The Quagmire of Outrage:

How Political Incivility Impacts Engagement on Social Media

By

Anthony Armellini

A Senior Honors Thesis Submitted to the Department of Political Science at the University of California San Diego

March 31, 2025

Acknowledgements

First and foremost, I would like to thank my mentor, Professor Seth Hill, for guiding me throughout this senior thesis project and equipping me with the tools and resources necessary to pursue any research objective I set my mind to. Your patience and support allowed me to test my own boundaries in developing a work I couldn't have completed alone.

On that note, I would also like to express my gratitude to the TA for Poli 191B, Alex Zhao, for introducing me to the intimidating yet efficient coding software that is R Studio and for strengthening my comprehension of AI tools that will only become more essential to academia over time.

I also extend my gratitude to Professors LaGina Gause and James Fowler, as well as the students of Poli 191A, for the insights and suggestions that helped me integrate the vast literature on my topic with my own personal perspectives into a workable research question. This collective environment of encouragement and inspiration provided me with the confidence and clarity that kept me committed to this project from start to finish. I can only hope to collaborate with such intelligent and ambitious colleagues wherever my professional career takes me.

Finally, I couldn't forget to mention my peers, Nicole Cordova and Pranav Madhav, for offering their attention and constructive criticism through everyday conversations related to my work. Your individual expertise as fellow political science undergraduates and your support as close friends complemented my resolve in navigating a complex phenomenon that permeates contemporary political discussion beyond the university campus. I'm forever grateful for the unique perspectives and suggestions that strengthened my command of this topic and enhanced my personal knowledge.

The Quagmire of Outrage:

How Political Incivility Impacts Engagement on Social Media

Table of Contents

Abstract

Shifting patterns in media production and consumption complicate the ability to generalize statistical findings across diverse research models and platforms that cater to distinct types of content and audience demographics. Within this fragmented landscape, the rise of political incivility across news media thereby poses an even greater threat to productive online discourse, as its effects remain fairly ambiguous yet often sensationalized by social media users. In response to these challenges, my study compares prevailing theories of uncivil rhetoric across Instagram, the most popular social networking platform among Gen Z Americans (Dixon 2024). By evaluating the content posted by major cable news networks (Fox News, CNN, and MSNBC) within two salient international and domestic political topics from the past year-the Israel-Palestine humanitarian crisis and the series of criminal trials against Donald Trump-and accounting for differences in content type (video reels and non-video posts), my analysis suggests that incivility has a disparate impact on engagement metrics based on these factors and in some cases, the types of incivility that are employed. Passive engagement metrics such as likes tend to have a positive relationship with general incivility across the general population, increasing by 0.085% increase for every 1% rise in uncivil language. This effect is amplified in video content with a slope of 0.14%, while name-calling is associated with increases in both likes (0.095%) and views (0.12%). MSNBC sees the strongest gains in engagement from incivility, with a 0.3% rise in likes, 0.16% in comments, and 0.41% in shares, whereas Fox News experiences a decline in engagement as incivility increases. These findings underscore the importance in accounting for methodological nuance when studying the impact of political incivility on social media engagement.

I. INTRODUCTION

Since the advent of social media and online communication in the beginning of the 21st century, a worrisome phenomenon has fomented itself within the American political media landscape. It goes by a variety of names and has its fair share of references across infomercial headlines and academic literature, often being associated (or even confused) with other deleterious consequences of the American duopolistic system, namely partisanship and voter apathy (Skytte 2019, 13; Skytte 2021, 2; Stryker et al 2016). Political incivility, which I define as discourse designed to elicit emotional responses (e.g. anger, fear, moral indignation) or even support from its audiences by attacking the reputation or credibility of a political opponent, has become a predominant element across major media networks and programs that once adhered to conventional reporting formats. Although this method of discourse has proven to captivate public attention and spur public debate (Mutts 2015; Rossini 2020), it can also contribute to increased partisanship and reduced public trust (Skytte 2020; Goovaerts and Marien 2020; Mutz and Reeves 2005). The effects of these disparate factors on engagement itself remains unclear, especially within the unique context of social media commentary and the partisan organizations that use it.

Following the conclusion of the 2024 presidential election and what Donald Trump's campaign declared the "greatest political movement of all time", conservative headlines such as *The Federalist* touted that the "corporate media industrial complex" was "2024's biggest loser" (Stelter 2024). Similar to prior election cycles, the dubious nature of Big Data election forecasts aroused contempt and distrust amongst audiences-particularly conservatives-when the Democratic opponent to Donald Trump was yet again incorrectly projected as the likely winner of the key battleground states amongst mainstream news programs (Breur 2016; 270TOWIN.com 2024). Accusations of misrepresentative and biased news coverage of President Trump throughout his campaign became another argument used by his followers in demonstrating the prejudicial nature of "liberal media". Meanwhile, academic scholarship and liberal pundits have consistently shown that a disproportionate amount of inflammatory rhetoric comes from conservative and populist outlets (Barry and Sobieraj 2014, 42; Barbera 2020, 37), including a proclivity toward "political incorrectness". After all, their presidential nominee quickly earned a reputation for the series of insensitive remarks and misinformative statements about his political opponents and the electoral integrity of 2020 election (Dimock and Gramlich 2021), the latter which earned him his second impeachment in Congress and a criminal indictment. These generalized narratives not only indicate different types of incivility between the two political factions but also demonstrate a consensus in where they gain traction. The emphasis on the role of mass media in disseminating uncivil rhetoric amongst supporters suggests a top-down weaponization of the news by partisan media outlets and commentators that generate embroiled audiences in the process.

1.1 The Phenomenon of Political Incivility

Uncivil discourse has proven to be on the rise over the past decade, as technological innovations in social media and other types of interactive online discourse give voice to hostile and offensive language (Barry and Sobieraj 2014; Kim and Hwang 2018; Nithyanand et al 2017). These circumstances do produce some superficial observations, although the logic that supports them is hotly debated (Massarino and Stryker 2012, 433-434). Through the evaluation of partisan social networks that tend to consolidate under “echo chambers”, many scholars posit the theory that incivility gives voice to extremism and thereby contributes to affective polarization in how politically neutral opinions become replaced with those that reinforce a specific set of partisan beliefs, all the while vociferously attacking opposing narratives-known as the “hostile media effect (Kim and Hwang 2018; Kim et al 2021; Kosmidis and Theocharis 2020; Brady et al 2017; Nithyanand et al 2017). The normalization of such combative discussion across American news media appears to substantiate this claim, as audiences are ostensibly more captivated towards partisan combat that evades compromise and bipartisanship in favor of violating social norms (Mutts 2015; Gervais 2018).

When considering social qualities of the individual, some scholars derive other results. Social factors and personality traits tend to act as confounding variables that impact a media user’s interest towards engaging with such material in the first place, typically captivating particularly combative and politically invested audiences while disengaging politically neutral or non-confrontational audiences (Sydnor 2019; Feinberg and Frimer 2022; Druckman et al 2018).

