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Do I sound American?

How message attributes of Internet Research Agency (IRA) disinformation relate to Twitter engagement

Jiyoun Suk
University of Connecticut

Josephine Lukito
The University of Texas at Austin

Min-Hsin Su
University of Wisconsin-Madison

Sang Jung Kim
University of Wisconsin-Madison

Chau Tong
Cornell University

Zhongkai Sun
Amazon Alexa AI

Prathusha Sarma
Curai

Abstract

Ongoing research into how states coordinate foreign disinformation campaign has raised concerns over social media's influence on democracies. One example is the spread of Russian disinformation in the 2016 US presidential election. Russia's Internet Research Agency (IRA) Twitter accounts have been known to deliver messages with strategic attempts and political goals. We use publicly available IRA Twitter data created during and after the 2016 US election campaign (2016 and 2017) to examine the nature of strategic message features of foreign-sponsored online disinformation and their social media sharing. We use computational approaches to identify unique syntactic features of online disinformation tweets from IRA compared to American Twitter corpora, reflecting their functional and situational differences. More importantly, we examine what message features in IRA tweets across syntax, topic, and sentiment were associated with more sharing (retweets). Implications are discussed.

Keywords: Disinformation, Twitter, Internet Research Agency, corpus linguistics, computational social science

Conspiracy theories, rumors, and the selective presentation of information have always been part of political campaigns and persuasion messages. However, their production within the digital landscape, especially combined with disinformation campaigns, has disrupted the healthy information environment and exacerbated epistemic failure (Bennett & Livingston, 2018).

One such disruptive force is the disinformation campaign by Russia's "troll farm," the Internet Research Agency (IRA). Employees of the troll farm operate hundreds of fake accounts that impersonate authentic US persons or groups across social media. During the 2016 US presidential election, IRA accounts interacted with 677,000 Americans on Twitter (Twitter, 2018), with the intent to "sow discord" among American public (United States v. Internet Research Agency LLC, 2018). To do so, the IRA utilized influence operations known as disinformation campaigns, an intentionally coordinated strategy to disseminate false information, where false information encompasses a false context, fabricated identity, or imposter content (Fetzer, 2004). The IRA operates different types of accounts (Linvill & Warren, 2020) and engages in strategic network positioning, such as by micro-targeting specific communities (Starbird et al., 2019). By blending their activities with those of legitimate users, a disinformation campaign's influence can go beyond one election and create social confusion about what sources of information are authentic.

Extant literature has attempted to identify and cluster the profile and activity characteristics of disinformation actors by types, purposes, and strategies (Keller et al., 2020; Alizadeh et al., 2020). However, little attention has been paid to the sociolinguistic aspects of disinformation. As politically motivated strategic agents, disinformation actors like the IRA construct messages to maximize user engagement while disguising their identities. Complementing previous research, we take a sociolinguistic perspective to examine how message construction could help foreign disinformation actors gain traction and build retweets. Focusing on Twitter, where the IRA operated for the longest (Howard et al., 2018), we first (a) document a linguistic profiling of IRA messages that are different from non-IRA messages from the US and (b) examine the relationship between IRA message features across linguistic styles (e.g., syntax), subject, and sentiment and user engagement via retweets.

This study makes several important contributions to the literature. First, we introduce sociolinguistic perspectives by studying linguistic features in anti-democratic discourses. We look at how certain functional and situational factors provide important contexts for IRA's language use, making IRA messages systematically different from non-IRA English tweets. In addition, by exploring the sociolinguistic features of popular and unpopular disinformation content, our results contribute to ongoing efforts to detect and combat disinformation that has yet focused on sociolinguistics. Lastly, our study presents interdisciplinary perspectives, drawing theoretical insights from sociolinguistics, persuasion, and strategic communication, along with computational methods. Through highlighting the importance of contextualization of social media analysis and disinformation studies, we aim to advance a research agenda that leverages the strengths of computational methods to deepen our understanding of the *social* nature of the current information disorder.

Disinformation Campaign and Audience Engagement

Disinformation refers to "the distribution, assertion, or dissemination of false, mistaken, or misleading information in an intentional, deliberate, or purposeful effort to mislead, deceive, or confuse" (Fetzer, 2004, p. 231). Disinformation is persuasive and strategically employed to manipulate the nature, intention, and goal of others. Although not every piece of information disseminated by disinformation agents is factually inaccurate (Fallis 2009), the use of fabricated identities "disinforms" the public and breeds distrusts (Wardle & Derakshan, 2017).

Embedded within a broader political communication system, social media contain structural vulnerabilities. The lack of gatekeeping, coupled with crowd- and algorithm-driven information flows (Bradshaw & Howard, 2018) allowed disinformation operatives to maximize their influence by crafting the "right" messages to the "right" audience, exploiting the already polarized American electorate. In an environment where information sources are often masked and contexts are collapsed (Pearson, 2020), traditional source cues may not act as credibility heuristics, and other message features and language styles can be especially important for increasing perceived authenticity.

One factor contributing to the success of disinformation campaigns is their ability to attract shares (or retweets). The scope of the influence lies in how effectively disinformation actors are able to motivate the audience to retweet their messages and trigger information cascade organically while disguising their identity. Users' decisions about whether to share certain messages not only convey communicative and political power, but also carry far-reaching implications for disinformation campaigns. Online, the amplification of such messages grants credibility to false accounts and increases the newsworthiness or popularity of messages created in an inauthentic context (Lukito et al., 2019). More troubling, pro-Russian online disinformation may change individuals' opinions in support of pro-Russian positions, even when they had been inoculated (Zerback et al., 2020).

Troll messages are "powerful weapon in modern hybrid warfare" (Monakhov, 2020, p. 2). For state-backed anti-democratic agents seeking to shift power dynamics, language can be a crucial resource for the strategic amplification of messages (Lundberg & Laitinen, 2020). Topics and sentiments that accompany words operate simultaneously in a message. Therefore, we consider how the sociological and linguistic elements in IRA messages—language style, topic, and sentiment—were related to more user engagement through retweets, above and beyond structural factors like follower/following network size. In what follows, we first consider the linguistic features of IRA messages that we anticipate reflect their functional goals and situational factors, which are unique from non-IRA, US-based English messages, and associate those features with user engagement. We also discuss how IRA messages with specific topics and targeted sentiments, embedded in linguistic elements, will be related to higher retweets.

What message features are related to the spread of IRA tweets?

Syntax: Under what language structure?

Communication styles are affected by social contexts and audience interactions. The persuasiveness of communication is shaped by the language structure and styles (Giles & Ogay, 2006). As Sornig (1989) said, "it is the *way* things are said (or done), irrespective of the amount of genuine information carried by an utterance" (p. 95).

Undergirding the operations of IRA agents are unique contextual and situational factors: First, they are strategically motivated to impersonate and deceive audiences; second, as they are backed by a foreign state, the IRA utilizes a language variation that is different from that used by the target audience (i.e., the US public). Literature suggests that linguistic styles, such as the use of pronouns or the length of messages, reflect authors' emotions, social and political identity, and communicative motivations (Eberl, 2019; Perloff, 2021). Notably, deceptive messages may be distinct from authentic ones in their linguistic features (Newman et al., 2003). Considering the functional goals and situational factors, IRA messages' language structure likely differs from that of organic messages of non-IRA users.

Although prior evidence has noted that Russian troll messages differ lexically from non-IRA English-speaking content (Boyd et al., 2018; Eberl, 2019), few studies have explored how linguistic manifestations relate to social media shares. Focusing on three prominent persuasion tactics in political messages—linguistic complexity (Bene, 2017; Heiss et al., 2019), linguistic similarity (Dyagilev & Yom-Tov, 2014), and use of personalization language (Alavidze, 2016; Proctor et al., 2011)—we investigate how these features correlate to the number of retweets among disinformation messages.

