Is Aggression Contagious Online? A Case of Swearing on Donald Trump's Campaign Videos on YouTube

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Abstract

This study explores whether aggressive text-based interactions in social media are contagious. In particular, we examine swearing behaviour of YouTube commentators in response to videos and comments posted on the official Donald Trump's campaign channel. Our analysis reveals the presence of mimicry of verbal aggression. Specifically, swearing in a parent comment is significantly and positively associated with the likelihood and intensity of swearing in subsequent 'children' comments. The study also confirms that swearing is not solely a product of an individual speech habit but also a spreadable social practice. Based on the findings, we conclude that aggressive emotional state can be contagious through textual mimicry.

1. Introduction

Emotional outspokenness has become a defining characteristic of political culture in the social media era. While some scholars have suggested that sharing of emotions facilitates mobilization of sympathizers both off and online [1-3], there is a consensus among many political scholars that too much of emotional arousals may potentially impair democracy by increasing hate speech [4,5], and lead to biases in decision making [6,7] and deterioration of deliberation quality [8].

Swearing is one explicit way to convey high-arousal emotions. In face-to-face interpersonal interactions, the use of swear words may sometimes function as a social lubricant that increases a sense of informality and in-group cohesion [9]. However, in online communities where social interactions mostly occur among strangers or in an anonymous public setting, swearing has been linked to emotional disinhibition that accompanies verbal aggression, interpersonal attack, and incivility [10-12]. While swearing as an emotional speech act may sometimes induce the feeling of liberation, the impact of swearing on political discursive culture online can be agonistic for two reasons. First, online swearing often occurs without contemplation whether or not other users would perceive it as acceptable [10,13]. Second, it is unclear whether the effect of swearing on mediated discursive culture is transitory or more indelible. The current study pays attention to the latter. Specifically, this study attempts to respond to the main research question: *Does an individual act of swearing increase the swearing tendency at the collective level?*

We define swearing as a verbal mannerism that expresses high-arousal emotion and aggression to a varied degree. The goal of this study is to examine a non-random incidences of swearing, particularly through verbal mimicry. Mimicry is a fundamental mechanism underlying emotional contagion [15]. Based on the mimicry theory [15] and online emotional contagion literature [15, 16], we explore whether swearing is mimicked during online textual interactions. We choose YouTube for our study due to the relative prevalence of aggressive comments on this platform [11]. We collect and examine audience comments posted on the official campaign channel for one of the U.S. presidential candidates, Donald Trump. Trump's channel is selected due to the high interest and controversy surrounding his candidacy. His candidacy was prone to inducing polemics from supporters and detractors alike.

2. Literature

2.1. Swearing, Verbal Aggression, and Political Discussions in Online Communities

Swearing is an utterance of "offensive emotional languages" that are usually inhibited by "social convention or aversion" (p. 153) [17]. Although the degree of offensiveness may vary depending on the nature of communicative context and the tolerance level of message receivers to taboo words, the common

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understanding is that *emotional arousal* –often aggressive one –is an inherent characteristic of swearing [17]. Therefore, understanding pragmatics of online political swearing begs a far-reaching scholarly question on the role of high-arousal emotions in shaping online discursive culture [11].

2.1.1. Interpersonal swearing. Provided that swearing is a form of aggressive emotional utterances [19], we identify the following two types of swearing in online political commenting contexts. First, *interpersonal swearing* refers to a designative use of taboo-words, targeting specific individuals who involve in the social interactions. Unless communicators share mutual consent that swearing be an acceptable norm for their interactions [19, 20], swearing can promote interpersonal attacks or inflammatory behaviors [13]. In particular, Alonzo and Aiken [20] point out profanity as a prominent characteristic of Internet flaming and trolling. Other studies have suggested negative consequences of the exposure to verbal aggression –for example, aggravation of uncivil and impolite social interactions [11], spillover of verbal aggression into physiological aggressiveness [16, 21] and building up negative self-concept [22].

