Understanding the Bystander Effect on Toxic Twitter Conversations

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ABSTRACT
As more users continue to embrace social media, online harassment and abusive language have become a growing concern. In this study, we explore the power of group dynamics to shape the toxicity of Twitter conversations. First, we examine how the presence of others in a conversation can potentially diffuse Twitter users’ responsibility to address a toxic direct reply. Second, we examine whether the toxicity of the first direct reply to a toxic tweet in conversations establishes the group norms for subsequent replies. By doing so, we outline how bystanders and the tone of initial responses to a toxic reply are explanatory factors which affect whether others feel uninhibited to post their own abusive or derogatory replies. We test this premise by analyzing a random sample of more than 156k tweets belonging to ~ 9k conversations. Central to this work is the social psychological research on the “bystander effect” documenting that the presence of bystanders has the power to alter the dynamics of a social situation. Twitter users may rely on cyberbystanders to condone his or her derogatory behaviors towards others. If the first direct reply reaffirms the divisive tone, other replies may follow suit. We find evidence of a bystander effect, with our results showing that an increased number of users participating in the conversation before receiving a toxic tweet is negatively associated with the number of Twitter users who responded to the toxic reply in a non-toxic way. We also find that the initial responses to toxic tweets within conversations is of great importance. Posting a toxic reply immediately after a toxic comment is negatively associated with users posting non-toxic replies and Twitter conversations becoming increasingly toxic. Thus, understanding how social media users respond when they witness uncivil comments or abusive language reveals social norms as powerful determinants of human behavior online.

CCS CONCEPTS
• Information systems → Social networking sites.

INTRODUCTION
Social media and online communities allow individuals to freely express opinions, engage in interpersonal communication, and learn about new trends and news stories. However, these platforms also create spaces for uncivil behavior. In particular, toxicity as explicit language, derogatory, aggressive, or disrespectful content has become endemic on online platforms [1, 18, 27, 39, 56]. There is growing concern over incivility over social media platforms and its effects on online communities [17, 42]. How groups react to divisive behavior or the use of hateful language reflects social norms online- either spreading negative behaviors, calling out racist or sexist behavior, or ignoring toxic behaviors [4].

Toxic behavior often occurs in the presence of bystanders whose behaviors can play a key role in changing the dynamics of a social situation. Bystanders are central to shaping the reactions to toxic behaviors, whether users actively follow the perpetrator’s behavior by posting toxic replies, attempting to stymie the toxicity of the conversation, or simply watching the conversation unfold. The belief that people behave differently in groups is a well established social psychological tenet. But less attention has been made to how these dynamics play out on Twitter, as one of the leading micro-blogging social media platforms. In-person and online, the presence of bystanders often inhibit prosocial behavior such as attempting to come to the aid of a person who has become a target of hate speech, cyberbullying, or trolling. The presence of others can diffuse one’s sense of responsibility to help, with users believing another individual will act. Inversely, in a smaller group setting people feel a greater responsibility to intervene in incidents of cyberbullying [38].

In this paper, we assess a random sample of Twitter conversations to examine how group dynamics can be a social determinant of online behavior. How does the presence of others in a conversation diffuse Twitter users’ responsibility to address a toxic direct reply? How does the response to a toxic reply shape the tone of conversation by serving as a social cue, indicating the unacceptability of such language to other users.
HYPOTHESES
The current study proposes and tests a series of hypotheses about the effects of group dynamics on the toxicity of Twitter conversations. We hypothesize the number of Twitter users who participated in the conversation will be viewed as bystanders and affect whether users feel it necessary to respond to a toxic reply: H1: The number of users participating in a conversation before observing the first toxic reply is negatively associated with the number of users who post non-toxic replies after the first toxic reply.