To this degree, increased incivility is a consequence of an overrepresentation of polarized opinions in popular media, creating the impression that political extremism runs rampant across most users when it only represents a small minority in reality. Alternatively, some even suggest that civil debate remains the norm within online communication and even spurs user participation more than unmannered commentary, which instead receives condemnation (Papacharissi 2004). Thus, a dominant narrative continues to elude general scholarship as to how incivility pervades and shapes modern political discourse.

1.2 The Puzzle: Varying Approaches in Contemporary Research

Divergent findings in the expanding literature on political incivility makes this topic particularly troublesome to analyze and research even before considering differences across social media platforms. Scholarship continues to posit opposing definitions of the phenomenon in varying contexts to which it is being studied, particularly between two competing approaches that I describe as "hyper-generalization" and "hyper-operationalization". Work such as Stryker's demonstrates the former in advocating for standardized measures of political incivility consistent with perceptions by the American public, recognizing the reality that "researchers have defined incivility somewhat differently, and even when they define it similarly, they have operationalized it in different ways in both surveys and content analysis" (Stryker et al 2016, 1). Multiple other works similarly follow suit in assenting to the statistical validity of public opinion through survey research in their studies across various social media platforms (Kosmides and Theocharis 2020; Sude and Dvir-Gvirsman 2023). This model also tends to emphasize the variability in how audiences react to uncivil rhetoric based on nuanced factors such as conflict orientation, personal significance (appraisal theory), and partisan identity (Sydnor 2019; Roseman and Craig 2001; Kim and Hwang 2018).

In contrast to this ideological camp exists the body of research that employs operational definitions in establishing a scholarly construct of uncivil discourse examined through media content rather than through the public directly. The research produced by Barry and Sobieraj in addition to Sydnor for example develops an intricate classification system of "outrage" media that has been used across multiple political mediums from talk radio to cable and broadcast television (Barry and Sobieraj 2014; Sydnor 2015). Recent studies have even employed AI tools specifically designed to identify types of uncivil commentary based on operational definitions (Feinberg and Frimer 2022; Sun et al 2021; Weld et al 2021; Nithyanand et al 2017; Nguyen and Diederich 2023; Medina Serrano et al 2020). Other examples of objective baseline indicators include party-line voting patterns or self-reported measures of incivility among congressional representatives (Ahuja and Sawyer 2008; Uslaner 1993), though these have limited applicability to the general public. This research model has consequently produced results comparable to one another across different content and periods of time, but are more or less taken at face value. While there are multiple studies that use a mix of the two approaches (Sydnor 2015; Feinberg and Frimer 2022), the methods to which they are executed can substantially differ. Both methods consequently have benefits and disadvantages in how they contribute to burgeoning academic literature but fail to complement one another in critical ways.

1.3 The Puzzle: Differences Across Platforms

The second issue that plagues this body of research is the various types of media formats examined between studies. While scholars can agree on the denotative construct of political incivility as the "fundamental tone and practice of democracy" in a general context and may use research formats consistent with at least one of the aforementioned theories (Herbst 2010, 3; Stryker et al 2016, 1), they still conduct research within mediums that can express incivility differently. Prior research stresses that audio and video news mediums such as radio and television are generally more uncivil than text-based sources such as newspaper columns or (to a lesser extent) blogs, with the former capable of expressing non-verbal behaviors and effective emotional displays while deviating from conventional civil discourse (Barry and Sobieraj 2014; Sydnor 2015).

This is further confounded when comparing media with a spectrum of "sub-formats". Research across television for example finds that incivility is effectively used as a vehicle for stoking audience engagement among talk radio hosts and cable news programs (Barry and Sobieraj 2014), though similar studies claim general "videomalaise" to instead be responsible for political mistrust and disapproval (Mutz and Reeves 2005; Goovaerts 2022). The "digital architecture" of social media platforms also evince variety in the structure, functionality, algorithmic filtering, and datafication process between networking services which offer different content styles and cater to particular audiences (Bossetta 2018). Consequently, these conditions impact both the prevalence of incivility and the ways how it is perceived by users immersed within "technical protocols that enable, constrain, and shape user behavior in a virtual space" (Ibid, 3; Sude and Dvir-Gvirsman 2023).

The fleeting nature of major events within the spotlight of social media discourse at any given point of time further obfuscate data results that intend to capture audience behaviors in a static media environment, producing news topics or popular sentiments that happen to be dominating a given platform for a particular period (e.g. before/after an election cycle or in light of a major national/international crisis). The acquisition of Twitter by Tesla and SpaceX CEO Elon Musk in October of 2022 demonstrates a unique example of how changing policies in content moderation and engagement metrics contributed to a shift in political narrative that rebranded the platform beyond its iconic “X” insignia (Fung and Duffey 2023; Goldman and Duffey 2025). Given these circumstances, research on political incivility across the contemporary media landscape demands a holistic approach that can account for various styles of content and innovations across platforms by either controlling for these factors independently or conducting studies within them exclusively.

1.4 Research Focus and Objectives

For the purposes of my study, I contribute to both approaches of hyper-generalization and operationalization by positing hypotheses based on the operationalized language of incivility, while using conventional metrics of engagement across a narrowly sampled population of social media content that best captures audience engagement from a public lens (even if this “engagement” can only be vaguely described). Although my findings may consequently be less descriptive, they are narrowly tailored to the specific topics that I examine while retaining generalization capabilities sufficient for comparison between different studies. In addressing the convoluted nature of format analyses, I control for these confounding distinctions within sampled content through procedures that are both effective yet consistent with prior research. My study focuses on addressing the question of how political incivility impacts audience engagement within a given media environment, and to what extent does it perpetuate such dialogue by engaging partisan users or entire echo chambers. Regarding such social networks, I also wish to determine which political ideology predominantly contributes to such discourse between different media environments.

This task requires an in-depth analysis of previous literature that independently addresses specific format styles, allowing me to determine the optimal platform to conduct research within (if one exists) while effectively accounting for potential dispersions of content variety that such a representative platform may have. If such a goal cannot be met, the only logical alternative would be to develop different research methods across select media formats and carry out in-depth analysis from there. Fortunately, the following literature review reveals an auspicious solution to the former.

II. LITERATURE REVIEW

The digital age has introduced a plethora of content styles that have become dominated by particular social media platforms. In disentangling contemporary research within the overgeneralized medium of "social media", I evaluate research tactics that sample diverse types of content within these unique media environments. Examples include text-based forums, image-based content (photo posts), short-form and long-form video content, and audio content formats which social networks tend to adopt based on user interests. Differentiating these formats is critical to understanding how incivility disseminates across platforms rather than social media at large.

2.1 Incivility Across Television and Other Traditional News Mediums

One of the most influential contributions to our understanding of political incivility within television is the conceptualization of the "outrage industry" by Barry and Sobieraj. In prefacing the systematic changes within the media landscape and the socio-political networks over the past century, they express "outrage" as an unprecedented genre of political discourse (even more discourteous than mere incivility) that embraces sensationalized ridicule of political opponents at the behest of loyal supporter bases (Barry and Sobieraj 2014). In disseminating this dramatic rhetoric, news programs effectively garner politically homogeneous audiences within an oversaturated media industry that offer promising marketing opportunities to advertisers. Technological advances and deregulation transformed broadcasting capabilities from a public good intended to produce quality information for the public interest into a consumer-driven commodity that promises generous profits to rancorous entertainment corporations. This narrative is ultimately described as a "perfect storm of political transitions, regulatory shifts, and technological advances that have fundamentally altered the relationship between producers, advertisers, media content, and the public" (Ibid, 90). They substantiate their central argument by using an elaborate classification system of "outrage" tactics to determine which practices are most common across traditional media formats and between political orientation among show hosts. Their codebook included a spectrum of 13 types of outrage "incidents"[1], from relatively mild instances of "emotional language" to outright "conflagration" and "emotional display", tested across the most prominent cable talk shows, radio hosts, blogs, and newspaper columns.