Linguistic complexity. Literature suggests that messages with a deceptive motivation tend to be shorter, less cognitively complex, and offer fewer details than truthful messages (Newman et al., 2003; DePaulo et al., 2003) because detailed messages are more cognitively demanding. Much less is known about whether linguistic complexity in political disinformation messages relates to higher engagement. Although simple messages can be rhetorically effective, syntactic complexity may contribute to message readability and persuasiveness (Lowrey, 1998). On social media, where source cues are less visible, argument quantity and elaboration may function as information shortcuts, increasing a message's perceived strength and acceptance (Petty & Cacioppo, 1984). Supporting this cognitive heuristic perspective, research has found that politicians' long social media posts, signaling great deliberation and reasoning, tend to receive high user engagement (Heiss et al., 2019). Similarly, syntactically complex news headlines gain more popularity on Twitter (Piotrkowicz et al., 2017). On the basis of these arguments, IRA tweets with complex linguistic structures would be perceived as more persuasive than non-IRA tweets and attract more retweets.

Linguistic similarity to American English. Accommodation in communication styles establishes intimacy, promotes social approval, and strengthens social ties (Giles & Ogay, 2006). In the online sphere with reduced social cues, linguistic similarities in lexicon, syntax, and structure can enhance solidarity and reduce social distance between communicators (Scissors et al., 2009). For disinformation campaigns, this argument means that syntactic similarity serves as heuristics that produce perceptions of familiarity and trustworthiness. Enhanced familiarity creates "an illusion of truth," making the content credible, especially in the absence of source-specific cues (Henkel & Mattson, 2011). By contrast, syntactic unfamiliarity can signal low trustworthiness of the interlocutor and decrease processing fluency, thereby lowering engagement (Simmons, 2006).

Given that IRA agents come from a different language group from that of their target audience (i.e., the US public), IRA tweets may be expected to be syntactically distinct from non-IRA US ones. In such cases, "speaking like others" may be particularly important for IRA messages to gain credibility and popularity. As "speaking like others confirms both a respect for local conventions and communal bonds" (Jamieson, 2020, p. 120), IRA messages with high syntactic similarity to the language used by the US public are likely to be retweeted.

Personal pronoun use. The use of personal pronouns is a critical linguistic element in persuasive political messages, delivering a sense of personalization and shared identity (Alavidze, 2016; Proctor et al., 2011). Using personal pronouns demands an understanding between interlocutors about the self, others, and the polarizing categories of "us vs. them" in the service of the speaker's goals (Pennebaker, 2011). Given their intent, IRA accounts likely use first-person pronouns ("I") to signal a false American identity, inviting attention to the self.

In addition, priming group identity may be especially useful given the polarized American political environment wherein group pronouns are not merely categorical references, but also social relationship indicators (Íñigo-Mora, 2004). The presence of group pronouns invokes in-group solidarity, creates personal relevance, and mobilizes reaction, as demonstrated in Donald Trump's strategic use of pronouns to evoke nationalism and to mobilize support (Săftoiu & Toader, 2018). It may also generate norms that motivate groups to engage with content to achieve positive intergroup differentiation (Chilton, 2017), particularly on social media where engagement is often motivated by a shared group identity or affiliations (boyd et al., 2010). We therefore expect that IRA tweets with more personalization language markers, as indicated by the use of personal pronouns, will be retweeted more.

Personalization and modal verbs. Personalization can take on a direct function when utilized in a call to action. For example, the popular phrase "[yes,] we can"—consisting of a first-person plural term and a modal verb—can mobilize voters and create a sense of political progress (Bista, 2009). Modal verbs are often used to reflect cultural values (Talmy, 1988). The combination of personal pronouns and modal verbs can therefore be linguistic markers that increase users' collective efficacy (i.e., be positively related to engagement).

In sum, syntactic features are one crucial element to understand the effectiveness or persuasiveness of a message. Given its functional and situational factors (i.e., deceptive motivation and divergent linguistic background), we examine how IRA tweets are distinct from non-IRA messages in the use of these language structures (RQ1) and further look at the relationship with user engagement via retweets (H1).

RQ1: *How do IRA tweets display unique linguistic features in terms of* (*a*) *the level of syntactic complexity,* (*b*) *the use of American English syntax, and* (*c*) *the use of personalization language?*

H1: *IRA tweets with* (*a*) *higher syntactic complexity,* (*b*) *more use of American English syntax, and* (*c*) *more personalization language markers* (*including personalization and modal verbs*) *will be associated with more retweets than IRA tweets without.*

Subjects: What do IRA accounts tweet about?

In addition to language structure, the topics discussed by the IRA are important to examine. Generally, people's motivations to retweet are tied to building a new community around content that a user believes is worth sharing (boyd et al., 2010). Evidence suggests that tweets with newsworthy information are widely retweeted, including content about policy, social actors, or politics (Keib et al., 2018) or messages with practical or public value (Berger & Milkman, 2013), suggesting that online audiences may prioritize topics of high informational value, similar to the news selection process (Shoemaker & Cohen, 2006). That is, people retweet information and content they anticipate is of interest to their followers (Rudat & Buder, 2015).

Besides informational value, messages about controversial issues or social conflicts can trigger attention and sharing. The focus on conflict may work in tandem with IRA's attempts to target specific communities. For example, IRA accounts exploited divisive topics such as police shooting, Islam and war, and race and religious identities (Badawy et al., 2019; Ghanem et al., 2019), which align with politically contentious agenda in the

US IRA accounts also impersonated local news, using journalistic tones, to focus predominantly on controversial and contentious topics such as gun violence and immigration (Bastos & Farkas, 2019). In light of the IRA accounts' tendency to capitalize on contentious US political issues, and in connection with the identity-based news sharing patterns on social media (Marwick, 2018), we propose the following hypotheses:

> **H2:** *IRA tweets with news and/or information only will be associated with more retweets than IRA tweets without.*

> **H3:** *IRA tweets on controversial political issues will be associated with more retweets than IRA tweets that do not refer to such issues.*

Sentiments: How do they express it?

Beyond syntax and topics, effective communication messages convey social meanings. One way to deliver meanings is by expressing sentiment. Emotional appeals are part of effective persuasive tactics and are frequently employed in propaganda messages (Wardle & Derakshan, 2017). Evoking emotions can deceive and mislead, as strong sentiment can strengthen a message's persuasiveness, enhance attention and involvement, and dramatize and personalize political causes (Berger & Milkman, 2013).

As affective intelligence theory posits, political messages with heightened emotions can mobilize engagement (Marcus et al., 2000). Evidence shows that politicians' social media posts with a negative tone were shared more as followers were mobilized to express and perform their political self (Bene, 2017; Heiss et al., 2019). Positive sentiment can also attract engagement and continued support from followers (Eytan et al., 2011). Though specific mechanisms through which sentiment mobilizes engagement may vary, scholars agree that messages with heightened sentiment are more likely to gain engagement than those without. We therefore expect, given that the IRA operated during a politically contentious period, that IRA messages with heightened sentiment—positivity, negativity, or a presence of both—will be retweeted more.

Given the strategic nature of disinformation operation, IRA crafts messages to target specific audiences (Wardle & Derakshan, 2017). As such, IRA tweets likely directed their sentiment along party lines, especially focusing on the two candidates of the 2016 US election (Hillary Clinton and Donald Trump) and their partisan supporters, in line with the IRA's goals to demotivate support for Clinton and promote support for Trump (Starbird et al., 2019).