We make this prediction because the bystander effect has been well documented offline, often in a laboratory setting [21]. The phenomenon of the bystander effect is the presence of people (e.g., bystanders) in a situation that influences an individual’s likelihood of helping a stranger or intervening on another’s behalf [9]. Both diffusion of responsibility or audience inhibition have been used as explanatory factors for the bystander effect, especially in online settings. Extant scholarship has found that the anonymity provided through online platforms can lead to disinhibition [50], deindividuation, and a lack of accountability [7, 33], which can encourage negative behavior [20, 28, 34, 47]. Diffusion of responsibility occurs because the presence of others makes one less likely to intervene in a situation, believing that someone in the crowd or group will respond. Existing research has documented the diffusion of responsibility effect on online message boards [35] and over email when multiple recipients were included in the request for help [5].

Bystanders can be central to shaping the reactions to toxic behavior online, whether they actively follow the perpetrator’s behavior by posting toxic replies or attempting to re-establish norms of decorum. Once established it is not surprising that individuals generally conform to group norms [2]. Other work shows that observing trolling behavior by others influences new users [8]. In other words, individuals may be more likely to post toxic replies after seeing others do it, believing it to be the norm.

Peer conformity is positively associated with in-person bullying [16] and cyberbullying [3, 6]. In this instance, we might expect the toxicity of tweets within the conversation to alter based on the introduction and reaffirmation of toxic content. If the first toxic tweet was met with derision and that user informally sanctioned or ignored by other users, one might view such tweets as inappropriate. But if users see an initial toxic reply followed by another toxic tweet, others might follow suit believing that toxic behavior to be the norm. Thus, we propose the following two hypotheses: H2: If a Twitter user posts a non-toxic reply immediately after the toxic reply then more users post non-toxic replies. H3: If a Twitter user posts a non-toxic reply immediately after the toxic reply then the toxicity of the conversation after this reply is more likely to be non-toxic.

RELATED WORK
Bystander Intervention: Foundational social psychological literature documents a bystander effect in which people are less likely to help a stranger or to intervene on their behalf [9, 32]. Research on cyberbullying has demonstrated that increasing the number of bystanders decreases intentions to intervene [38]. However, other scholarship has shown that when individuals are aware they are visible to others, by using a webcam or making participants’ screen-names more salient can reverse this effect [54]. Additionally, cohesive groups are often less susceptible to the bystander effect [43]. Understanding the victim’s perspective or empathizing with the target influence one’s intentions of helping the victim [15, 22, 40]. Other scholarship has found that users’ tend to intervene out of a sense of moral duty or feel responsible to help [12, 15, 30, 38]. Victims of online aggression or adolescent cyberbullying are more also likely to stand up for others [11, 26, 46].

Detection and Classification. Empirical work on toxicity has employed machine learning based detection algorithms to identify and classify offensive language, hate speech, and cyberbully [10, 29, 41, 57]. The machine learning methods use a variety of features, including lexical properties, such as n-gram features [37], character n-gram features [36], character n-gram features [36], character n-gram, demographic and geographic features [55], sentiment scores [13, 23, 49], average word and paragraph embeddings [14, 37], and linguistic, psychological, and effective features inferred using an open vocabulary approach [19]. The state-of-the-art toxicity detection tool is available through Google’s Perspective API [24]. Perspective API has been studied and used extensively in the previous literature [19, 25, 31, 44, 45, 48, 56]. Hence, in this project, we will use Google Perspective API to detect toxic tweets in conversations.

DATA COLLECTION
We used Twitter API [53] to collect a random sample of recent public tweets during the period of August 14th to September 28th, 2021. We pulled out English tweets that are retweets or replies in other public conversations. We also removed the conversations where the replies for the tweets were all posted by the author of the initial tweet. We then used Twarc [52], to collect the full conversation for each initial tweet in the dataset. We call the user who posted the initial tweet as root author and we present a full conversation as a tree that started with the initial tweet named the root tweet. As illustrated in Figure 1, each conversation is represented as a tree structure whose tweets (nodes) are connected when one is a reply to the other. We also removed tweets that only had links, images, and videos instead of text as Perspective API is a text based toxicity detection tool [24]. Thus, the cleaned dataset consists of 79,799 conversations with 528,041 tweets, posted by 328,390 unique users.