Their findings revealed related trends within these mediums and between partisan lines, with mockery, misrepresentative exaggeration, insulting language, and name-calling (from most to least prevalent) each accounting for more than 10% of all recorded outrage while ideologically extremizing language followed closely behind. When accounting for outrage use between partisan lines, their results determined that the right used decidedly more outrage speech than the left, engaging in more than a third of outrage incidents per studied case on average and dominating 10 of the 13 categories[2]. Additionally, they establish a positive correlation between outrage and audience levels in associating outrage probability with the popularity of each media type (from the entirely uncivil talk radio transcripts to the marginally less uncivil cable news programs and finally the blogosphere and conventional newspaper columns), while accounting for the potency of elaborate psychological processes that fosters political companionship. Such a

[1] These include "insulting language, name-calling, emotional display, emotional language, verbal fighting/sparring, character assassination, misrepresentative exaggeration, mockery, conflagration, ideologically extremizing language, slippery slope argumentation, belittling, and obscene language".
[2] Note that conservative media also dominated these mediums at the time that this study was conducted in the spring of 2009, particularly within talk radio.

comprehensive study indicates a similar pattern of incivility behaviors within television and other contemporary media formats of the 2000s, even if they use a disparate amount of the material in general.

Building from this scholarship is Emily Sydnor's elaborate assessment of political incivility across network and cable television, validating previous content-analysis findings while employing qualitative surveys that strengthen the correlation between uncivil media and engagement. In stressing the importance of conflict orientation theory from previous scholarship, Sydnor compares empirical findings of incivility to the behaviors of survey respondents towards "conflict" within political discourse when considering the impact of such commentary on general political participation. By adapting Goldstein's Conflict Communication Scale questionnaire to fit a given sample population (Goldstein 1999), she confirmed that individuals who demonstrated conflict-avoidant tendencies were most likely to disengage from conflict-oriented news coverage while those who expressed conflict-approaching behaviors were typically drawn to it (Sydnor, 2015). Additionally, conflict orientation proved to be an effective measure of incivility salience when comparing participants' perceptions of incivility to their respective categories within her content analysis model. By condensing Barry and Sobieraj's 13 outrage categories into 5 main themes (Blame, Hyperbole, Accusations of Lying, Name-Calling, and Threatens American Values), Sydnor coded for incivility across major cable and network media outlets (FOX News, MSNBC, CNN, ABC, and NBC) in testing the degree and nature of uncivil discourse between the two sub-mediums[3].

Preliminary findings indicated that 70% of the 666 sampled news segments contained incivility (less than 100% found in Barry and Sobieraj's sample on talk radio) and 25% contained

[3] It should be noted that Sydnor only accounts for the presence or absence of incivility types within news segments, not the *frequency* of each (Sydnor 2015, 43).

3 or more incivility types, with cable displaying the most incivility (particularly MSNBC and FOX) at 2 instances per segment on average while network television exemplified moderately less at 1.7 instances. Blame and Hyperbole were the most common incivility types used across both network types, while Name-Calling and Accusations of Lying were less common. Due to the contemporary lack of research on how users engage with this material on social media, the extent of her research could only assume that audiences would react to such material in ways consistent with "face-to-face" discussion, thereby concluding that social media likely acted as a low-conflict source of political information. In addressing this critical information gap, my research will need to build upon this content-analysis model while accounting for conflict orientation indicators that may illustrate user engagement differently.

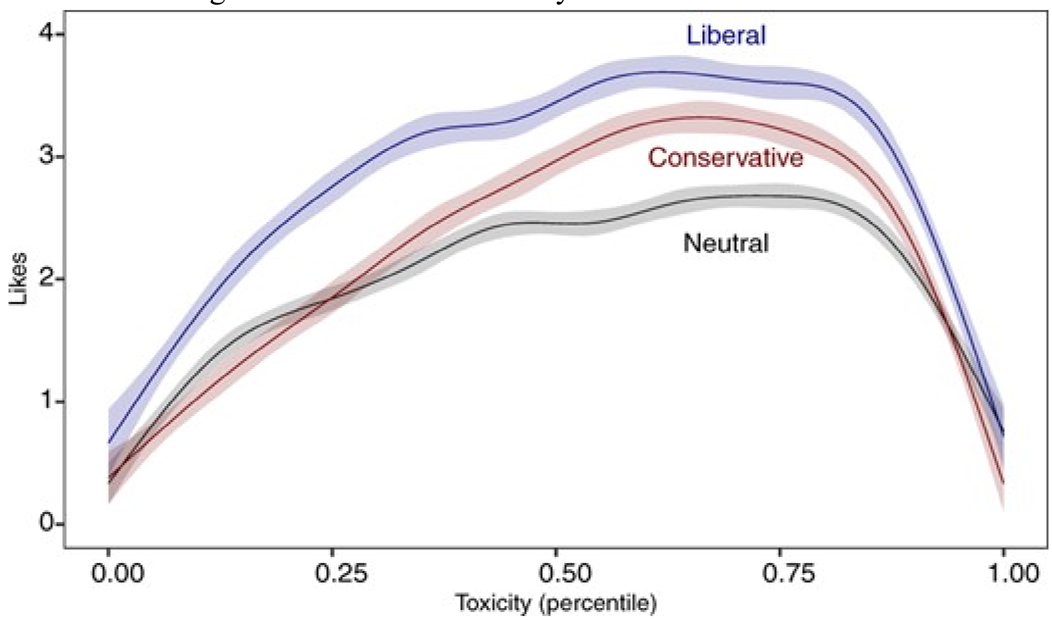
2.2 Political Incivility On Facebook

In deviating from traditional forms of political media, I next explore uncivil content across major American social media platforms. Publicly launching in the Fall of 2006 was the fledgling website known as Facebook, which would go on to incorporate its iconic "news feed" in addition to multiple engagement features that allowed audiences to interact with primarily text and photo-based content until the maturation of video autoplay and Facebook Live in the mid 2010s. Researchers acknowledge the lack of anonymity of this platform in particular as a potential deterrent for uncivil engagement, as users are required to use real names with picture profiles and conspicuous social connections (Rossini 2020; Sude 2023). Combined with Facebook's massive content moderation system oriented towards user reporting and machine-learning (Singh 2019), it comes to no surprise that the community is found to have less incivility than anonymous spaces such as news sites and Youtube (Halpern and Gibbs 2013; Rowe 2014).