IRA tweets with sentiment toward different targets (Trump and Clinton) may be related to varying levels of retweets. At a personal level, conservatives are more vulnerable to the reception of disinformation messages than liberals (Hjorth & Adler-Nissen, 2019). Conservatives possess greater motivations for identity confirmation and cognitive stability (Boutyline & Willer, 2017), which can lead conservatives to share IRA messages with partisan cues and heightened identities. At an online network level, conservative networks are more fragmented and cloistered than their liberal counterparts (Faris et al., 2017), which can help disseminate IRA messages within a homogenous circuit. Coupled with prior evidence showing that IRA communication targeting conservatives outnumbered those against liberals (Howard et al., 2018; Linvill & Warren, 2020), we expect that the level of engagement of IRA tweets with different target groups will not be uniform. However, given the dearth of evidence on how a specific combination of target *and* expressed sentiment will be related to engagement, we propose the following:

H4: *IRA tweets that express sentiment, either* (*a*) *positive,* (*b*) *negative, or* (*c*) *both, will be associated with more retweets compared to tweets without such sentiments.*

RQ2: *How will IRA tweets with positive or negative sentiments against* (*a*) *Trump and* (*b*) *Clinton be associated with more retweets?*

Lastly, we examine how three dimensions of text—syntax, topic, and sentiment—work together to increase a message's retweetability. Notably, the role of message features in communication differs across contexts (Newman et al., 2003), emphasizing an interrelationship between the style of language, the content of communication, and its emotional component. Similarly, we expect that the interaction of message features can relate to user engagement (e.g., retweets). Despite initial evidence of potential interactive effects in the domains of customer engagement (e.g., Davis et al., 2019), little is known about strategic political communication such as online disinformation. Therefore, we ask the following:

RQ3: *How will syntactic features in IRA tweets interact with tweet subjects and sentiments to be associated with more retweets***?**

Method

IRA Twitter data

In October 2018, Twitter released a full corpus of IRA tweets, including all accounts, related content, and engagement metrics, including the number of retweets. We focus on tweets that were created during and after the 2016 US presidential election period, from January 1, 2016 to September 30, 2017, when the IRA activity was disclosed. To analyze the written text, we retained the original English tweets from IRA accounts, resulting in a dataset with 802,618 unique tweets posted by 1,049 unique IRA accounts. In the dataset, Twitter provided the number of retweets that IRA tweets received, *removing* the counts from suspended accounts, which excludes retweet behaviors from other IRA accounts. In our dataset, 38.6% of tweets (N = 310,040) received a minimum of one retweet; the maximum number of retweets was 121,190 (see Supplementary Materials A.1. for more[1]).

US Twitter data

To identify the systematic linguistic differences of IRA tweets (RQ1), we built a corpus of US-based tweets using the Twitter API V2. We first made sure that accounts from both IRA corpus and comparison corpus are comparable in terms of such characteristics as the number of accounts, verification status, and the number of followers. We sampled 1,049 accounts (the same number as the IRA accounts in the dataset) that are non-verified, based in the US, and used English language, using keywords about US politics and election[2]; that is, the comparison corpus consists of English-speaking ordinary Twitter users who talked at least once about politics from January 1, 2016 to September 30, 2017 (the same time span as the IRA corpus). Of the tweets posted by these accounts, we took a sample to ensure a comparable distribution of tweets across the IRA and comparison corpus, resulting in a total number of 808,089 tweets (see Supplementary Materials A.2. for details).

Variable Construction

Syntax variables. The syntactic complexity of IRA tweets was measured by (1) the average dependency length and (2) counts of syntactic structures that increase cognitive processing: appositional modifiers, clausal complements, open clausal complements, and nested prepositions. This multidimensional approach is consistent with previous linguistics research (Lu, 2017), which has operationalized syntactic complexity in two ways: by dependency length (Temperley, 2007) and by identifying uses of complex syntactic units, the latter of which tends to be language-specific (Kuiken et al., 2019).

Then, we looked at six syntactic structures that are different between English and Russian languages: subject–verb structure (Slobin, 1969), copula verb conjugation (e.g., “to be”; Unlu & Hatipoglu, 2012), articles (e.g., “the”; Ionin & Wexler, 2002), indefinite pronouns (e.g., “all”), auxiliary verbs (e.g., “be”, “do”; Ionin & Wexler, 2002), and gerunds (e.g., verb-ing; Pazelskaya, 2012). To compare the similarity to American English syntax, we averaged the degree of correspondence to these six American-syntax structures for each IRA tweet. For personal pronouns, we counted first-person singular, first-person plural, second-person, and third-person plural per tweet (see Supplementary Materials B for the selection of syntax variables).

Subject and sentiment variables. We used a supervised machine learning technique to classify tweets into topic and sentiment variables. Four trained graduate students coded the following variables, all of which obtained the satisfactory level (>.70) of Fleiss’ kappa (FK): (1) whether the tweet only delivered factual information or not (FK = .71); (2) whether the tweet was about salient or controversial political topics in the US, such as racial issues (FK = .78), immigration (FK = .85), terrorism (FK = .88), foreign/international policy (FK = .83), or not; (3) whether the tweet contained positive, (FK = .73) or negative sentiment (FK = .90), or neither; (4) if so, whether it was toward Donald Trump (FK = .75), Hillary Clinton (FK= .75) or neither (see Supplementary Materials C for a detailed coding scheme).

Using the 4,000 labeled tweets, we applied a supervised machine learning method to predict unlabeled tweets’ categories (see Figure 1). The supervised machine learning includes two steps: first, finding an appropriate method to convert a short text (tweet) to a numerical vector; second, building high-quality models for each category. In our case, we chose InferSent Sentence Encoder (Conneau et al., 2017), which is a sentence encoder model to represent semantic information of English sentences, to convert tweets to vectors. InferSent is trained on natural language inference tasks so that it can learn universal English sentence representations. Recent studies show that this pre-trained model generalizes well on different tasks (Conneau & Kiela, 2018). We applied InferSent model to our dataset which produced a meaningful numerical vector with a dimension of 4,096, which represents every tweet.

We used logistic regression as our basic classification method and trained different logistic regression models for each of our variables. For each category, a Grid-Search with 5-fold cross-validation was used on the training set to select the best hyper-parameters (l1 or l2 penalty, regularization strength, and class weight) for these categories’ logistic regression model. As some categories were extremely skewed in distribution, we applied an oversampling method called “SMOTE (Synthetic Minority Over-sampling Technique)” to the training

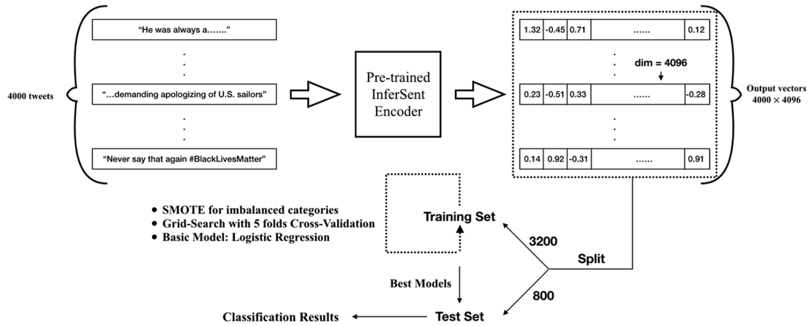


Figure 1. Supervised Machine Learning Process

process (Chawla et al., 2002), which allowed us to synthesize training data for the smaller category. For our final models, precision scores ranged from .81 to .99 and F1 scores from .53 to .80 (see Supplementary Materials D for details).

Analysis Strategy

To answer RQ1, we employed register analysis, which is a corpus linguistics method that compares the use of pervasive syntactic features in multiple corpora (e.g., Staples et al., 2018). Typically, register analysis is conducted by comparing two corpora of different registers to identify whether syntactic features are used more in one corpus than the other; for this reason, chi-square tests are common (Freddi, 2005; Crawford & Csomay, 2015).