Discovering Conversations with Toxic Replies. To identify all the toxic tweets in our dataset, we employed Google’s Perspective API [24]. Google Perspective API applies different machine learning models to score the toxicity of textual data, including Toxicity, Severe Toxicity, etc. In this paper, we are only considering scores for the Severe Toxicity attribute since Google’s Perspective API defines a text having this attribute as rude, disrespectful, or unreasonable comment which meets the general standards for a comment which might be considered to be hateful or toxic. We created a binary variable to label if a tweet is toxic or not toxic. In more detail, a tweet is labeled as toxic if its severe toxicity score is higher or equal to 0.5. The score threshold of 0.5 was established by two independent coders who manually labelled 200 random tweets with an inter-rater agreement of 94% and a Cohen’s kappa of 0.69. Such results indicate a substantial agreement for severe toxicity between the manual coders and the Google Perspective API for scores
We use multivariate regression analysis to test the hypotheses regarding the bystander effect in our dataset. Below, we explain our dependent, independent, and control variables in detail.

**Independent Variables** We define the following independent variables: (1) users_before_toxic: the number of unique users engaged in the conversation before the first toxic comment occurred. Examples of such tweets are colored in blue in Figure 1. Note that even though some replies are at the higher level in the conversation tree, it does not necessarily mean that they occurred before the first toxic comment. Similarly, some replies might be at the lower depth level in the conversation tree, but can still be posted after the first toxic comment. Consequently, this variable has been computed by chronologically ordering all tweets in the conversation from the oldest to the youngest, and then calculating the number of unique users that posted tweets older than the first toxic tweet. For this variable, we could instead use the number of followers that victims have, but knowing that their accounts are public implies that there might be more people observing the conversation. Furthermore, followers might be observing the conversation, however, as they do not engage in the conversation before the first toxic tweet, it is hard to claim that they are interested in this conversation. Therefore, we use the number of followers as a control variable in our regression models. (2) reply_toxicity: the toxicity score of the first comment posted that is a direct reply to the first toxic comment in the conversation, e.g., circled in green in Figure 1.

**Control Variables** We controlled for factors that can potentially impact the group behaviors in Twitter conversations. We added controls for root authors’ activity, i.e., num_friends, num_tweets and account_age, because more active users might have different audiences. For example, if a user posts many tweets, then the followers might engage less in their conversations. We also controlled for the visibility i.e., num_followers, listed_counts and verified. For example, users who have verified accounts or are influencers, with many followers might receive more help from others when they are under the toxicity attack. Additionally, we controlled for profile characteristics, such as description_length, has_URL, has_location and has_image. Users who provide more information on their accounts might experience a higher level of bystanders effect as other users might not want to defend the anonymous users. Finally, we used the width and depth of the conversation tree to control for different conversation structures. Depth is the length from the root tweet to the conversation’s deepest node, and width represents the maximum number of tweets at any level in the conversation tree.

**DATASET CHARACTERIZATION**

Our final dataset consists of 9,171 conversations with 156,655 tweets, posted by 101,419 unique users. The minimum number of tweets in conversations is 2 and the maximum is 1,842. The mean number of tweets included in these conversations is 17. Table 1 shows the descriptive statistics of the variables used in the statistical models. In more than half of conversations, the number of users engaged in the conversation before the first toxic reply (users_before_toxic) is 2, while the maximum number is 1710. At the same time, the average of reply_toxicity is 0.21. The mean number of unique_users_non_toxic is 0.41, indicating that in more than half of the conversations, there are no users who posted non-toxic comments after the first toxic reply. Additionally, the minimum remaining_toxicity is 0.03, while the maximum remaining_toxicity is 0.9.
### RESULTS

To test hypotheses H1 and H2, we employed a Poisson regression model as the distribution of `unique_users_non_toxic` does not follow a normal distribution. We ran a linear regression model to test hypothesis H3, as `remaining_toxicity` follows a normal distribution.