As the most widely used social media network in the United States (Sidoti and Dawson 2024),[4] there exists copious studies that evaluate its content and user base. In testing for the impact of interpersonal political attitudes on the proliferation of uncivil content, Kim's research analyzed more than 11,000 Facebook news article posts belonging to mainstream news outlets and the millions of comments they received, in conjunction with independent survey data that examined respondents' own proclivity towards "toxic" commentary in online political discussions (Kim et al, 2020) . After confirming in their surveys that habitual commenters show increased interest, are more informed, exhibit greater levels of affective polarization, and produce slightly more uncivil commentary regarding politics than non-commentators, they consequently find that uncivil comments on the platform share a quadratic relationship with engagement specifically in the form of "likes" and subsequent uncivil commentary. They also find substantial differences in comment toxicity between news sources and political ideology, with partisan discussion from the left having the strongest relationship before leveling off regarding especially obscene commentary. When considering Facebook's algorithmic selection process of top comments, the group concludes that the visibility of toxicity across the platform is increased by this pre-existing relationship.

[4] Although Youtube is often recognized as the most popular social media platform globally, my type of scholarship doesn't recognize it as a social network since it primarily fulfills an entertainment purpose rather than functioning as an atmosphere for diverse types of communication, with the comment section of videos as the only source of direct user discourse.

Figure 1: Variation in Toxicity Across Partisan News Sources



Kim et al, "The Distorting Prism of Social Media", *Journal of Communication*, vol. 71, no. 6, 2021. 936.

Su's team further explores incivility patterns among users within the Facebook pages of news media outlets, employing their own operationalized content analysis model between national, local, and partisan news accounts. By using three categories of incivility (civility, rudeness, and extreme incivility) while accounting for their respective target (personal or impersonal attack), they analyzed more than 243 million Facebook comments across 8 national, 18 local, and 8 partisan news networks (Su et al, 2018). Their findings revealed local news outlets to be associated with the most uncivil commentary (particularly with comments that showed "extreme incivility" and personal attacks), while national outlets exemplified more comments with "rudeness" and impersonal attacks. Additionally, liberal media outlets were found to have the most civil discussion (75%) while conservative programs had moderately less (63%) and particularly more extreme incivility (19% compared to 9% from liberal outlets). Their research suggests that the type of outlet matters when navigating Facebook social networks, contributing to the nuance in how a platform's community and the means to which they can interact directly impacts opportunities for uncivil discussion

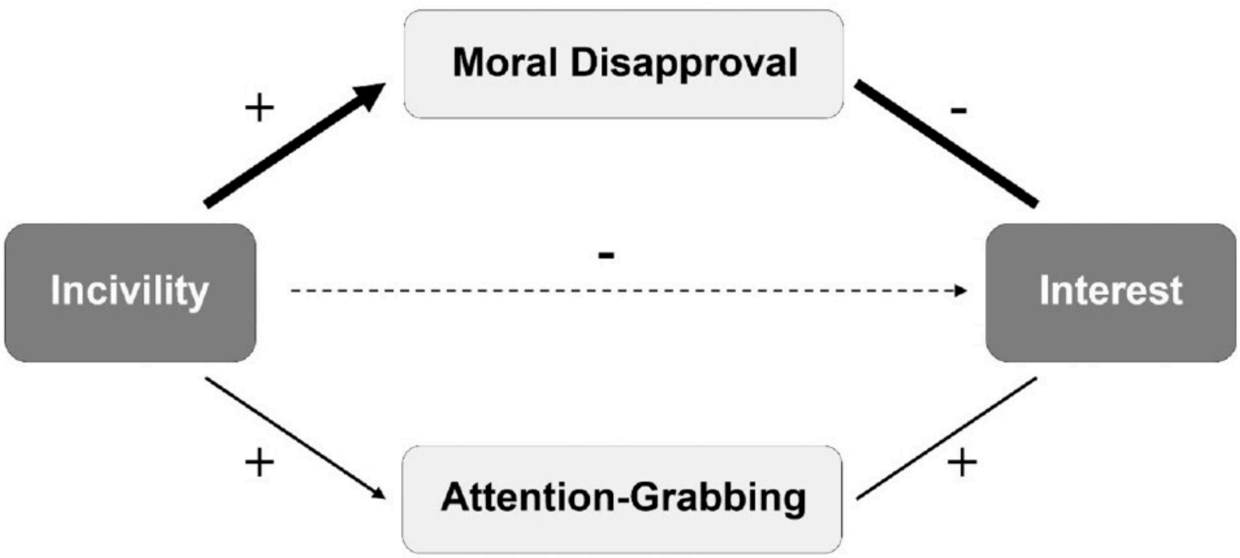
2.3 Political Incivility On Twitter

Scholarship surrounding Twitter (now "X") is notably less unanimous in demonstrating key attributes of uncivil media across the platform. To exacerbate these circumstances, Musk's recent acquisition and rebranding of Twitter has resulted in a significant shift both in policy and user demographic within recent years, making a significant comeback with the return of the "Trump era" (Goldman and Duffey 2025). Due to the current lack of research on the site before and after this significant transition, I focus this contextual analysis on the former. As another major social media network among Americans (Sidoti and Dawson 2024), Twitter earned its namesake as an SMS text-based service that limited its posts to only 140 characters, then 280 characters in 2018, and finally an unrestricted number for paid subscribers by 2023 (X Developer Program 2025). Although image and video-based content existed in earlier years, longer videos and higher resolution content wasn't incorporated until after the platform was rebranded. Like Facebook and many other social networking sites, it uses its fair share of metric counters and human-AI moderation techniques that expand and regulate interaction capabilities among users, although the platform's recent transition has also allowed greater anonymity regarding engagement (X Help Center 2025).

One study in particular that effectively captures top-down dissemination of uncivil "tweets" on this platform is that of Feinberg and Frimer. In expressing skepticism towards the conventional belief that politicians' and networks' use of incivility rewards them with captivated audiences and greater political influence, they instead posit that moral distaste towards such content outweighs its attention-grabbing allure and instead turns users away (Feinberg and

Frimer 2022). The two base this assertion on their theory of countervailing responses, one that stimulates interest (primarily from supporters, to which they refer to as "co-partisanship") and a more commanding response from a general population that expresses disapproval, ultimately determining collective reaction. This logic builds upon previously established norms of civil conduct in asserting that a "primacy of morality" supersedes vulgarity.

Figure 2: Feinberg and Frimer's Countervailing Responses Theory



Feinberg and Frimer, "Incivility Diminishes Interest in What Politicians Have to Say", *Social Psychological and Personality Science*, vol. 14, no. 7, 2023.2.

By capturing the longitudinal observed follower counts of Joe Biden (from his first tweet in 2012 to until the summer of 2021) and Donald Trump (from the beginning of his first presidential campaign in 2015 to his account suspension in January of 2021), they test whether incivility decreases a user's interest in their content. Incivility was coded through Google's Perspective API program, which determined that heightened levels of incivility did in fact produce an inverse relationship with their followership, further confirmed by Granger causality tests (Granger 1969). Specifically, these measures found that Donald Trump's account received about 43,000 new followers after days when his posts were civil and only about 16,000 when they weren't, whereas Biden earned 45,000 followers following civil tweets but only 11,000 after posting very uncivil content. This was reinforced with supplementary surveys of about 1,100 and 600 respondents respectively, who expressed limited interest in tweets and speeches considered uncivil. At least from the perspective of leading political actors, Twitter appears to have greater accountability when it comes to disseminating offensive political commentary compared to other social networking sites, perhaps due to the limited means to which it can be spread across the platform.