Interpersonal swearing may occur more readily in some online community settings where anonymity decreases personal identifiability and accountability, and thus can promote users' disinhibition tendency [4, 23, 24]. For example, [25] showed that anonymous textual comments in Washington Post website contained twice more interpersonal attacks than in its counterpart Facebook page where comments are explicitly linked to commenters' real identities. Another comparative study between Facebook page (i.e., low anonymity) and YouTube channel (i.e., high anonymity) of the White House [26] showed a similar result: YouTube comments contained more impolite messages than Facebook. The study's [26] operationalization of impoliteness was inclusive of swearing: "Curses and insults" that indicate "pejorative speak" (p.1163).

2.1.2. Public swearing. The second type of swearing is *public swearing*. Public swearing is distinguished from interpersonal swearing in that verbal aggression does not target specific users and thus not intend an immediate interpersonal attack. Instead, public swearing functions to emphasize –in an aggressive manner – speaker's opinions or feelings toward an entity, issue, or event beyond the discussion participants. While an immediate interpersonal attack is less obvious, public swearing is nonetheless a form of emotional outbursts, characterized as potentially agonistic and uncivil [27].

For example, an experiment-based study [28] has used swearing to manipulate an uncivil comment condition and tested its impact on readers' assessment of a public policy issue (i.e., nanotechnology). Their findings suggest a polarizing tendency of uncivil commenting: Supporters of nanotechnology became even more supportive while opponents became more negative when exposed to uncivil comments. Conversely, the perception gap between supporters and opponents were smaller in the control group that were exposed to civilized comments.

Another research [29] examined a large-scale dataset of audience comments posted across 26 news websites. They found that audiences' political swearing not only attracted more attention from fellow commentators but also received more positive votes, suggesting a potential role of swearing in promoting political 'we-ness'. That said, most of swearing incidences were public swearing that offends different political views, and thus potentially elicited animosity against out-group members and values.

These studies suggest that public swearing as an aggressive emotional expression can exacerbate political biases. In the context of online environments where social presence is reduced, such aggressive emotional utterances potentially enhance polarization of group identities [30], hindering free flow of different opinions or producing "spiral of silence" effect against minority viewpoints [31,32].

In sum, both interpersonal and public swearing could be detrimental to the cultivation of civil discursive environments in social media. Occasionally, swearing might be "functional" by heightening in-group cohesion or by creating the sense of informality [15,18]. However, in many discursive contexts in which diversity, openness, and civility are valued, swearing may elicit aggressive emotional exchanges that deteriorate the quality of discursive interactions.

2.2. Mimicry and Emotional Contagion in Online Networks

The dark side of swearing is that it has potential to provoke the contagion of aggressive emotion. Swearing could be contagious by mimicking [12] and social reciprocation [19] process, both as a verbal mannerism and as an outspoken emotion,

2.2.1. Mimicry. Mimicry is an interpersonal synchronization that occurs during social interactions [33]. Mimicry can occur in both conscious and unconscious manners. Behavioral mimicry is an imitation of gestures, postures, and facial motions. Chartrand and

Baaren [33] call behavioral mimicry "chameleon effect" because individuals adopt others' behaviors to blend into the immediate social environment that they engage in. A vast majority of mimicry studies have been conducted in offline settings with a focus on physical behaviors and movements.

While online, text-based interactions do not accompany the physical signals that are prevalent in offline settings, it may be possible for users to mimic other users' textual mannerism (e.g., logic-oriented, sentimental, cynical, humorous, and aggressive writing styles). In a computer-mediated environment where non-verbal cues are often hidden, users communicate their emotional states by creatively exploiting what text-based medium can afford, including emojis, emotional words, linguistic and paralinguistic cues [34].

Convergence in writing styles can be understood as 'verbal mimicry', which specifically refers to mimicking speech characteristics such as "syntax, speech rate, accents, utterance duration, latency to speak" (p.225) [33]. Similar to behavioral mimicry, verbal mimicry mostly occurs by picking up the same kind of words and clauses [33]. Previous studies have used the Language Style Matching (LSM) technique to demonstrate the existence of verbal mimicry both in-person and computer-mediated settings [35-37]. The current study also takes a similar approach by automatically detecting and computing occurrences of swearing.

2.2.2. Emotional contagion. Mimicry facilitates emotional contagion. The majority of emotional contagion studies in face-to-face contexts claim a superior role of nonverbal mimicry in conveying emotionality than words [12]. However, some recent research on online social networks has supported a sufficient role of textual messages in signaling emotional states [14, 38].