To conduct this analysis, we first tokenized both Twitter corpora using an R wrapper for the Python library *spaCy*, then employed register analysis by conducting chi-square tests, a popular approach to comparing two datasets in corpus linguistics (e.g., Liu & Myers, 2020; Degaetano-Ortlieb et al., 2012). We then used multilevel negative binomial modeling via the R package *glmmTMB* to answer the hypotheses and RQs, given the non-independence and nested structure (tweets within accounts) of our dataset. As our dependent variable is the number of retweets (a count variable) and its distribution is highly skewed (positively), a multilevel negative binomial analysis was theoretically and statistically appropriate.

Results

RQ1 asks how IRA tweets would display distinct linguistic characteristics compared to US-based tweets. The comparison process serves a dual purpose of not only documenting syntactic differences in IRA tweets but also guiding a syntax variable construction for the subsequent predictive analysis.

First, we tested the difference in syntactic complexity. Results show that IRA corpus generally had shorter sentences and simpler syntax structures. For example, the average dependency length of IRA tweets (M = 2.27) was smaller than that of US ones (M = 3.49), t(1, 1377740) =398.66, p < .001. As Table 1 illustrates, the IRA corpus had fewer counts with complex syntax structures. For example, tweets in the IRA corpus used fewer modifiers, fewer clausal complements, fewer open clausal complements, and fewer nested propositions. Consistent with prior evidence on deceptive messages, IRA tweets were less likely to use cognitively complicated and long structures.

For American-English syntax similarity, we looked at six language features that are mainly different between English and Russian languages. Our results show that the IRA corpus had less correspondence to American-English syntax features (see Table 1). Overall, tweets in the IRA dataset had more tweets with incorrect subject–verb structure, including misplaced verbs-before-subjects and objects-before-subject structure.[3] IRA also had more incorrect copula–verb conjugations, fewer tweets with articles (e.g., "a", "the"), fewer indefinite pronouns (e.g., "all," "any"), auxiliary verbs (e.g., "be," "do," "have"), and gerunds (e.g., verb-ing; see Supplementary Materials B for examples). As expected, IRA agents who employ a Russian native, English-as-a-second-language variation (that differs from the language used by their target audience) showed fewer correspondences to the syntactic features of the US comparison corpus.

Finally, we looked at personal pronouns. Generally, we find that US tweets used more personal pronouns, including first-person singular ("I"), first-person plural ("we"), second-person ("you"), third-person singular ("s/he"), and third-person plural ("they"). Overall, the effect sizes of the relationships (see Cramer's Vs in Table 1) suggest that the magnitude of associations is low to moderate. However, given that the impact of subtle linguistic differences can be substantial (Pennebaker, 2011), even small differences would be meaningful.

Multilevel modeling

For our main analysis—regarding how features across syntax, topic, and sentiment in IRA tweets are associated with retweets—we conducted random slope multilevel modeling. The user handle was set as the group level and the account life span (i.e., the timespan that the account has been active before its disclosure) as the random slope. For

Table 1. Linguistic Differences Between IRA Tweets and US Tweets

	# in IRA tweets	# in US tweets	Chi-Square	Cramer's V
Syntactic complexity				
Appositional Modifier	173,008	177,399	38,317**	0.153
Clausal Complements	135,715	195,217	93,084**	0.238
Open Clausal Complements	83,345	103,507	39,809**	0.156
Nested Prepositions	229,764	243,675	72,206**	0.210
American English-syntax similarity				
Incorrect S-V Inversion				
Verb before Subject	26,584	21,032	2,476**	0.038
Object before Verb	9,047	9,898	2,488**	0.390
Object before Subject	1,344	236	168**	0.010
Incorrect Copula Verb Conjugation	502	113	577.34**	0.019
Use of Article	167,585	398,844	154,238**	0.307
Use of Indefinite Pronouns	7,423	21,560	1,366.61**	0.028
Use of Auxiliary Verbs	246,729	347,640	145,863**	0.298
Use of Gerunds	186,368	277,274	47,933**	0.171
Personal Pronoun				
First-person Singular	5,499	8,970	3,916.24**	0.048
First-person Plural	36,405	129,855	80,660**	0.222
Second-person	35,228	89,945	57,776**	0.188
Third-person Singular	30,995	79,101	28,918**	0.132
Third-person Plural	19,034	51,004	33,873**	0.143

Note. For Verb before Subject structure, grammatically correct inverted sentences, declarative sentences, passive voice, and questions were excluded.
$^{*}p < .01$, $^{**}p < .001$

syntax variables, we included 1) the average dependency length of a tweet as a syntactic complexity,[4] 2) the degree of correspondence to American-syntax similarity, and 3) counts of personal pronouns. Subject and sentiment variables were entered, along with several controls, including account life span, number of followers, number of hashtags, number of mentions, presence of visuals (videos, images, or animated GIFs), presence of URLs, and hour/day of posting (see Supplementary Materials E for details).

H1 proposed that IRA tweets with (a) higher syntactic complexity, (b) more use of American English syntax, and (c) more personalization language markers (including those with modal verbs) were associated with more retweets than IRA tweets without. Our results show that IRA sentence

Table 2. Multilevel Modeling Predicting Retweet Counts of IRA Tweets

	B	SE	IRR
Fixed Parts			
(Intercept)	-4.322**	.242	0.013
Subject			
News/Information (1) vs Opinion (0)	0.197**	.006	1.218
Political issues (e.g., race, immigration, terrorism, foreign/international policy)	0.126**	.006	1.133
Sentiment			
Positive	-0.044**	.009	0.957
Negative	0.188**	.007	1.206
Mixed (Both positive and negative)	0.202**	.018	1.223
Target of Sentiment			
Positive toward Trump	0.144**	.020	1.155
Negative toward Trump	-0.007	.038	1.008
Positive toward Clinton	-0.077*	.027	0.926
Negative toward Clinton	0.167**	.010	1.181
Syntax			
Sentence complexity (Dependency length)	0.006**	.001	1.006
American English-syntax similarity	0.064**	.004	1.066
Personal pronoun use	-0.003	.006	1.003
Personalization and modal verbs	0.092**	.019	1.096
Control			
Account life span	-0.004**	.001	0.996
Number of followers	0.000**	.000	1.000
Visuals	0.997**	.007	2.710
Number of URLs	-0.207**	.008	0.813
Day of posting (weekday vs weekend)	-0.109**	.005	0.897
Hour of posting	-0.000**	.000	1.000
Number of hashtags	0.005**	.003	1.054
Number of mentions	0.027**	.002	1.027
Random Parts			
σ^2	3.797		
$\tau_{00,\text{user handle}}$	22.790		
$\tau_{11,\text{account life span}}$	0.0004		
Observations (Tweets)	802,618		
Observations (User handles)	1,049		
Deviance	2416330		

**p* < .01, ***p* < .001

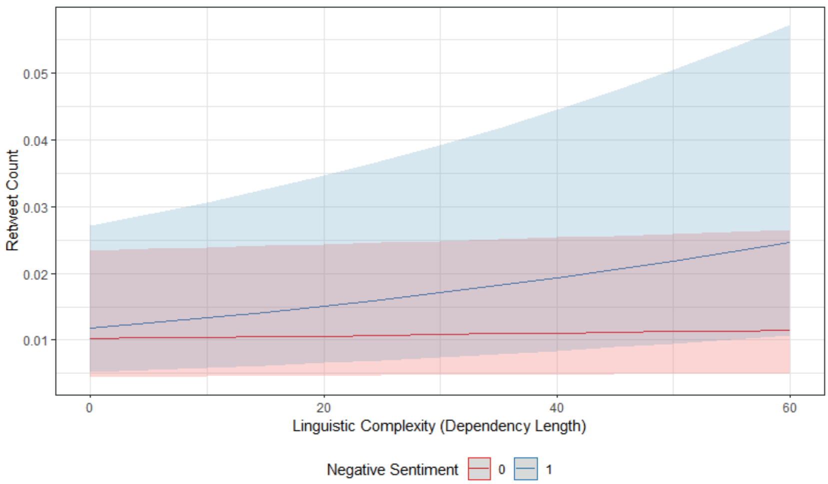
complexity was associated with more retweets (IRR = 1.006, $p < .001$). IRA tweets with more similarity to American English syntax was also associated with more retweets (IRR = 1.066, $p < .001$; see Table 1). The use of personal pronouns was not a significant factor predicting more retweets, but IRA tweets with personal pronoun–modal verb combinations predicted higher expected rates of retweets (IRR = 1.096, $p < .001$). This result supports H1(a)(b), but not H1(c).

