotation marks*, and *colons* drove diffusion can be explained thus: first, organizing and participating in protest does involve some work. Additionally, work covers topics of job and employment and since unemployment of youths is an enduring issue in Nigeria (Egbunike & Olorunisola, 2015; Hari, 2014), it makes sense that such tweets drove diffusion. As for *quantifier* words, they can be helpful in describing the rapid developments of a protest, allowing Twitter users to better follow events. Third, the use of quotations received diffusion, resonates that Sowore's direct statements received more popularity since he led the protest. Similarly, *colons* may be useful for organizing information into small pieces, allowing more complex thoughts to be conveyed in a single tweet.

Overall, findings suggest that language more compatible with the central topic (e.g., *work*), words that help to describe the situation more precisely with details (e.g., *quantifiers*, and quotes in *quotation marks*), and punctuations more advantageous in organizing complex messages (e.g., colon), will likely diffuse a tweet more widely via favorites, replies, and retweets in the case of a political protest, particularly in democracies where such problems (e.g., unemployment) endure.

As for the relationship between length of tweets and diffusion, word count, and words with more than six letters consistently predicted an increase in the three diffusion outcomes of favorites, replies, and retweets. It is surprising that word per sentence predicted diffusion only in terms of replies. Taking cue from Chung et al. (2015), takers (i.e., those who like, reply to, or retweet tweets) otherwise known as adopters of messages may be categorized into two—those who are more publicly reserved and prefer less engaging diffusion actions by simply "favoriting" a post, versus those more publicly engaged, who prefer to comment on a tweet by writing a “reply” or retweeting. Perhaps those who tend to publicly engage (by replying and retweeting) in online protests are drawn to complex words and detailed information that involves lengthy sentences. Meanwhile, those who are publicly reserved and not as vested in the protest as the first category simply engage in quick liking actions and possibly get distracted by complex words or wordy tweets. Such people can skip over words or get distracted while reading the tweet, given the speed at which various information streams on SM (Gandomi & Haider, 2015). Although it is not clear why word per sentence did not predict diffusion in terms of retweets, it is safe to conclude that length of tweets is a statistically significant predictor of information diffusion in #RN.

For linking mechanisms, findings are inconsistent. Replies represent the only diffusion outcome that can be predicted by all three linking mechanisms, in that the presence of URLs and hashtags and the absence of mentions increased replies. Perhaps the inclusion of URLs in a tweet provides more information to the tweet, thus overcoming the limitation of 280 characters and giving a user the opportunity to go to another website for more information. Thus, tweets with URLs may be perceived as having more information available to Twitter users to comment on, and as such attracted more replies. Similarly, when a tweet contains hashtags, it embeds itself within a larger conversation, giving more informational context to those tweets. Thus, the collection of tweets under the same hashtag provided more information for followers and triggered more replies. That said, only URLs achieved a small but notable effect size in increasing replies.

Surprisingly, mentions effect on decreasing replies is with a small effect size. Perhaps tweets with mentions appear to be a direct message to the account tagged with the linking mechanism @, creating the impression to the rest of the followers that they are irrelevant to the targeted message. Again, the Nigerian political context (i.e., the suppression of anti-government press and opinions) may discourage diffusion behaviors that involve publicly engaging in anti-government protests, which may lead to arrest or persecution, such as the case of Sowore (*Premium Times*, 2019). Hence, when mention is used, the person mentioned in a tweet may ignore the tweet for personal safety. Given the reasons of irrelevance and personal safety, tweets with mentions received less replies.

The presence of hashtags in tweets has no statistically significant relationship with diffusion in terms of favorites and retweets, while mentions and URLs tend to impede diffusion in terms of favorites and retweets (with negligible practical significance). Although previous research suggested that the use of hashtags can embed tweets in the larger movement, thus making followers on Twitter feel empowered by the larger movement, as in the case of #Ferguson in the United States (Blevins et al., 2019), the political climate in Nigeria is such that frowns at dissent. Perhaps, including a URL leads Twitter users to another website, and perhaps, for security sakes, users take no actions or share the link on a less public SM (e.g., WhatsApp). Similarly, favoriting and retweeting #RN or #Sowore indicates that a Twitter user is endorsing Sowore - an action implying insult to the president. Furthermore, as earlier indicated, there are two types of SM users: users who are publicly engaged who would employ the linking mechanisms of hashtags, mentions, and URLs in their tweets, while publicly reserved users will avoid openly endorsing such tweets through the quick actions of favorites and retweets. Only the publicly engaged would participate in such diffusion behaviors, while others may avoid this action to not risk their lives or families.

The regression results for RQ1 support the findings on hashtags, mentions, and URLs. The linguistic category of *other punctuations* (e.g., #, @, /, &) led to a statistically significant decrease in diffusion in terms of favorites and retweets. Thus, the findings for RQ3 that (a) the presence/absence of hashtags had no significant association with diffusion in terms of favorites and retweets, and (b) the presence of mentions and URLs led to a decrease in diffusion in terms of favorites and retweets mirror the findings for RQ1.