The results obtained from a Poisson regression model in Table 2 (column H1) reveals a statistically significant negative association between the `unique_users_non_toxic` and `users_before_toxic` (p < 0.001). This suggests that the higher number of users participating in the conversation before the first toxic comment, the lower the number of users posting non-toxic replies after that comment, supporting H1. Additionally, the results show that verified, older accounts with the longer description are less likely to receive non-toxic comments from users after the first toxic reply, while it is the opposite for root authors who specified locations on their profiles. Moreover, wider and deeper conversations are more likely to have a higher number of users posting non-toxic replies.

According to H2, the first reply immediately after the first toxic reply might play an important role in how the rest of the conversation continues. For this analysis, we discarded conversations that do not contain a direct reply to toxic tweet, leaving the dataset with 3,770 conversations, consisting of 58,869 tweets posted by 29,258 unique users. `Reply_toxicity` was used as the independent variable in the Poisson regression model. Table 2 (column H2) shows that there is a negative statistically significant association between `reply_toxicity` and `unique_users_non_toxic` (p < 0.001). Such findings indicate that more people are willing to post more toxic comments if the first reply after the toxic comment is toxic, supporting H2. The findings also show that conversations belonging to verified accounts receive more `unique_users_non_toxic`, which contradicts the results obtained when testing H1. The reason behind this trend could be the smaller dataset included in the model testing H2.

H3 shows that the toxicity of the first comment after the first toxic reply might determine the direction in which the conversation thread will emerge. In other words, if the first reply to a toxic reply is toxic, the whole conversation thread might become more toxic. In this case, conversations that have less than two tweets after the first toxic reply are removed, leaving 1,959 conversations for the analysis. Furthermore, `reply_toxicity` was used as an independent variable in the linear regression model, while the dependent variable used was `remaining_toxicity`. The model results (Table 2 - column H3) indicate that there is a positive statistically significant association between `reply_toxicity` and `remaining_toxicity` (p < 0.001). This shows that the higher toxicity of the immediate comment after the first toxic reply, the higher the probability that the entire conversation thread will become toxic, supporting H3. Furthermore, the results reveal that `remaining_toxicity` decreases as conversations `depth` and `width` increases.

### DISCUSSION

The present study sheds light on the practical question of how to fight toxicity online. Online settings afford us the opportunity to investigate how quickly such group norms are established and how closely one’s actions conform to what is deemed appropriate or expected in the group [51]. Within our study, we find that the initial response to toxic tweets within conversations carries great influence. If the first response to a toxic reply is more toxicity, then the conversation subsequently becomes increasingly toxic and harmful. However, by this logic, if users can ignore or attempt to respond to incivility with compassionate responses then the conversation might be salvaged. Future work should investigate the effects of a single tweet or the number of Twitter users who stand up against cyberbullying or the hate speech as potential interventions. One limitation was that our sample of main tweets was restricted to those in English due to the constraints imposed by the Perspective API toxicity classification program, which restricts the generalizability of our findings. Moreover, our study cannot capture the number of 'true' bystanders who see toxicity online and do nothing: opting to post neither toxic or non-toxic tweets. Lastly, within the scope of this study we were unable to qualitatively examine the intent of non-toxic tweets. Despite these limitations, our results suggest that the diffusion of responsibility through increased conversational participants is associated with fewer users attempting to stand up to toxic replies. These findings help
explain why bystanders often fail to intervene to defend a victim of bullying or harassment online.

CONCLUSION
In this study we assessed a random sample of Twitter Conversations to understand how group dynamics and a bystander effect can lead to disinhibition of users’ toxic replies. We find evidence of a bystander effect with increased conversational participants being associated with fewer Twitter users standing up to a toxic reply. We also highlight the importance of initial responses to a toxic tweets within a conversation. Our results demonstrate that posting a toxic reply immediately after a toxic comment predicts that the Twitter conversation will become increasingly toxic.