Other findings on the platform suggest the opposite. Brady's team finds that "moral-emotional" language within the platform rather increases the diffusion of their respective messages, emphasizing the importance of emotion throughout the social transmission process of politics (Brady et al 2017). This body of researchers conduct their study on existing Twitter feeds with the understanding that the interrelated nature of morality and emotion reflects societal norms and interests that produce "social contagion" between groups. Using an observational study of more than half a million tweets related to politically contentious topics such gun control, same-sex marriage, or climate change, they determine that every individual moral-emotional word within a given tweet increased its retweet rate by 20% on average. When considered separately, moral and emotional language offered minimal statistically significant findings. Passionately expressed moral imperatives, irrespective of the degree of hate used in the process, were found to be the best indicators of highly retweeted posts. When factoring for anger in particular, its impact was content-specific, leading to increased social contagion within tweets related to gun control and particularly climate change, but the opposite effect for same-sex marriage. When accounting for political ideology, their findings confirmed that moral-emotional language generally increased retweets within conservative in-groups compared to liberal ones, though this relationship was only statistically significant on the topic of climate change.

Similar to Brady, Kosmides and Theocharis emphasize the degree of emotion associated with responses to uncivil political discussion through multiple survey experiments on the posted statements of political actors and the comments they received. By comparing respondents' reactions to political tweets on climate change and immigration policy, they found that the groups assigned to uncivil tweets experienced substantial emotional changes, particularly with positive emotions such as enthusiasm (Kosmides and Theocharis 2020). This trend remained constant between liberal and conservative-framed discussions, as “enthusiasm” increased by roughly 10% across uncivil commentary between both studies for each respective party affiliation. Importantly, they side with neither scholar regarding partisan affiliation, suggesting instead that differences in partisan incivility is largely contingent on the political question at hand.

While these findings are substantive in their own right, a glaring difference between them that could explain their disparate arguments are the various dependent variables used to gauge emotion. A political leader’s follower count, the retweet rate of a given post, and the perceptions of survey participants may fluctuate differently across the time and topics where incivility thrives. This will be important to keep in mind regarding other platform studies.

2.4 Political Incivility On Reddit

Reddit is a community-driven platform based in the United States that offers forum-based discussions within a plethora of niche communities (referred to as “subreddits”). It grants users the right to full anonymity and regulates its content primarily through a decentralized system of individual subreddit moderators and automated bots, although it also has a small team of admins that enforce its content policies (Singh 2019). Content through Reddit gets attention through a simple upvote system, to which users can "upvote" or "downvote" individual posts or comments on the site to promote or reduce its visibility. This system directly impacts the credibility of individual users through their "karma" scores, as those with higher upvotes across their posts incur a higher score than those whose karma is reduced by downvotes. The platform is notably one of the few major social networks that still use any kind of visible dislike feature, as many of its counterparts made this feature private in recent years (Debois 2022). Additionally, its content archives are available to the public, making the platform especially popular for longitudinal datasets (Nithyanand et al 2017). As a dominant social network that has run for nearly two decades, it offers a rather unique and convenient environment for empirical research.

Due to the decentralized nature of the platform and the independent content moderation that takes place within its communities, Reddit has its fair share of uncivil discussions. One study conducted by Sun and two other UC Davis students applies an 11-year longitudinal analysis of Reddit's most popular subreddit discussions (representing 95% of annual user comments) relating to political, non-political, and mixed topics, to better understand the dynamics of incivility throughout the platform. Taking an operationalized approach, they next classified incivility as a binary variable for comments that used forms of name-calling towards individuals, aspersions directed towards an idea or policy, vulgarity or profanity, or pejorative remarks towards how users communicate. They found that incivility within political group discussions was higher than its mixed and non-political counterparts, accounting for a 10%-17% range of comments compared to 11%-13% for mixed discussions, and 8%-12% across the rest of the platform throughout the period (Sun et al, 2017). Most importantly, ideologically homogeneous and heterogeneous political groups experienced a 10%-20% population of uncivil comments and experienced surprisingly similar incivility rates to one another (though incivility was higher in mixed-heterogeneous groups). Additionally, these results did seem to fall in tandem with current political events and moderation updates, as liberal political and mixed groups oscillated from 11%-14% while conservatives similarly ranged from 9%-15% in response to inter-party events. Relative to other platforms, political discourse within Reddit appears to convey less ferocious exchanges between political ideologies and less substantial differences in the amount of incivility conveyed by liberals and conservatives.

In context to the diversity of news quality between Reddit communities, Weld's group presents a study on the concentration of biased and misinformative commentary within ideologically polarized communities, deriving a different narrative than Sun. Through another longitudinal analysis of Reddit conversations spanning four years, the team evaluated the mean bias and factualness of political material disseminated in subreddits using the Media Bias/Fact Check service. With respect to left and right-leaning communities, they found that the latter experiences a 105% greater variance in their political bias than their left-oriented counterparts, espousing biased news sources 35% more often than left-leaning communities when selected news sources deviated from the community average (Weld et al 2021). This type of material also remains concentrated within a small proportion of communities, as 99% of exposures to extreme content occurred within 0.5% of communities. Their analysis also indicated that community curation behaviors moderately reduced especially biased and misinformative information, indicating that a decentralized moderation system may be more efficient than other conventional systems in restricting deleterious content. A similarly formatted longitudinal study by Nithyanand and others confirms these partisan findings, postulating that Republican subreddits have become roused by a phenomenon they refer to as the "Trump effect", to the extent that

Republican subreddits have produced comments since 2015 that are 46% more offensive than Democrat subreddits and 7% more than their Libertarian counterparts (Nithyanand et al 2017, 6). Although this research doesn't focus on incivility in particular, it does expound upon the behaviors of politically homogenous communities that tend to engage with such material.

2.5 Political Incivility On Tiktok

Tiktok is the only top social media platform based outside of the United States, being originally released in China by the foreign developer company Bytedance in 2016. It features short-form video content, promoting video submissions based on user interaction trends and AI-driven recommendations on its "for you page". Its popularity among Gen Z users in particular makes it one of the fastest growing social networks in the country and the world, with roughly 59% of Americans under 30 having used the platform and a third of the country's population familiar with it altogether (Eddy 2024). Content moderation on Tiktok relies heavily on AI automated detection systems to flag inappropriate content, although it also employs some aspects of human content reviewers and user reporting (Tiktok 2025). In recent news, skepticism regarding its data privacy standards have raised alarms in Congress over the platform's threat to national security and its influence by the Chinese government, although efforts to restrict its access to American users have since been paused following negotiations to sell the platform to American owners (Hirsch and Manheshwari 2025). Nevertheless, its current dominance in the market of short-form video content (to which its competitors are strenuously trying to emulate) and combination of moderation techniques makes the platform an interesting research specimen regarding political discourse (Jones 2025).