Two dimensions of emotionality have been highlighted when examining emotional contagion. First, emotional valence – positive and negative –may have disproportionate consequences in the contagion process. [39] found a negativity bias such that the exposure to negative emotions escalates negative interactions in a dyadic relationship. [40] also discovered the spiral of negativity when studying group dynamics [40].

However, the mixed findings exist regarding the effects of emotional valence. For example, an offline experiment of group processes [41] found a robust evidence of emotional contagion, however for both positive and negative emotion. In the online context, some studies found either non-significant valence effect [14, 42] or a positivity bias in online content virality [43, 46-47].

Another dimension of emotionality is the level of arousal, also known as 'emotional energy' [41] or 'emotional activation' [43]. The arousal dimension has been consistently found to significantly affect the online contagion process. For example, an analysis of retweeting in Twitter [42] revealed that sentiment intensity in tweets was associated with greater retweeting outcomes. Another study [43] found that emotional activation has a causal effect on the willingness of information sharing.

2.2.3. Online swearing, verbal mimicry, and emotional contagion. To summarize, mimicry is an important mechanism for emotional contagion [12]. With absence or lack of nonverbal elements in text-based social interactions, swearing may be particularly functional as a high-arousal emotional marker. Swearing is also a linguistic mannerism. Therefore, picking up others' use of swear words can be understood as a form verbal mimicry that could transmit an aggressive emotional tone.

Previously, the mimicry theory and its applications have highlighted prosocial consequences of mimicking: Mimicry conduces rapport, affinity, and cohesion [33]. A similar branch of the sociolinguistic theory – Communication Accommodation theory –also assumes that linguistic convergence reduces social distance and increases social approval [37]. That is, the desire of affiliation has been proposed to be a primary motivation. However, mimicking disliked others also occurs [44] and such a disliking situation does not engender rapport. In this sense, an alternative explanation of mimicry beyond the affiliation desire could be the competition motive: Mimicking may occur in an attempt to claim one's equivalence in power to others. Especially in terms of swearing in an anonymous setting, rapport-seeking may not always be the primary goal of mimicry, if exist. It is possible that mimicry is rooted in the desire to display compatibility in power or strength. Under this motivation, swearing mimicry is likely to transmit aggression –a high-arousal negative emotional state – among the discussion participants.

3. Research Hypotheses

The main goal of this study is to examine whether or not verbal aggression is contagious in online political discussions. In this study, online emotional contagion is inferred from the occurrences of emotion words – specifically swearing. Our first hypothesis is to test whether swearing in online comments is contagious. Stated differently: Does the occurrence of swearing in the initial –or 'parent' – comment influence the occurrence of swearing in the subsequent –or 'children' – comments? Parent comments are posted directly in response to the main video content. Children comments refer to the follow-up comments that are posted as sub-comments under the parent comment. Therefore, children comments are second-level comments. Together, they constitute a discussion thread and each video has multiple threads.

Parent comments are considered to be important drivers of emotional contagion for two reasons. First, previous research suggests a strong influence of emotional display on the subsequent group dynamics, especially in the early stages of social interactions [38]. Second, mimicry and contagion require exposure to the preceding action(s). In an online discussion setting, commenters may not read every preceding comment; however, it is most likely that the children-level commenters are exposed, at least once, to the parent comment, because a child comment is a sub-comment directly made in reaction to the parent comment. Thus, our first hypothesis is:

H1: The presence of swearing in the parent comment is likely to result in the presence of swearing in its children comments within the discussion thread.

Our second hypothesis pertains to the intensity of swearing. The level of emotional arousal has been consistently linked to the greater likelihood of behavioral mimicking [39] and emotional contagion [42, 43]. While swearing itself is already a high-arousal verbal expression, the intensity of swearing may further influence the tendency of mimicry. We ask whether the intensity of swearing in the parent comment should affect the tendency of swearing occurrences in the subsequent comments.

H2: The intensity of swearing in the parent comment is likely to induce more frequent occurrences of swearing in its children comments within the discussion thread.