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REFERENCES
[1] Ashley A Anderson, Sara K Yeo, Dominique Brossard, Dietram A Scheufele, and Michael A Xenos. 2016. Toxic talk: How online incivility can undermine perceptions of media. International Journal of Public Opinion Research 30, 1 (2016), 156–168.
[2] Solomon E Asch. 1956. Studies of independence and conformity: I. A minority of one against a unanimous majority. Psychological monographs: General and applied 70, 9 (1956), 1.
[3] Sara Bastaensens, Sara Pabian, Heidi Vandeboel, Karolien Poels, Katrien Van Cleemput, Ann DeSmet, and Ilse De Bourdeaudhuij. 2016. From normative influence to social pressure: How relevant others affect whether bystanders join in cyberbullying. Social Development 25, 1 (2016), 193–211.
[4] Amy Bimis. 2012. DON’T FEED THE TROLLS! Managing troublemakers in magazines’ online communities. Journalism practice 6, 4 (2012), 547–562.
[5] Carrie A Blair, Lori Foster Thompson, and Karl L Wuesth. 2005. Electronic helping behavior: The virtual presence of others makes a difference. Basic and Applied Social Psychology 27, 2 (2005), 171–178.
[6] Danielle NM Bleieze, Martin Tanis, Doeschka J Anschütz, and Moniek Buijn. 2021. A social identity perspective on conformity to cyber aggression among early adolescents on WhatsApp. Social Development 30, 4 (2021), 941–956.
[7] Alexander Brown. 2018. What is so special about online (as compared to offline) hate speech? Ethnicities 18, 3 (2018), 297–326.
[8] Justin Cheng, Michael Bernstein, Cristian Danescu-Niculescu-Mizil, and Jure Leskovec. 2017. Anyone can become a troll: Causes of trolling behavior in online discussions. In Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing. 1217–1230.
[9] John M Darley and Bibb Latané. 1968. Bystander intervention in emergencies: diffusion of responsibility. Journal of personality and social psychology 8, 4 (1968), 377.
[10] Thomas Davidson, Dana Warmels, Michael Macy, and Ingmar Weber. 2017. Automated hate speech detection and the problem of offensive language. In Eleventh international aaai conference on web and social media.
[11] Ann DeSmet, Sara Bastaensens, Katrien Van Cleemput, Karolien Poels, Heidi Vandeboel, Greet Cardon, and Ilse De Bourdeaudhuij. 2016. Deciding whether to look after them, to like it, or to leave it: A multidimensional analysis of predictors of positive and negative bystander behavior in cyberbullying among adolescents. Computers in Human Behavior 57 (2016), 398–415.
[12] Dominic DiFranzo, Samuel Hardman Taylor, Francescak Kazerouni, Olivia D Wherry, and Natalya N Barazova. 2018. Upstanding by design: Bystander intervention in cyberbullying. In Proceedings of the 2018 CHI conference on human factors in computing systems. 1–12.
[13] Karthik Dinkar, Birgito Jones, Catherine Havasi, Henry Lieberman, and Rosalind Picard. 2012. Common sense reasoning for detection, prevention, and mitigation of cyberbullying. ACM Transactions on Interactive Intelligent Systems (TiiS) 2, 3 (2012), 18.
[14] Nemanja Djuric, Jing Zhou, Robin Morris, Mihajlo Grbovic, Vladan Radosavljevic, and Narayan Bhamidipati. 2015. Hate speech detection with comment embeddings. In Proceedings of the 24th international conference on world wide web. ACM–29, 30.
[15] Fernando Dominguez-Hernández, Lars Bonell, and Alejandro Martínez-González. 2018. A systematic literature review of factors that moderate bystanders’ actions in cyberbullying. Cyberpsychology: Journal of Psychosocial Research on Cyberspace 12, 4 (2018).
[16] Amanda L Duffy and Drew Nesdale. 2009. Peer groups, social identity, and children’s bullying behavior. Social development 18, 1 (2009), 121–139.