**Theoretical Implications and Limitations**

This study applied Rogers' (2003) DOI theory in measuring and predicting the contributors to #RevolutionNow diffusion. Although many Twitter studies have measured diffusion in terms of retweets only, this study measured diffusion in terms of favorites, replies, and retweets, representing a more holistic measurement of information diffusion on SM. Diffusion behaviors on SM take place in stages, whereby users view the information, like it, comment on it, and finally decide to share the message with others (in partial or full sequence, in linear or random orders). This suggests that information diffusion behaviors (i.e., favoriting, replying, retweeting) on Twitter can be theorized as combinatorial, concurrent, and/or sequential.

Furthermore, based on findings, the five innovation attributes principle (*relative advantage*, *compatibility*, *complexity*, *trialability*, and *observability*) seem to affect message diffusion on social media differently, compared to existing literature. This presents an opportunity to extend DOI. Considering how length of tweets (captured in LIWC as WC, WPS, and Sixltr) predicted diffusion outcomes, especially in terms of the number of replies, findings demonstrate relative advantage of longer sentences, but must be interpreted within the overall message context. For example, in a WordPress blog, shorter sentences are preferred compared to long blog posts because of their low complexity (Liang & Kee, 2018). On Twitter, however, tweets with maximum 280 characters or longer sentences have the relative advantage of being able to convey more within the character limit. Here are three theoretical implications: *complexity* is contextual, depending on the environment in which the information/innovation is introduced; *complexity* can be a positive predictor of diffusion outcomes; and *complexity* can generate *relative advantage*, hence Rogers' (2003) five innovation attributes may be generative of each other in some situations.

Furthermore, finding that linking mechanisms are positively associated with diffusion outcomes (Hoang & Mothe, 2018; Suh et al., 2010; Tanaka et al., 2014; Wang et al., 2013) may be strictly for contexts such as disasters, rumors, and crises, as findings in this study suggest otherwise. A tweet's inclusion of URLs and hashtags may portray visibility, and observability, at the same time a user's need for additional information (Tanaka et al., 2014), but endorsing a tweet linked to a controversial news site (URL) and/or movement (#) could be risky for the users. Similarly, mentions in a tweet shows who and what a tweet is about, and should encourage information diffusion in general political contexts (e.g., campaigns). However, given the Nigerian political activism context, which has been known for violence against protesters, public endorsements and diffusion may be discouraged.

Finally, this study shows that innovation attributes may have two layers—attributes of a core idea (i.e., political activism) and attributes of a specific message (i.e., tweets containing "RN" and "Sowore"). Diffusing #RN as a political protest depended on the adoption of both the core idea of political activism and the message design of the tweets. Theoretically, the innovation attributes invoked via message design adds a new dimension to understanding information diffusion on SM. Methodologically, the two layers may be collapsed, because computational and linguistic analyses of tweets can only get at diffusion at the message level, and not the ideological level.

A major limitation of this study is the relatively small variance explained by the predictors and possible implications for practical significance (i.e., predicting information diffusion during political activism events on the Nigerian Twittersphere). Although reported effects were statistically significant, this could partially be a function of the large sample size. Furthermore, the linguistic analysis generated a limited model for the three diffusion outcomes, suggesting that the LIWC software (designed for American English) may not be fully compatible with Nigerian data. Although English is recognized as the official language in Nigeria, three major native languages (Hausa, Yoruba, and Ibo) are accepted and commonly used in combination with English, raises the limitation that the data contained multilingual tweets, and as such, constituted noise in the LIWC analysis, which captured only English. In the same vein, the LIWC model may not be suitable for predicting the information diffusion on Twitter spaces of other African countries' Twitter and/or SM sphere with a similar linguistic structure.

The inconsistent relationship between linking mechanisms (hashtags, mentions, and URLs) and diffusion seems to be mediated by the Nigerian political climate (i.e., security concern for a Twitter user who supports anti-government protests). However, this pattern needs to be investigated further. Particularly, the role of popularity and reputation of the username mentioned. Such inquiries may provide useful information on the use of linking mechanisms in political activism contexts.

## Conclusion and Recommendations for Future Studies

This study examined how linguistic features contributed to information diffusion during a protest in Nigeria. However, a growing body of research shows that the presence of photos and video links in messages serve as emotional triggers encouraging users to view and share messages on SM (Cummins, Stone, Gong, & Cui, 2017; Esfandiari, Fridrich, & Yao, 2021). Hence, future studies will examine how visual content of tweets determine users' intentions to engage in diffusion behaviors (favoriting, replying, and retweeting) after viewing tweets with visuals versus text only. This approach would yield a more holistic and realistic understanding of information diffusion in the complex SM ecosystem. Regardless of the above limitations, this study represents an effort toward harnessing information diffusion on SM in Nigeria and other African societies where SM is instrumental to galvanizing sociopolitical movements and influencing pro-democracy change.

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