4. Research Design

To examine swearing contagion in an online political commenting context, we chose YouTube as an empirical site. A lot of political videos are uploaded, shared and commented on YouTube. Studies have found a nontrivial portion of profanity in YouTube political comments partly due to the possible use of fake accounts on the site [14, 24]. This nontrivial presence of profanity on YouTube comments makes YouTube data ideal for conducting reliable statistical modeling of contagion: For reliable modeling, it is required for the dataset to include some amounts of swearing comments. In addition, YouTube was chosen of the availability of the YouTube public API, a mechanism to collect users' public comments automatically and systematically. It enabled us to collect all the relevant multilevel (i.e., parent-children structure) and chronological comment histories necessary to conduct such a study as this.

4.1. YouTube Videos and Comments Data Collection

User comments were collected from 38 videos posted to the official channel of Donald Trump ("Donald J. Trump for Presidents"), spanning from January 18th, 2016 until the date of our data collection (April 29th 2016).

Using the API tool developed by Digital Methods Initiative at the University of Amsterdam (https://wiki.digitalmethods.net/Dmi/DmiAbout), we collected all public metadata and comments associated with the videos posted to the channel. Among the initial 38 videos, three videos blocked user commenting, resulting in null data. In sum, we collected the total of 23,925 comments from 35 videos. Among them, 13,852 comments constituted 2,075 discussion threads, each of which contained one parent comment and at least one child comment. The rest of the analysis was based on these discussion threads, specifically 2,075 parent comments and 11,777 children comments.

We also collected information about when each video was uploaded, the number of views, likes and dislikes (video level) as well as the date when each comment was posted and its 'like' count.

There were a few of non-English comments, the vast majority of which were in Spanish. These comments were automatically translated into English with the help of Google Translate and Google Spreadsheet.

4.2. Swearing Dictionary

To automatically detect swearing occurrences, we relied on a dictionary of swear words created as part of a previous research project by one of the authors [45]. The dictionary was developed based on the two primary sources: (a) public lists of English swear words freely shared on websites such as noswearing.com; and (b) a custom-built dictionary of swear words and abbreviations (e.g., smfh, stfu, wtf, wth) derived from the automated analysis of over 60,000 Twitter messages. The inter-coder reliability of the Twitter-derived swear words achieved 92.04% agreement, with kappa alpha = .87.

After combining swear words from both sources, we manually reviewed the resulting list and removed any ambiguous words to avoid false positives such as 'killer', 'gay', etc. In total, ours swear word dictionary consisted of 432 words (including derived forms). Finally, to compute the occurrences of swear words, we added the resulting dictionary to research software called Linguistic Inquiry and Word Count (LIWC) [48] and used it to analyze the full dataset.

4.3. Variables

4.3.1. Independent variables: Swearing in parent comments. The two primary independent variables were: (a) *presence of swearing in a parent comment* – a binary variable indicating whether or not any of the swear words from our dictionary was detected in the parent comment; (b) *intensity of swearing in a parent comment* – the total number of swear words detected in the parent comment. For example, a comment with five swear words received the intensity score of 5, while a comment with a single swear word received the intensity score of 1. Below are the exemplary comments (original).

"You fucking dictator! Fuck you! You don't know what it's like to live without a house and without freedom motherfucker! make America great again? Brainwashing people into voting for you! This is the new fucking Adolfo hitler motherfuckers!" (5 swear words)

"At least Hillary doesn't discriminate people like that nazi fuck Trump. You see how your boy Trump made fun of a disabled reporter a while back some guy. He hates women as well but your too blind to see that. I hope you enjoy voting for that cold hearted celebrity as our president" (1 swear word)

4.3.2. Dependent variables: Swearing in children comments. The two dependent variables were: (a) the *presence of swearing in children comments* – a binary variable whether or not any swear word occurs in at least one child comment following the given parent comment; and (b) the *intensity of swearing in children comments* – the total number of children comments that contained any swear words.

4.3.3. Comment-level control variables. Because the unit of analysis was an individual thread, we controlled for the following parent comment-related variables as they could potentially influence the results: *total word count*, *proportion of UPPERCASED words*, and *like vote count* for each parent comment. In addition, the time lag between the time of video upload and of the parent comment posting was controlled. This is to account for a potential temporal effect on swearing tendency. Finally, we also controlled for the *total number of children comments* within each thread due to a potential confounding effect of the quantity of comments on swearing occurrences.