[17] Marsee Dugan. 2014. Online harassment. Pew Research Center.
[18] William H Dutton. 1996. Network rules of order: Regulating speech in public electronic fora. Media, Culture & Society 18, 2 (1996), 269–290.
[19] Maria Elberich, Vivek Kulkarni, Dina Nguyen, William Yang Wang, and Elizabeth Belding. 2018. Hate lingo: A target-based linguistic analysis of hate speech in social media. In Twelfth International AAAI Conference on Web and Social Media.
[20] Pınna Fichman and Elizabeth Peters. 2019. The impacts of territorial communication norms and composition on online trolling. International Journal of Communication 13 (2019), 20.
[21] Peter Fischer, Joachim I Krueger, Tobias Greitemeyer, Claudia Vogrinic, Andreas Kastenmüller, Dietrich Frey, Moritz Heene, Magdalena Wicher, and Martina Kainbacher. 2011. The bystander effect: A meta-analytic review on bystander intervention in dangerous and non-dangerous emergencies. Psychological bulletin 137, 4 (2011), 517.
[22] Stephanie D Frei and Regan AR Gurung. 2013. A Facebook analysis of helping behavior in online bullying. Psychology of popular media culture 2, 1 (2013), 11.
[23] Niayi Dennis Gitari, Zhang Zuping, Hanyurwimfura Damien, and Jun Long. 2015. A lexicon-based approach for hate speech detection. International Journal of Multimedia and Ubiquitous Engineering 10, 4 (2015), 215–230.
[24] Google Perspective API. 2021. https://www.perspectiveapi.com/.
[25] Tommi Gröndahl, Luca Pajsola, Mika Juuti, Mauro Conti, and N Asokan. 2018. All You Need is ‘Love’ Evading Hate Speech Detection. In Proceedings of the 11th ACM Workshop on Artificial Intelligence and Security. 2–12.
[26] Billy Henson, Bonnie S Fisher, and Bradford W Reyns. 2020. There is virtually no excuse: The frequency and predictors of college students’ bystander intervention behaviors directed at online victimization. Violence Against Women 26, 5 (2020), 505–527.
[27] Hyeonae Hwang, Porimita Borah, Kang Namkoong, and A Veenstra. 2008. Does civility matter in the blogosphere? Examining the interaction effects of incivility and disagreement on citizen attitudes. In 58th Annual Conference of the International Communication Association, Montreal, QC, Canada.
[28] Sara Kiesler, Jane Siegel, and Timothy W McGuire. 1984. Social psychological aspects of computer-mediated communication. American psychologist 39, 10 (1984), 1123.
[29] Animesh Koratana and Kevin Hu. [n. d.]. Toxic Speech Detection. [In n. d.].
[30] Robin M Kowalski, Amber N Schroeder, and Carrie A Smith. 2013. Bystanders and their willingness to intervene in cyberbullying situations. From cyber bullying to cyber safety: Issues and approaches in educational contexts (2013), 77–100.
[31] Nihal Kumarswamy et al. 2022. "Strict Moderation?" The Impact of Increased Moderation on Poster Content and User Behavior. Ph. D. Dissertation.
[32] Bibb Latané and John M Darley. 1969. Bystander apathy". American Scientist 57, 2 (1969), 244–268.
[33] So-Hyun Lee and Hee-Woong Kim. 2015. Why people post benevolent and malicious comments online. Communication. ACM 58, 11 (2015), 74–79.
[34] Paul Benjamin Lowry, Jun Zhang, Chuang Wang, and Mikko Siponen. 2016. Why do adults engage in cyberbullying on social media? An integration of online disinhibition and deindividuation effects with the social structure and social communication norms and composition on online trolling. Computers in Human Behavior 16, 2 (2000), 183–188.
[35] Yashar Mehdayd and Joel Tetreault. 2016. Do characters abuse more than words?. In Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue. 299–303.