We also hypothesized that IRA tweets with information only would be associated with more retweets (H2) and IRA tweets on controversial political issues would be associated with more retweets (H3). Our findings show that IRA tweets delivering information/news only had 1.218 times the rate of retweets than those without. IRA tweets on contentious political issues (e.g., race, immigration, terrorism, foreign/international policy) also had 1.133 times incident rates of retweets than without, supporting H2 and H3.

H4 proposed that IRA tweets that expressed sentiment—(a) positive, (b) negative, or (c) both—would be associated with more retweets compared with tweets without sentiment. Our analysis shows that negative tweets had 1.206 times the rate of retweets than those without negative sentiment, whereas positive tweets had 0.957 times the rate of retweets than those without such sentiment, supporting H4(b) but not H4(a). Tweets with both sentiments (positive and negative) had 1.223 times the rate of retweets than those without, supporting H4(c). RQ2 asked how IRA tweets with positive or negative sentiment against (a) Trump and (b) Clinton would be associated with retweets. IRA tweets with negative sentiment toward Clinton had 1.181 times the rate of retweets, whereas for IRA tweets about Trump, those with positive sentiment had 1.155 times the rate of retweets than those without. IRA tweets with positive sentiment about Clinton had 0.926 times the rate of retweets. Taken together, IRA tweets with negative sentiment had significantly higher expected retweet rates, and this tendency was more pronounced when the conveyed negativity was directed toward Clinton.

RQ3 asked about the interaction between syntactic, subject, and sentiment features of IRA tweets. Our findings show that negative tweets with more complexity predicted higher expected rates of retweets (IRR = 1.010, $p < .001$). Figure 2 shows that IRA tweets with negative sentiment were more likely to receive more retweets when associated with higher dependency structures, indicating that long, articulated IRA tweets with negative sentiment garnered more retweets. Interestingly, calls to action (measured as a combination of personal pronouns and modal verbs) with higher dependency

(a) Predicted incidents for retweet counts from negative sentiment and sentence complexity



Note. Shades are 95% CI levels.

(b) Predicted incidents for retweet counts from call-to-action marker and sentence complexity

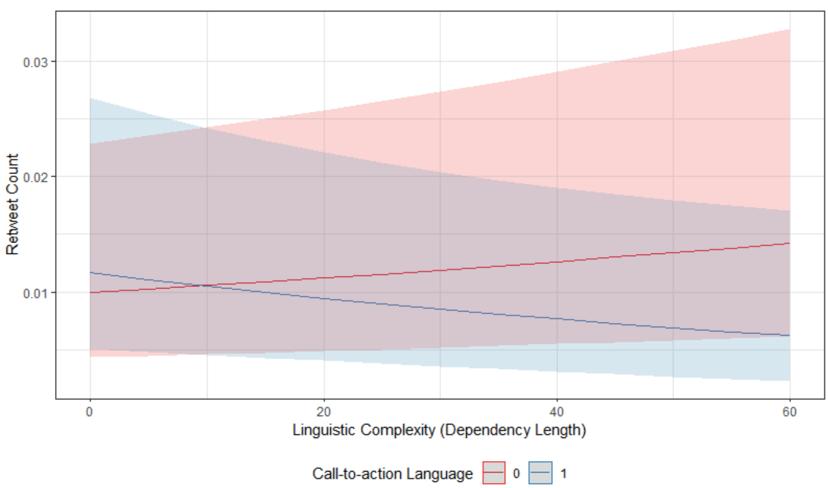


Figure 2. Interaction Plots Predicting Retweet Counts of IRA Tweets

structures were associated with fewer retweets (IRR = 0.984, $p < .01$). Thus, when IRA tweets had call-to-action markers (combination of personal pronouns and modal verbs), the number of retweets was higher when they were written in shorter, less complicated structures (full tables are in Supplementary Materials F).

Discussion

By using a combination of computational approaches, this study examined the nature of foreign-sponsored online disinformation messages and explored how syntax, topic, and sentiment features were related to Twitter sharing. First, by documenting the syntactic features in IRA tweets that differed from authentic US-based users, we find that IRA tweets were syntactically simpler and demonstrated features distinct from tweets by authentic users. This distinction may reflect their deceptive intents (Newmann et al., 2003) and the challenges of producing disinformation for a different language group (Giles & Ogay, 2006).

Importantly, our findings provide insights into how sociolinguistic features in IRA messages were related to their likelihood of being retweeted. Supporting prior evidence on how linguistic similarity builds higher trust (Scissors et al., 2009), IRA tweets with higher similarity to American-English syntax structures were retweeted more. Those with more complicated structures tended to receive more retweets, indicating the potential role of argument length and linguistic complexity as persuasion heuristics in source-blind environments like social media (Pearson, 2020). Considering that syntactic complexity is often accompanied by reasoning and elaboration, well-reasoned messages likely evoked favorable feelings and appeared persuasive (Heiss et al., 2019). Although IRA tweets overall had simpler language structures and deviated from standard American-English syntax, those that demonstrated syntactic complexity or "sounded more like" authentic US Twitter users tended to attract more retweets, enabling them to blend their activities with those of authentic users. This finding indicates the important role of syntactic cues in message sharing and highlights the difficulty of distinguishing disinformation messages from authentic ones, especially those capable of gaining traction.

For research on disinformation campaigns, our study highlights potential interactions among sociolinguistic features. Specifically, messages expressing negative sentiment were more powerful when accompanied by elaborated content, whereas pronoun–modal combinations received more retweets when conveyed through simple languages. Well-articulated IRA tweets emphasizing negative sentiment likely enhanced the credibility and stimulated sentiment heuristics, producing more engagement. By contrast, mobilizing tweets attracted more retweets in shorter and simpler language structures. Lastly, although personal pronouns alone did not elicit more retweets, their use with mobilization cues were significantly related to retweets, suggesting that the effect of pronouns may be moderated when associated with certain pragmatic functions. These results confirm that the effect of communication styles is not constant but contingent on content context (Newmann et al., 2003).

Our findings also aligned with current scholarship showing that divisive topics (e.g., issues with racial or ideological implications) were associated with more retweets. IRA tweets with only news or information were retweeted more, resonating with prior findings of informational value and virality (e.g., Keib et al., 2018). It is noteworthy that news/information delivered by the IRA is likely a subjective selection tailored to a target audience, some of which may be factually incorrect. Troublingly, several IRA accounts presented as local news (Farkas & Bastos, 2018), which may create a false sense of credibility and induce confusion about information trustworthiness.

Regarding sentiment and persuasion, our findings join work that considers the *target* of sentiment, particularly in an era of political microtargeting (e.g., Park et al., 2021). Specifically, we show that not *all* negativity has "news value" worth sharing (Mueller & Saeltzer, 2022). In the case of IRA operations, although tweets with negative sentiment toward Clinton were associated with more retweets, those with positive sentiment toward Trump also garnered more retweets compared with neutral ones, corresponding to IRA's goal to amplify pro-Trump rhetoric.