As a relatively newer trending platform across American users, there is limited research that examines the tone of political messages disseminated through Tiktok. An analysis of such communication by Juan Carlos Medina Serrano and his team of researchers from the Technical University of Munich stresses the novel interactive nature of political discourse across the video-sharing platform and its proclivity to induce cross-partisan discussion. The synergy between background audio and recorded videos produces a distinctive work that is both captivating and capable of effective storytelling, particularly through the "duet" feature which promotes "response videos" to posted content. Through a comprehensive content analysis of hashtag queries related to "#democrat" and "#republican", the team classified thousands of videos according to their partisan affinity. They determined that there was double the amount of pro-Republican content compared to pro-Democrat, which also received more indirect and basic forms of engagement in the form of likes, shares, and comments (Medina Serrano et al, 2020). Conversely, pro-Democrat content was more likely to engage in cross-partisan discussions, with 80% of such content being directed toward Republican supporters compared to the 77% of Republican videos that instead engaged with other Republican content. These findings corroborate the existence of predominantly Republican social networks prevalent across other platforms.

Nguyen and Diederich introduce their own approach when accounting for political incivility. Across their sampled corpus of more than 300,000 Tiktok comments related to videos with educational hashtags, they use Google's Perspective AI program to detect incivility speech in the form of "toxicity", "personal insults", and "profanity". Although they found that only 1.5% of comments include uncivil commentary, further analysis within this data subset revealed a surprising lack of correlation with their tested engagement variables (Nguyen and Diederich 2023). Between the top 25% of comments with the most incivility and the bottom 75% that used less, they observed no statistically significant difference in the number of likes, comments, and shares that each received, although the former notably included less commentary from unique users. This limited body of research ultimately gives credence to the theory that uncivil commentary may attract a limited number of users comfortable in engaging or perpetuating such discourse, although it falls short of proving that incivility promotes or limits general engagement.

Figure 3: Summary of Existing Literature Table

Platform/Medium:	**Television**	**Facebook**	**Twitter**	**Reddit**	**Tiktok**
Primary Content Type:	Long video-based content (TV broadcasts)	Photo and video-based content	Short text-based content	Long text-based content	Short video-based content
User Anonymity:	Yes	No	Yes	Yes	No
Content Moderation Method:	Not Applicable	AI and User Moderated	AI and User Moderated	Mostly User Moderated	Mostly AI Moderated
Incivility-Engagement Relationship:	Positive	Positive	Mixed; Leans Positive	Positive	No Relationship
Partisan Association With Incivility:	Republican	Mixed	Mixed	Republican	Inconclusive

III. THEORY AND ARGUMENT

3.1 Research Design Within Instagram

The present literature provides critical insights as to how ordinary users and partisan networks engage with uncivil content across popular media. While this analysis is clearly incomplete, it does lay the groundwork for other ambitious projects such as my own. A particular discrepancy to note is the disproportionate research that has been conducted on some major social media platforms over others, specifically the lack of insights into Instagram, the most popular social networking platform among Gen Z Americans (Statista.com 2024). One reason that comes to mind for explaining this status quo is its co-ownership by Facebook along with the diverse types of content it has to offer to its users, ostensibly making such a study redundant or too inconclusive. On the contrary, I argue that such diverse content makes the platform an excellent candidate for my study, as it provides yet another example of how similar style content (primarily photo and video posts) can differentiate across platforms in their respective concentrations of offensive commentary. I therefore wish to contribute to expanding literature on this topic by introducing another key player to the discussion while designing a research model that incorporates essential aspects of previous studies.

To address my research questions related to incivility and user engagement, I've chosen to adopt an operationalized approach by drawing directly from the work of Barry and Sobeiraj, as well as Sydnor, to ensure consistent categorization of the generally ambiguous phenomenon of incivility. Secondly, I also incorporate perceptions from the broader public of Instagram users by considering all of their fundamental engagement metrics, from passive features such as likes and views to active forms of engagement such as comments and shares. While this method fails to hold a candle to the aforementioned descriptive survey analyses, it retains some reference of comparison to other platforms that use nearly identical features. In borrowing from these same studies, I also intend to differentiate partisan groups within the leading political networks that they engage with, particularly the conservative cable network Fox News, the center-left network CNN, and its left-oriented counterpart, MSNBC. This allows me to effectively differentiate user behaviors across partisan lines, though admittedly an incomplete analysis given the other leading network accounts on Instagram. With these resources at my disposal, I intend to answer the following:

3.2 Research Question 1: Incivility-Engagement Relationship

Q1: How does political incivility impact audience engagement across photo and video posts on Instagram, and to what extent does it perpetuate such dialogue by engaging partisan users?

Based on the dominant narrative evinced in my literature review, I predict that users are most likely to engage with metrics such as likes and comments when uncivil discussion is present and thus captivating to audiences and assume that views and shares similarly follow suit based on how such commentary permeates across other platforms. Consequently, I predict that there exists a positive relationship between political incivility and all four of these engagement metrics. On that note, a subsidiary factor that contributes to this process is the partisan affiliates that are most likely to engage with this material, which leads us to my second key question.

3.3 Research Question 2: Partisan Affiliation

Q2: Which political ideology predominantly contributes to such discourse within Instagram?

Although slightly mixed, popular consensus indicates that right-leaning social networks are primarily to blame for the prevalence of political incivility in general, though it has also been stated that this is largely contingent on current political developments. In light of the recent presidential victory of returning Republican nominee Donald Trump and the tumultuous series of events that led to the full control of the presidency and Congress by the Republican party, I estimate that incivility predominantly stems from exhilarated Republican communities.

IV. METHODS AND ANALYSIS

4.1 Sampling Across News Topics

In establishing my population of Instagram posts to run my linear regression analyses, I decided on two parameters, topic salience and date, that best captured media content that was sufficiently relevant to my selected topics. For the former, I limited my search to only content that directly mentions the military conflict in Israel and Palestine or the legal proceedings of the Donald Trump Criminal Trials (civil cases were not considered). This condition includes any discussion and commentary on details or emerging developments pertaining to these topics. Regarding the Israel-Palestine conflict, my sampled content therefore only included commentary on the war itself or international events directly related to the conflict (e.g. protests and encampments). For the latter, this content was focused on discussion and commentary revolving around Donald Trump's four criminal cases; The Hush Money Case (*The People of the State of New York v. Donald J. Trump*), The Mara Lago Classified Documents Case (*United States of America v. Donald J. Trump, Waltine Nauta, and Carlos De Oliveira*), The Federal Election Interference Case (*United States of America v. Donald J. Trump*), and The Georgia Election Interference Case (*The State of Georgia v. Donald J. Trump, et al*).

My condition of time ensured that my population consisted of media that remained within the timeframe that these events were making headway across the platform and American media in general. For the Israel-Palestine conflict, I set my timeframe from October 7th of 2023, the day of Palestinian military offensive that reignited the decade-long conflict, to the 25th of November 2024. As for the Trump trials, I generally considered media beginning from the 15th of October 2024, the commencement of Trump's Hush Money criminal trial, and ending on the 27th of December of the same year, a point in time where verdicts were reached between all but one of these cases (The Georgia Election Interference Case is still ongoing). An exception to this rule was made exclusively for CNN in accounting for the insubstantial net population of posts that CNN made on this topic (a mere 37); the earliest post dates back to December 19th of 2023. Although an optimal cutoff date for my sampled topics would incorporate the latest coverage on the Israel-Hamas armistice or details regarding the delayed sentencing of Trump's "hush-money" trial, my population nevertheless suits my research purposes.