4.3.4. Video-level control variables. Comment threads were nested in different videos. Therefore, we controlled video-level variables that could confound the result. First, video popularity, represented by the *total view counts*, was controlled. Second, favorability of video, computed by *like votes* divided by sum of like and dislike votes, was controlled.

5. Results

Considering the hierarchical data structure (comments nested in each video), we employed random effect modeling to address both the video-level as well as comment-level effects. Specifically, multilevel logistic modeling was performed to examine our hypothesis number 1 (H1), and multilevel linear modeling to examine hypothesis number 2 (H2). However, the intra-class correlation coefficients (ICC) were relatively small, .026 and .065 respectively, indicating that only a small proportion of the total variance was accounted for by the video-level random effect. We also compared the results from multilevel models to the conventional logistic and OLS regression modeling results. All but binary variables were log-transformed to reduce skewness.

5.1. Descriptive Analyses

Table 1 shows the summary of mean and standard deviation of each variable. On average, the parent comment was 27.59 word long, was posted 9.15 days after the video upload, received 16.31 likes, and included 9.26% of uppercased letters. About 24% of parent comments included swearing to some extent. The average number of swear words in a parent comment was 0.41 words. Swearing appeared almost twice more in children comments, 42%, than in parent comments. The average number of swear words in children comments was also higher than in parent comments, 1.41 words.

5.2. Multilevel Logistic Modeling (H1)

H1 posits that the presence of swearing in the parent (initial) comment will increase the likelihood of swearing in its children comments. To test, multilevel logistic model was performed (Table 2). The overall classification accuracy was 77.3%.

Not surprisingly, the total number of children comments was strongly associated with the probability of swearing occurrences in children comments, b = 2.25, t = 19.40, $p < .001$. In addition to the effect of the quantity of children comments, another significant predictor was the presence of swearing in the parent comment, b =0.57, t = .43, p <. 001.

These results remained consistent when compared to the ordinary logistic model (Table 3). The ordinary logistic model indicated that swearing in children comments was 1.78 times more likely to occur when the parent comment contained swearing than not. The result supported H1. Figure 1 visualizes the effect of swearing on the subsequent presence of swearing.

Table 1. Descriptive Statistics (RC *N* = 2,075)

Variables	Original		Log-Transformed	
	M	SD	M	SD
Like count in PC	16.31	61.52	1.31	1.50
Time lag	9.15	17.78	1.28	1.30
Word count in PC	27.59	39.86	2.83	0.97
Swearing Intensity in PC (Count)	0.41	1.03	0.22	0.43
Swearing Presence in PC (Binary)	0.24	0.43	-	-
Uppercases in PC	9.26	17.23	1.67	1.02
# of CC	5.68	12.71	1.38	0.82
Swearing Frequency in CC (Count)	1.41	4.16	0.48	0.71
Swearing Presence in CC (Binary)	0.42	0.49	-	-
Video popularity	163K	165K	11.50	1.04
Video favorability	0.50	0.04	0.41	0.03
Note: PC = parent comment; CC = children comments				

Table 2. Multilevel logit model of the effect of swearing presence in the parent comment on the likelihood of swearing in its children comments

	B	SE	t	C.I.	
				L	U
Intercept	-2.2	2.7	-.83	-7.51	3.05
Swearing Presence in PC ***	**.57**	**.13**	**4.43**	**.32**	**.82**
# of CC ***	**2.25**	**.12**	**19.40**	**2.02**	**2.47**
Word count in PC	-.01	.06	-.10	-.12	11
Uppercase in PC	.05	.06	.96	-.06	.17
Like count in PC	-.06	.05	-1.09	-.16	.04
Time lag	.07	.06	1.28	-.04	.18
Video popularity	.04	.10	.43	-.16	.25
Video favorability	-4.7	4.24	-1.10	-12.97	3.68
Note: PC = parent comment; CC = children comments; *** *p* <.001					

Table 3. Ordinary logistic model of the effect of swearing presence in the parent comment on the likelihood of swearing in its children comments