On the one hand, this finding calls for more attention to the highly contingent role of emotion in persuasion research, which traditionally did not differentiate the target of sentiment. On the other hand, these findings inform how IRA activities could leverage asymmetrical American partisan ecology and polarized partisan behavior. Research shows that disinformation operations tend to promote conformity and normative influence (Wardle & Derakhshan, 2017). To the extent that pro-Trump and anti-Clinton IRA messages motivated subconscious "moral systems" and salient rhetoric among conservatives (Lakoff, 2010), sharing such content may serve as useful tactics for identity performance (Wardle & Derakshan, 2017). Moreover, through publicly expressing conformity to group norms, the act of retweeting contributes to a strengthened partisan self (Klein et al., 2007). This tendency is likely more pronounced in cloistered conservative communities than in liberal ones (Faris et al., 2017). Given that the Twitter population has a liberal bias (Wojcik & Hughes, 2019), it is striking that the IRA disinformation campaign could amplify conservative-leaning messages compared with liberal ones.

Although our study focuses on the IRA disinformation campaign on Twitter, it has broader implications for contemporary challenges surrounding the strategic disguise of identity and intention in computer-mediated contexts. Many IRA activities, as outlined above, capitalized on existing strategies of Internet trolling, impersonation, and astroturfing that have been widely applied across contexts, including social activism initiatives and public relations management. For instance, the IRA frequently "operate as agents of chaos" by exploiting hot-button issues and provoking others emotionally, demonstrating typical trolling behaviors (Hardaker, 2010); or they may exploit bottom-up grassroots efforts to create a false impression of widespread support for a cause that is nonexistent, benefiting from common astroturfing tactics (Lock et al., 2016). Apparently, as with foreign disinformation operations, these practices have led to shared concerns about distorted perceptions of social reality, undermining trust and transparency, and disrupting the integrity of digital media ecology (Zerback & Töpfl, 2022). We believe our approach to identify sociolinguistic limitations and strategic and deceptive properties can inform broader research agenda on inauthentic agents and their hidden persuasive intents.

This study contains several limitations. First, we did not consider the nature of those retweeting IRA tweets. Although the current dataset by Twitter does not include "retweeter" information, given the evidence on online political homophily and IRA's strategy (Starbird et al., 2019), we expect that IRA tweets were circulated differently along party lines. Investigating how these IRA tweets reached different audiences would be an important avenue for further investigation. Second, we focused on the IRA's original messages only. Although retweeting messages written by political figures or pundits can be an important strategy and, relatedly, we cannot rule out the possibility of IRA tweets being generated by automated agents, our study sheds light on the nature and reach of human-produced messages constructed by foreign-sponsored online disinformation agents. Lastly, we acknowledge that the political issues in our study are only a subset of issues that were largely covered during the 2016 US election cycle. Besides practical infeasibility to cover all potentially relevant issues, our study chose to focus on issues that achieved a satisfactory level of machine learning performance in order not to undermine the validity of our results.

In conclusion, our findings add to ongoing scholarly conversations about disinformation by integrating novel theoretical and methodological insights. By uncovering syntactic patterns reflecting IRA's situational motivations, we highlight sociolinguistic characteristics inherent to anti-democratic discourses. Given the global reach of disinformation campaigns, we hope our approach contributes to future research on troll messages in various linguistic and sociocultural settings and intervention efforts against state-backed disinformation spread.

Furthermore, our findings deepen the understanding of how a highly coordinated state-backed disinformation campaign operated in fueling the spread of messages with certain syntactic, topical, and sentiment features, leveraging the polarized and fragmented American online ecology. We underscore the importance of contextualization reflected in such anti-democratic discourses and their dissemination. As more retweeted IRA messages unwittingly lend credibility and trust to false accounts, retweetability may help inauthentic narratives circumvent the newsroom gatekeeping process (Lukito et al., 2019). This vicious cycle shows how the disinformation campaign can exacerbate the disruption of democratic discursive norms, undermine legitimacy in platforms and institutions, and lower trust in other social groups, facilitating alternative information systems that endanger "normal democratic order" (Bennett & Livingston, 2018).

Although the current study focused on Russian IRA's activities targeting the US, such political meddling by disinformation agents is not a geographically bounded phenomenon, and the Russian IRA is not the only information operation attempting to interrupt foreign politics. Foreign disinformation campaigns also produce conspiratorial and partisan messages on topics like the COVID-19 outbreak and elections in Latin America and North Africa (e.g., Moreno, 2020). We hope future studies build on our research to investigate the nature of disinformation messages and their disruptions in online information flows in comparative contexts.

Acknowledgment

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Supplementary Materials

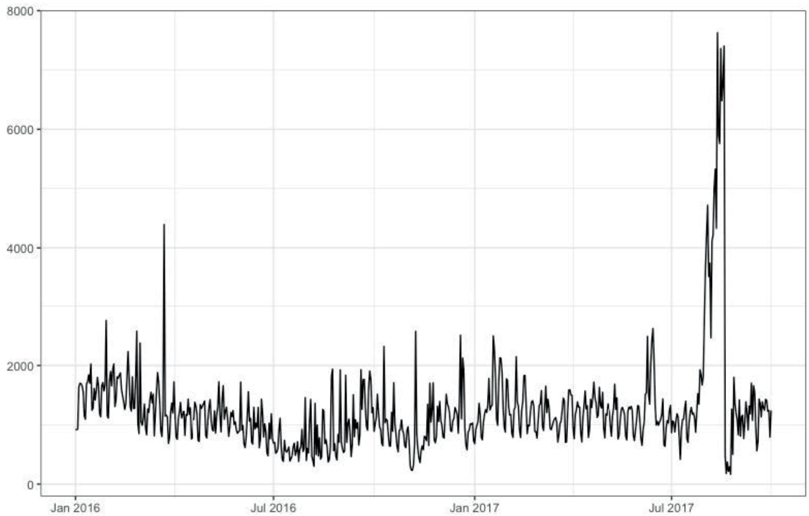
A. Russian IRA twitter dataset and comparison dataset

A.1. Russian IRA twitter dataset

We used a full corpus of IRA tweets provided by Twitter. In 2017, Twitter disclosed activities on Twitter linked to the information operations, including Russia's Internet Research Agency (IRA), and later in October 2018, released all accounts, related content, and engagement metrics, including the number of retweets and likes, to the public (https://transparency.twitter.com/en/

information-operations.html). This study uses the one released in October 2018. According to Twitter, the “engagement counts exclude engagements from users who are suspended, deleted or otherwise actioned against by Twitter at the time of this data release.” (Twitter, 2018)

This resulted in a dataset of 802,618 unique tweets posted by 1,049 unique IRA accounts. The following figure illustrates the frequencies of IRA tweets during our study period.



A.2. Comparison dataset

As a counterpart of IRA corpus, we focused on collecting samples of American Twitter users who *ever* talked about politics between January 1, 2016 and September 31, 2017 (which is the same time span as the IRA activity in our dataset). We took an accounted-based approach, where we identified a comparable list of accounts first, then collected their tweets.

We first made sure that accounts from both IRA corpus and comparison corpus share similar characteristics in terms of the number of accounts and their characteristics, such as the verification status and the number of followers. Using the Twitter API v2, which allows the access to the historical archive of public Tweets, we sampled 1,049 accounts (which is the same number as the IRA accounts in our dataset) that are non-verified (to ensure that we collect ordinary users, not organizations), based on the US, used English language, and had a comparable number of follower distribution, which mentioned one of the keywords about the US politics and election between 01/01/2016 and 09/31/2017. The keywords included Clinton, Donald Trump, election, MAGA, Syria, terrorism, terrorist, Ukraine, BlackLivesMatter, policebrutality, racism, lgbt, gunrights, guncontrol, refugee, immigration, muslim, which reflected the prominent political topics during and after the 2016 US election and therefore largely targeted by the IRA. This procedure ensured that we identified accounts that talked about politics *at least once* during the time period.