[36] Chikashi Nomata, Joel Tetreault, Achint Thomas, Yashar Mehdad, and Yi Chang. 2016. Abusive language detection in online user content. In Proceedings of the 25th international conference on world wide web. International World Wide Web Conferences Steering Committee, 145–153.
[37] Magdalena Obermaier, Nayla Fawzi, and Thomas Koch. 2016. Bystanding or standing by? How the number of bystanders affects the intention to intervene in cyberbullying. New media & society 18, 9 (2016), 1491–1507.
[38] Zizi Papacharissi. 2002. The virtual sphere: The internet as a public sphere. New media & society 4, 1 (2002), 9–27.
[39] Jeremy L Paterson, Rupert Brown, and Mark A Walters. 2019. The short and longer term impacts of hate crimes experienced directly, indirectly, and through the media. Personality and Social Psychology Bulletin 45, 7 (2019), 994–1010.
[40] Georgios K Pitsilis, Heri Ramampiaro, and Helge Langseth. 2018. Detecting offensive language in tweets using deep learning. arXiv preprint arXiv:1803.04643 (2018).
[41] Katja Rost, Lea Stahel, and Bruno S Frey. 2016. Digital social norm enforcement: Online firestorms in social media. PLoS one 11, 6 (2016), e0155923.
[42] Gabriel K Rutkowski, Charles L Gruder, and Daniel Reyner. 1993. Group cohesiveness, social norms, and bystander intervention. Journal of Personality and Social Psychology 44, 3 (1983), 545.
[44] Nazanin Salehabadi, Anne Groggel, Mohit Singhal, Sayak Saha Roy, and Shirin Nilizadeh. 2022. User Engagement and the Toxicity of Tweets. https://doi.org/10.48550/ARXIV.2211.03856
[45] Martin Saveski, Brandon Roy, and Deb Roy. 2021. The structure of toxic conversations on Twitter. In Proceedings of the Web Conference 2021. 1086–1097.
[46] Karina Schumann, Jamil Zaki, and Carol S Dweck. 2014. Addressing the empathy deficit: beliefs about the malleability of empathy predict effortful responses when empathy is challenging. Journal of personality and social psychology 107, 3 (2014), 479.
[47] Jane Siegel, Vitaly Dubrovsky, Sara Kiersle, and Timothy W McGuire. 1986. Group processes in computer-mediated communication. Organizational behavior and human decision processes 37, 2 (1986), 157–187.
[48] Mohit Singhal, Chen Ling, Pujan Paudel, Poojitha Thota, Nihal Kumarswamy, Gianluca Stringhini, and Shirin Nilizadeh. 2022. SoK: Content Moderation in Social Media, from Guidelines to Enforcement, and Research to Practice. https://doi.org/10.48550/ARXIV.2206.14855
[49] Sara Sood, Judd Antin, and Elizabeth Churchill. 2012. Profanity use in online communities. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM, 1481–1490.
[50] John Suler. 2004. The online disinhibition effect. Cyberpsychology & behavior 7, 3 (2004), 321–326.
[51] Henri Tajfel. 2010. Social identity and intergroup relations. Vol. 7. Cambridge University Press.
[52] Twarec. 2020. Collect Twitter Data with Twarec! https://scholarslab.github.io/learntwarc/.
[53] Twitter. 2022. Twitter API. https://developer.twitter.com/en/docs/twitter-api
[54] Marco Van Bommel, Jan-Willem Van Proosijen, Henk Elffers, and Paul AM Van Lange. 2012. Be aware to care: Public self-awareness leads to a reversal of the bystander effect. Journal of Experimental Social Psychology 48, 4 (2012), 926–930.
[55] Zeerak Waseem and Dirk Hovy. 2016. Hateful symbols or hateful people? predictive features for hate speech detection on twitter. In Proceedings of the NAACL student research workshop. 88–93.
[56] Savvas Zannettou, Mai ElSherief, Elisabeth Belding, Shirin Nilizadeh, and Gianluca Stringhini. 2020. Measuring and Characterizing Hate Speech on News Websites. In 12TH ACM WEB SCIENCE CONFERENCE. ACM.
[57] Justine Zhang, Ravi Kumar, Sujith Ravi, and Cristian Danescu-Niculescu-Mizil. 2016. Conversational flow in Oxford-style debates. arXiv preprint arXiv:1604.03114 (2016).