	B	SE	Wald	Exp(B)
Intercept	-2.32	2.15	1.16	.10
Swearing Presence in PC ***	**.58**	**.13**	**20.12**	**1.78**
# of CC ***	**2.24**	**.12**	**379.37**	**9.41**
Word count in PC	-.01	.06	.02	.99
Uppercase in PC	.06	.06	1.13	1.06
Like count in PC	-.06	.05	1.43	.94
Time lag	.06	.05	1.50	1.06
Video popularity	0.08	.08	1.07	1.08
Video favorability	-3.89	3.36	1.34	.02
Note: PC = parent comment; CC = children comments; *** *p* <.001				

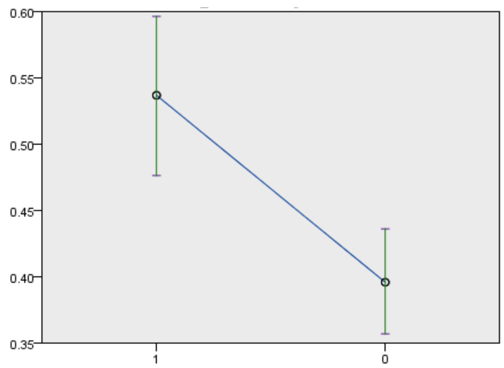

Figure 1. Effect of initial swearing on the likelihood of subsequent swearing. X-axis = Swearing in the parent comment; Y-axis = Probability of swearing in its children comments.

5.2. Multilevel Linear Modeling (H2)

H2 posits that the intensity of swearing in the parent comment should increase the frequency of swearing in its children comments. To test, multilevel linear modeling was performed (Table 4).

Similar to the logistic model, the total number of children comments increased the swearing frequency in children comments, b = .71, t = 50.64, p < .001. In addition to the quantity of children comments, two other variables were also significant. First, the time lag of the parent comment was weakly yet positively associated with swearing frequency in its children comments, b = .026, t = 2.787, p < .01. That is, swearing is more likely to target the comments that are posted a while after the video is uploaded.

Another significant variable was the intensity of swearing in the parent comment, b = .138, t = 6.247, p < .001. More swearing in the parent comment resulted in more frequent swearing in its children comments. The model was replicated with the OLS regression design (Table 5), which accounted for 65.8% of variances. The results were mostly consistent, except that the OLS model additionally resulted in a weakly positive effect of the video popularity, b = .04, t = 2.189, p < .05. Both multilevel and OLS linear models supported H2.

Table 4. Multilevel linear model of the effect of swearing intensity in the parent comment on the swearing frequency in its children comments

	B	SE	T	C.I.	
				L	U
Intercept	-.51	.45	-1.12	-1.40	.38
Swearing Intensity in PC ***	**.14**	**.02**	**6.25**	**.10**	**.18**
# of CC ***	**.71**	**.02**	**50.64**	**.68**	**.74**
Word count in PC	-.02	.01	-1.47	-.03	.00
Uppercases in PC	.01	.01	.93	-.01	.03
Like count in PC	-.01	.01	-1.24	-.03	.01
Time lag**	**.03**	**.01**	**2.79**	**.01**	**.04**
Video popularity	.02	.02	1.07	-.02	.05
Video favorability	-.57	.72	-.79	-1.98	.84

Note: PC = parent comment; CC = children comments; *** p <.001; ** p <.01

Table 5. OLS linear model of the effect of swearing intensity in the parent comment on the swearing frequency in its children comments

	B	SE	t
Intercept		.35	-1.84
Swearing Intensity in PC ***	.085	.02	**6.32**
# of PC ***	.82	.01	**50.77**
Word count in CC	-.02	.01	-1.52
Uppercases in CC	.013	.01	.99
Like count in CC	-.02	.01	-1.35
Time lag**	**.04**	**.01**	**2.66**
Video popularity*	**.04**	**.01**	**2.18**
Video favorability	-.02	.55	-.82

Note: PC = parent comment; CC = children comments; *** p <.001; ** p <.01; * p <.05; adjusted R-Square = .658

6. Conclusion and Discussions

Aggressive emotional exchanges have become increasingly common in contemporary online culture. Online political discussions are no exception. When the Internet's culture of self-expression meets with political polemics, belligerent emotional exchanges that deter respectful discussions seem to be, unfortunately, one of the frequently occurring by-products. Based on the mimicry and emotional contagion theories, the current study demonstrates how users' aggressive emotional displays shape the communal discourse on YouTube.