Of the tweets posted by these accounts between January 1, 2016 and September 30, 2017, we sampled tweets in a way to ensure the comparable distribution of tweets across accounts between the IRA and comparison corpus, therefore sampling a total number of 808,089 tweets.

	IRA accounts	American accounts
# of accounts	1,049	1,049
# of followers		
Min	0	0
1st Quantile	83	83
2nd Quantile	301	301
3rd Quantile	1809	1799
Max	257638	250606
Total # of tweets	802,618	808,089
Verification status	Non-verified	Non-verified

B. Selection of syntax features

Linguistic complexity was measured in two ways. First, we calculated complexity as the average length of the dependencies within a tweet; in corpus linguistics, this is called the “dependency length” (Temperley, 2007). Second, we counted the use of grammatical constructions that are known to make a message or sentence more complex. This includes clausal and open clausal complements (Domsch, Richels, Saldana, Coleman, Wimberly, & Maxwell, 2012), appositional modifiers (Green, 2019), and nested propositions (Halpern, 1995; Bhutani, Jagadish, & Radev, 2016).

To calculate American-syntax similarity, we considered syntactic constructions that Russian speakers struggled to use when learning American English (Native Russian speakers for whom English is a second language are sometimes called Russian L1 English L2 speakers). This included both correctly used syntactic features and incorrectly used syntactic construction.

Syntactic features that Russian L1 English L2 speakers struggle with include articles like “a” and “the” (Ionin, Zubizarreta, Philippov, 2009), indefinite pronouns like “something” (Haspelmath, 1997), auxiliary verbs like “may” and “will” (Ionin & Wexlr 2002), and gerunds which, in U.S. English, are identifiable by adding an “-ing” suffix to a verb (Pazelskavya, 2012). Incorrect syntactic constructions that we identified included incorrect subject-verb constructions as American English typically adheres to a “subject-verb-object” order (Tuniyan, 2013) and (2) incorrect conjugations of the copula verb “to be” (Unlu & Hatipoglu 2012).

Below are some IRA tweet examples:

“Yeah, he was always musslim... :) Even when senator. Who was the folks that really thought he was Christian???” (Incorrect copula-verb conjugations)

“In defense of Katy, note the position of thumb. This is more in line with finish of US military style salute” (Missing articles)

“whether you support or don’t Trump is the only one has has acknowledged Vets exist” (Incorrect subject-verb structure)

“U.S. constitution says, is the POTUS job to do it” (Copula conjugation error)

C. Coding scheme (IRA tweet subject and sentiment variables)

I. Type of content (News vs Opinion)

1. General rule:
    a. News headline – code 1. News headline should read like a headline.
    b. Hashtags: #world, #news, #local – most likely news hashtags, so 1.
    c. Other opinionated hashtags – those that convey a direction of opinion (support or oppose, e.g., #MAGA, #TrumpTrain, #LoveTrump, #ObamaOut, #WithHer, #AntiTrump) – should be coded 0
    d. Quoting someone else’s comments/statements should be coded as 1, unless it is accompanied with opinionated hashtag(s), which will be 0.

Code 1	News; information: delivering information only without any comments/ “opinionated” hashtags. If it reads like a news headline, feel free to google the sentence.	Ex. SeaWorld admits to planting spies in animal rights group #news
Code 0	Opinion: delivering thoughts, positions, arguments, etc. **Information + Opinion should be coded as 0.** **Opinion includes “opinionated” hashtags.**	

II. Topic

1. Politics or not

Code 1	Any references to political parties, issues, politicians, policies, partisans, and elections, etc.
Code 0	Non-political content, including entertainment, sports, citing lyrics/proverbs, etc.

2. (If political) Political issues

1) Racial issues

Code 1	Any references to BLM, racism, police shootings; any comments raising racial issues (e.g. white vs black)	Ex. Feb.17-19. If you have friends or family in the NY let them know about the protest. #BlackLivesMatters #StopGenocide #NY #UN
Code 0	No references	

2) Immigration

Code 1	Any reference to transit of people across the borders into the US. This is likely to include statements about legal immigrants, illegal immigrants (e.g. Mexicans taking jobs, building walls, etc), and refugees (e.g. refugee admission).	Ex. #MexicanVerificationQuestions In USA: Can I see your ID, please? https://t.co/2SkPyD4cEw
Code 0	No references	Sweden: 77% of rapes committed by the 2% Muslim population STOP ISLAMIC IMMIGRATION! #tcot https://t.co/socNyNbvWf

3) ISIS/terrorism/refugees

Code 1	Any references to ISIS, terrorism, terroristic attacks, only. Refugees and/or Muslims are usually referenced to relate to ISIS and terrorism, but not always. If refugees and/or Muslims are referenced with the discussion of terrorism, terrorist organizations, attacking the US, etc, we code 1 for this category	Ex. Refugees are ISIS. Even a 5 year old could tell that's their plan #IslamKills #StopIslam
Code 0	No references	

4) Foreign/international issue

Code 1	Foreign/international issue, not related to racial/immigration/terrorism issue. Includes Fukushima/Ukraine issues.	Ex. Have you read what CNN wrote about nuclear disaster in Ukraine? You don't know what you're talking about! #FukushimaAgain
Code 0	No references	

III. Valence

1. General Rule:
   a. We code only "clearly expressed sentiments."
   b. Let's ignore sarcasm and irony – those should be coded as 0 for both positivity and negativity.
   c. If we have to make a separate assumption about the sentiment, then 0. Unclear/ambiguous sentiments = 0

   In other words, if the tweet can be interpreted in both positive and negative way, code 0.
   d. Neutral statement (or news) with opinionated hashtags: follow the sentiment of hashtags.
   e. Neutral statement (or news) with neutral hashtags: should be neutral (0)
   f. Neutral statement (or news) with opinionated hashtags with mixed directions: we have to assume the intention of the tweet, so should be 0.
   g. Generally, supportive statements show positive sentiments and oppositional statements show negative. But, not always. For example, aggressive or uncivil support is likely to fall into a negative category.

1. Tone of tweet

1) Positive: pos

Code 1	Any "clearly positive" sentiments in the content: Love, smile, happy, excited, celebratory, etc.
Code 0	Not positive. Includes **unclear** expressions.

2) *Negative: neg*

Code 1	Any “clearly negative” sentiments in the content: Downbeat, sad, mad, angry, defiant, frustrated, etc.
Code 0	Not negative: Includes **unclear** expressions. Sarcasm and irony should be coded as 0.

2. Target of the sentiment

General rule: If sentiment is 0, the target of the sentiment should be 0 as well.

1) *Trump*

Code 1	The valence of tweet is specifically toward Donald Trump
Code 0	Not about him

2) *Clinton*

Code 1	The valence of tweet is specifically toward Hillary Clinton	Ex. If she cant carry two phones how can she rule the huge country? #HillaryNoThnx
Code 0	Not about her	

D. Precision and F1 scores for subject and sentiment variables

Category	**Precision**	**F-1**	**Category**	**Precision**	**F-1**
News	0.82	0.74	Politics	0.81	0.80
Racial issue	0.96	0.64	International	0.98	0.75
Terrorism	0.96	0.64	Immigration	0.97	0.60
Positive	0.84	0.53	Negative	0.79	0.67
Trump	0.94	0.46	Clinton	0.93	0.66

There are two key validation metrics to assess machine learning performance: precision and recall. Precision indicates how many of the classified observations are truly relevant, while recall signifies how many of the relevant cases were correctly classified. Often researchers choose a tradeoff between the two. The F1 score is the harmonic mean of recall and precision. In this study, we opted to weigh precision over recall, because of our goal to minimize type-1 errors (i.e., false positives) to precisely capture the relevant content. The low F1 score for some variables is due to the low recall, but we note that these variables were difficult to be coded consistently even for human coders given the variant forms of ideas and nuances present in IRA tweets. Nonetheless, as the goal of the study is not to examine the volume of certain tweets, but to see the relation with retweets, we decided it is more important to obtain lowest level of false positives in our dataset.