4.2 Sampling Across News Networks

In deciding the Instagram news accounts to conduct my study on, I resorted to using the shared networks between Barry and Sobieraj's operationalized study and that conducted by Sydnor soon after. In addition to being regarded as the "Big Three" cable television networks, Fox News, MSNBC, and CNN in particular function as relatively accurate representations of partisanship in the United States, as each network retains the highest disproportion of Republican-to-Democrat viewers among the major political sources in context to political and election news (Jurkowitz et al 2020). As the most watched news channel (Neilson 2025), Fox News is estimated to have a whopping 43% difference between the proportion of its Republican viewer base (60%) and its Democrat audience (23%), whereas CNN and MSNBC are technically tied with a 24% difference (CNNs' Republican and Democrat share is 24% and 53% while MSNBC's is 14% and 33%). Although popular culture sometimes tends to group both of these networks as "left-leaning", empirical research has found that CNN is both the most popular and the more moderate program (Blake 2014; Grieco 2020). Although these rankings change slightly within Instagram itself (likely due to younger audience exposure), these programs still function as an effective baseline for my study.

4.3 Sampling Across Content Type

When accounting for different types of content, I focus my research on distinguishing between the two types of content on Instagram; Posts and Reels. A "post" is a general term used to describe photo-based content that is often accompanied by a short text-based description[5], whereas a "reel" is a short-form video that can also include a description (Sonnenberg 2024). My sampled media within the feed of each network consists of only these forms of content, giving me the opportunity to compare the impact of political incivility across the engagement metrics of both content types.

4.4 Data Collection and Proposed Hypotheses

In total, my net population of Instagram posts and reels amounted to 1,541, 1,185 pertaining to the Israel-Palestine conflict and the remaining 356 covering the Trump trials. Fox News produced the lion's share of this population with 699 for Israel-Palestine and 145 for the Trump Trials, CNN coming second with 420 and 37, and finally MSNBC with 66 and 174. The sample population was then derived from 50 randomly selected posts or reels within each news source and on both topics (with the exception of CNN's 37 posts on the Trump trials), totaling 287. Each individual post and reel within the net population can be referenced under the Instagram Total Content Population section under Supplementary Materials.

For each of these posts, engagement metrics were collected according to the number each post was liked, commented on, shared between users[6], and viewed in video format[7]. Due to the exclusive availability of the relatively new share and view count features on the mobile

[5] Note that this term is also used to describe Instagram content more broadly, so being mindful of the context in which it appears is helpful in avoiding confusion. Given that I use the term in both contexts, such caution is especially warranted.
[6] The share count feature on Instagram records the number of times a post was shared between both the sender and recipient, accounting for both actors in aggregating the total value (Redsocial 2025).
[7] The view count feature on Instagram considers content as "viewed" if a user watches a video for at least three seconds within the Instagram app. Each instance also counts as a separate view (Kashyap 2024).

Instagram application, in addition to being consistently featured only on Instagram video reels (Perloff 2023), my sampled data omits these values for 105 and 114 of my posts respectively. In situations where engagement variables became publicly available after initial recording (particularly for shares and views) or were corrected due to error, values were used within the same post but from a later date past the sampling period. Additionally, it should be clarified that engagement values rounded to the nearest hundred by Instagram are taken at face value, as these are the numbers publicly available on the platform (this applies primarily for values upwards of 100,000 or more). In accounting for my incivility explanatory variable, each post was individually coded for instances of incivility based on the five categories derived from Sydnor's study: "Blame", "Hyperbole", "Accusations of Lying", "Name-Calling" and "Threatens American Values"[8]. Similar to Sydnor, transcripts-including the words found within captions and those generated from audio-to-text conversions of video reels-were individually assessed to determine the presence of the aforementioned variables. To the nature of this study, any use of uncivil commentary within these categories-whether it comes from the news outlet itself or references the material from another source-is accounted for. Since news outlets can just as easily weaponize their opponents' crude remarks as their own commentary to discredit them, such behavior tends to generalize these infractions across the entire political demographic.

Rather than code these incivility categories as binary variables (present or not present) within each post as done by Sydnor, my study instead descriptively quantifies the total value that each category was used, producing an incivility ratio based on the average number of incivility instances for every 50 words (rounded to the hundredth decimal place). Let this formula be expressed as the following:

(50/(total word count of sampled post)) * (total number of incivility instances)

[8] The specific definitions used to code for these incivility types are listed under the Codebook section.

Once the independent and response variables were recorded between each sample, the topic, news source, content type (video or non-video) date, word count, and post link were recorded from each individual post for the purposes of running my regression analyses. Using R Studio as my coding environment, I then calculate the mean distribution of the incivility ratio variable and each of the engagement variables between the three news programs. Taking the logarithmic values between these variables[9], I then individually ran bivariate and multivariate regressions between incivility ratio and my engagement variables for the entire sample population (general) and under each topic (the Israel-Palestine Conflict and the Trump Trials), news source (FOX, CNN, and MSNBC), and content type (Video-Based Reels and Non-Video-Based Posts),[10] using these same variables as controls. These calculations will express linear relationships found within my sample population along with their statistical significance with and without controls. Finally, using the different incivility categories (Blame, Hyperbole, Accusations of Lying, Name-Calling, and Threatens American Values), I then ran the same models for the general population except with each incivility type as the independent variable. These models will indicate which types of incivility contribute most to any existing relationships that I find in the second part of my analysis.

The different hypotheses that this study will be examining are as follows:

- **Q1 Null Hypothesis:** There is no relationship between incivility and audience engagement. This theory is proven within my regression analyses by an inconsistent slope indicated by a weak coefficient value at or near 0 within a 95% confidence interval. Given the dubious nature of user activity across Instagram and other social media

---

[9] A base value of 0.1 was added to my incivility ratio variables to prevent values of 0 from becoming undefined
[10] Since the "views" engagement variable was only available for video-based content, no regression for this variable was used for "non-video" content. This explains why these values appear as "NA" in my multivariate regressions tables.

platforms, compounded by a robust algorithm and limited transparency in how the platform operates, these limitations may reasonably obscure the direct relationship between incivility and engagement found across other mediums.

- **Q1 Alternative Hypothesis #1:** There exists a positive relationship between incivility and audience engagement. As Barry and Sobieraj suggest based on their studies related to talk radio, increased incivility towards political opponents may better captivate supporters and general audiences than passive news coverage. This would be proven within my regression analysis by a positive slope (coefficient value above 0) within a 95% confidence interval.
- **Q1 Alternative Hypothesis #2:** There exists a negative relationship between incivility and audience engagement. As the latter camp of my literature finds, the use of incivility by trusted news programs may instead compromise their credibility and reputation amongst politically informed audiences. This relationship would be proven within my regression analysis by a negative slope (coefficient value below 0) within a 95% confidence interval.