In particular, swearing is an explicit speech act that provokes high-arousal –i.e., aggressive –emotion. The study chooses to investigate swearing as an indicator of aggressive emotional display. The function of swearing as an emotional marker may be especially prominent in text-based social interaction contexts where other nonverbal cues are largely absent. Provided that a fundamental mechanism underlying emotional contagion is mimicry [12], the study examines mimicry tendency of online swearing.

The results provide evidence of swearing contagion, in terms of both its presence and intensity. The presence and intensity of swearing in parent comments increase the probability and frequency of swearing in their children comments. Our findings are consistent with previous literature on speech mimicry in text-based social interactions and emotional contagion in online social networks [14, 36]. Although we should be cautious about equating verbal mimicry of swearing to actual emotional convergence, our results demonstrate that individual swearing may (and likely do) propagate from comments to comments, echoing some of the previous concerns about negative consequences of emotional contagion in online political discussions [4-8].

Note the study is based on the assumption that swearing practice conveys negative valence and high activation of emotion. Further validation should be done to confirm whether online swearing in the context of political discussions indeed induces negativity and high-arousal emotion.

As this is the first stage of a larger initiative on studying aggressive emotionality in social media, our future work will expand this line of research into the following directions. First, while the literature review discusses the difference between interpersonal and public swearing, the current analysis did not distinguish between the two. Given that the two types of swearing are subtly different in their conceptual boundaries and outcomes, further discussion is required to determine the impact of public swearing on the occurrence of interpersonal swearing, or vice versa, and whether public swearing should be regarded as mimicry or contagion. Understanding the extent to which aggressive expressions occur interpersonally as opposed to publicized outbursts may help develop specific policy recommendations for reducing incivility online.

Second, one interesting finding from this study is a positive effect of a time lag between when a video was posted and when a comment about the video was posted e.g. earlier comments in a video are more civil as compared to comments that are posted later. For example, YouTube could inform channel subscribers (pro-Trump audiences in this study context) about video uploads immediately, and creating a time lag in the comments before non-subscribing outsiders who found the video via a different route joined the conversation.

In addition, the dimension of message attributes also deserves further examination. For example, different swear words convey a different level of emotional intensity. While the current study measured the intensity of swearing basedcould have on the count of swear words, some swear words could convey much harsher connotations than 'milder' swear words. Also, a single comment could be quoted by other commenters multiple times. Future analysis will need to check and account for this possibility.

Another limitation of this study is that we have not accounted for potential user- or video-related biases. Regarding the user bias, we have not examined whether a single user's leaving multiple messages influence our results. Also, user's anonymity was not taken into consideration in modeling. Regarding the video content, emotional valence and emotion activation expressed by a video message could influence swearing tendency. Since the current analysis only focused on the video-level metadata (i.e., video popularity and vote-based favorability), our future work will also consider video content itself. For example, we would like to examine whether a politician's aggressive speech in the video facilitates audiences' swearing mimicry?

Lastly, our findings are based on a particular political candidate campaign (Donald Trump) on a particular social media platform (YouTube). Our future work will compare swearing behavior among commenters on other candidates' YouTube channels. This will help us understand the relationship between the nature of political candidates/topics and online public's tendency for emotional aggression.

Swearing is a verbal marker of high-arousal emotion as well as a speech habit. Mimicry of swearing could potentially induce negative emotional contagion. While the majority of mimicry literature have addressed prosocial motives and positive outcomes [33, 36, 37], mimicry of hostile verbal expressions –especially in anonymous social online interaction contexts –could manifest different goals and be linked to negative consequences. The gap between the existing mimicry theory and the phenomena of online swearing mimicry –and other negative emotional contagion –calls for further theoretical development. From a practical perspective, the findings of the study suggest an important role of initial comments in setting the tone for the subsequent discussion. When there is a need to moderate an online community for the sake of maintaining respectful discussions and promotion of civility, it is recommended for community managers to pay special attention to the parent posts and implement intervention efforts during the initial phase of discussions as needed.

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