Additionally, we acknowledge that issue variables (racial issue, international, terrorism, and immigration) are only a subset of political issues that were prominent during the 2016 US campaign. We focused on these variables to ensure the validity of the results; other issue categories as LGBTQ and gun policy which were also targeted by IRA agenda yielded poor machine learning performance, therefore lowering the validity of the results.

E. Multilevel Modeling

Analysis strategy and justification

It was necessary to isolate the individual tweet features from potential effects of the account, as a more popular account may elicit more retweets than other accounts. We included the account life span (i.e., the timespan that the account has been active before its disclosure) as a random slope, as the longer an account has been active, the larger followings it accumulates. The current dataset released by Twitter only contains the fixed number of followings for all tweets created by one account, which is the number at the time of the disclosure. Therefore, the number of followings is an account-level predictor, while the account life span is a tweet-level predictor.

The intraclass correlation coefficients (ICC), the degree of association among observations within the same account, of retweet count was 0.74, suggesting 74% of retweet counts were attributable to account-level differences, therefore justifying the use of multilevel modeling in our study context.

Control variables in multilevel models

In multilevel modeling predicting the retweet counts from message features across syntax, subject, and sentiment, we additionally included several controls: including the account life span, the number of followings, the number of hashtags, the number of mentions, the presence of visuals such as videos, images, or animated GIFs, the presence of URLs, the hour of posting, and the day of posting. Prior research has generally identified these controls as significant factors relating to retweet rates. For example, using hashtags (#) or mentions (@) in one's tweet is a prominent way to reach a large audience by helping curate conversations and engaging in specific communities (Zappavigna, 2011). Visual components such as images or videos add vividness and interactivity to the text, therefore attracting more engagement (Luarn et al., 2015). URLs not only add vividness and interactivity to text but also indicate sources for further information and news. While there has been mixed evidence about the relationship between including a URL in a tweet and retweet rate (e.g., Suh et al., 2010; Yang et al., 2018), studies suggest a significant role of a URL in predicting higher retweets. Hour and day of posting also matter in retweet rates as they are related to online information traffic (Khan & Ahmad, 2021; Suh et al., 2010)

F. Multilevel random slope modeling (full interaction models of Figure 1)

F.1. Interaction Model (Negativity * Syntax Complexity) Predicting Retweet Counts

	B	SE	IRR
Fixed Parts			
(Intercept)	-4.036***	0.242	0.013
Subject			
News/Information (1) vs Opinion (0)	0.198**	0.006	1.219
Political issues	0.125**	0.006	1.133
Sentiment			
Positive	-0.434*	0.009	0.958
Negative	0.146**	0.009	1.157
Mixed (Both positive and negative)	0.200**	0.018	1.222
Target of Sentiment			
Positive toward Trump	0.144**	0.021	1.155
Negative toward Trump	0.006	0.039	1.006
Positive toward Clinton	-0.008*	0.028	0.927
Negative toward Clinton	0.166**	0.010	1.181
Syntax			
Sentence Complexity (Dependency length)	0.002*	0.001	1.002
American-syntax Similarity	0.063**	0.004	1.065
Personalization	0.003	0.006	1.004
Call-to-Action Language	0.092**	0.019	1.096

Control			
Account life span	-0.004**	0.001	0.996
Number of followers	0.000**	0.000	1.000
Visuals	0.997**	0.007	2.710
Number of URLs	-0.207**	0.008	0.813
Day of posting (weekday vs weekend)	-0.109**	0.005	0.897
Hour of posting	-0.000**	0.000	1.000
Number of hashtags	0.005**	0.003	1.054
Number of mentions	0.027**	0.002	1.025
Interaction			
Negative * Sentence Complexity	0.014**	0.001	1.010
Random Parts			
$\tau_{00,\, user\ handle}$		22.8122	
$\tau_{11,\, account\ life\ span}$		0.0005	
Observations (Tweets)		802618	
Observations (User handles)		1049	
Deviance		2416281	

F.2. Interaction Model (Call-to-Action * Syntax Complexity) Predicting Retweet Counts

	B	SE	IRR
Fixed Parts			
(Intercept)	-4.322**	0.242	0.013
Subject			
News/Information (1) vs Opinion (0)	0.198**	0.006	1.219
Political issues	0.125**	0.006	1.133
Sentiment			
Positive	-0.044**	0.009	0.957
Negative	0.188**	0.007	1.207
Mixed (Both positive and negative)	0.202**	0.018	1.223
Target of Sentiment			
Positive toward Trump	0.145**	0.020	1.156
Negative toward Trump	0.007	0.034	1.007
Positive toward Clinton	-0.077*	0.027	0.926
Negative toward Clinton	0.166**	0.009	1.181
Syntax			
Sentence Complexity (Dependency length)	0.006**	0.001	1.006
American-syntax Similarity	0.063**	0.004	1.065
Personalization	-0.004	0.006	1.004
Call-to-Action Language	0.157**	0.028	1.170

	B	SE	IRR
Control			
Account life span	-0.004**	0.001	0.996
Number of followers	0.000**	0.000	1.000
Visuals	0.997**	0.007	2.710
Number of URLs	-0.207**	0.008	0.813
Day of posting (weekday vs weekend)	-0.109**	0.005	0.897
Hour of posting	-0.000**	0.000	1.000
Number of hashtags	0.005**	0.003	1.054
Number of mentions	0.027**	0.002	1.027
Interaction			
Call-to-Action * Sentence Complexity	-0.016*	0.005	0.984
Random Parts			
$\tau_{00,\ \textit{user handle}}$		22.8023	
$\tau_{11,\ \textit{account life span}}$		0.0005	
Observations (Tweets)		802618	
Observations (User handles)		1049	
Deviance		2416320	

Notes

1. Supplementary Materials and R codes are available at https://doi.org/10.17605/OSF.IO/6B4N5.
2. The keywords we used include the following: "Clinton," "Donald Trump," "election," "MAGA," "Syria," "terrorism," "terrorist," "Ukraine," "BlackLives-Matter," "policebrutality," "racism," "lgbt," "gunrights," "guncontrol," "refugee," "immigration," "Muslim." We relied on these keywords as political issues that were prominent during and after the 2016 US election and therefore largely targeted by the IRA (Freelon & Lokot, 2020; Freelon et al., 2020).
3. For incorrect object–verb inversion, another type of subject–verb–object error, the American corpus had more tweets with such cases (= 25.69, $p <$ .001), likely due to incomplete sentence structures in tweets; however, this type of error was the least frequent word-order inversion.
4. We used the number of dependencies as an indicator of sentence complexity in the multilevel modeling, due to a high correlation between the number of complex structures and dependencies.

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About the authors

Jiyoun Suk is an Assistant Professor at the Department of Communication at the University of Connecticut. Josephine Lukito is an Assistant Professor at the School of Journalism and Media at The University of Texas at Austin. Min-Hsin Su is a Ph.D. candidate at the School of Journalism and Mass Communication at the University of Wisconsin-Madison. Sang Jung Kim is a Ph.D. candidate at the School of Journalism and Mass Communication at the University of Wisconsin-Madison. Chau Tong is a Postdoctoral Associate at the Department of Communication at Cornell University. Zhongkai Sun is an applied scientist at Amazon Alexa AI. Prathusha Sarma is an ML researcher at Curai.