Secondly, I intend to determine which partisan group is associated with uncivil discourse by the following hypotheses:

- **Q2 Null Hypothesis:** Neither partisan affiliation is statistically proven to produce more incivility than the other, and neither experiences statistically significant changes to their engagement metrics. In theory, this finding would be indicated by a relatively indistinguishable proportion of incivility between the conservative tested network (FOX News), the “moderate” network (CNN), and the liberal-oriented network (MSNBC). Additionally, there would be no statistically significant patterns of engagement between the three networks when accounting for the prevalence of incivility. Nguyen and Diedrich derived such results in analyzing their sample population of Tiktok videos, indicating that such a theory may be more plausible in practice.

- **Q2 Alternative Hypothesis #1:** The conservative-oriented network (FOX News) both produces more incivility and experiences increased engagement as such commentary becomes more prevalent. This second condition is important since the commercial interest in perpetuating such insensitive coverage must also be present in comporting with previous literature. Consistent with the theories proposed by most scholars referenced in this work, this narrative is supported if FOX News does disseminate proportionately more uncivil posts, and experiences uniform increases across its engagement variables that are statistically significant within a 95% confidence interval.
- **Q2 Alternative Hypothesis #2:** The liberal-oriented network (MSNBC) both produces more incivility and experiences increased engagement as such commentary becomes more prevalent. As exemplified by Kim's evaluation of Facebook comment toxicity within liberal groups, this theory is substantiated if MSNBC produces proportionately more uncivil posts and experiences uniform increases across its engagement variables that are statistically significant within a 95% confidence interval.

To demonstrate the coding process in practice, Figures 4 and 5 demonstrate instances of civil and particularly uncivil content, with the latter expressing four of the five incivility categories (Blame, Hyperbole, Accusations of Lying, Name-Calling). References to pro-Palestinian protestors as "anti-Israel agitators" and sensationalized remarks on former president Biden's foreign policy were classified as instances of name-calling and hyperbole respectively, whereas explicit accusations of blame and references to the tarnished reputation of America were considered blame and claims that American values were being threatened. Although the first example is a photo post while the second is a video reel, the word content of both are similarly coded as transcripts. Note that references to the same instance of incivility are counted as their own individual instance. The rest of my sampled posts can be viewed under the Instagram Post and Reels Transcripts document referenced in the Supplemental Materials section.

Figure 4: Instagram Post Sample 1

Topic: Criminal Trials of Donald Trump
News Source: CNN
Date: 30 May, 2024
Word Count:41
Like Count: 127,191
Comment Count: 9,690
Share Count:NA
View Count: NA
Video: No
Incivility Count: Blame: 0
Incivility Count Hyperbole: 0
Incivility Count: Accusations of Lying: 0
Incivility Count Name-Calling: 0
Incivility Count: Threatens American Values: 0
Incivility Ratio: 0

Post Description:
Trump found guilty in hush money trial
Jurors find Donald Trump falsified business records in New York hush money trial. He becomes the first former US president to be convicted in criminal court. Read more at the link in our bio.

Figure 5: Instagram Post Sample 2

Topic: Israel-Palestine Conflict
News Source: FOX News
Date: 23 April, 2024
Word Count:135
Like Count: 9,870
Comment Count: 1,088
Share Count:327
View Count: 153,000
Video: Yes
Incivility Count: Blame: 3
Incivility Count Hyperbole: 5
Incivility Count: Accusations of Lying: 0
IncivilityCount Name-Calling: 3
Incivility Count: Threatens American Values: 1
Incivility Ratio: 4.44

Post Description:
WATCH: Trump calls anti-Israel agitators a "disgrace," says it's all Biden's fault before heading into a New York City courtroom for his unprecedented criminal case. Live updates at the link in bio.

Video Transcription:
What's going on at the college level and the colleges, Columbia, N. Y. U. and others is a disgrace. And it's a-it's really on Biden. He has the wrong signal. It's got the wrong tone. He's got the wrong words. He doesn't know who he's backing, and it's a mess. What's going on is a disgrace to our country, and it's all Biden's fault. And everybody knows that he's got no message. He's got no compassion. He doesn't know what he's doing. He's got-he can't put two sentences together, frankly. He is the worst president in the history of our country.

V. FINDINGS

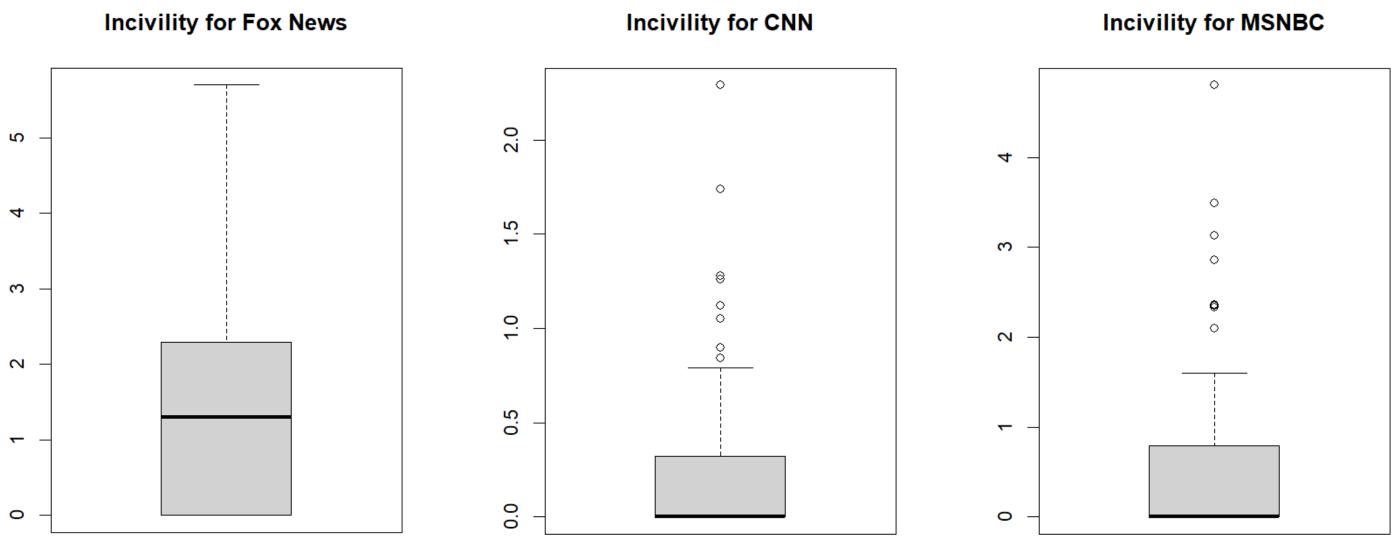
5.1 Content Differences Across News Networks:

Before analyzing content patterns between each Instagram account, I first evaluate basic differences in content performance and the variety of content that each produces in context to my study. Of the 287 sampled posts between each network, 155 of them (about 54%) included at least one instance of incivility. Beginning with the top conservative network on Instagram (Instagram.com 2025), Fox News boasts a follower count of 9.7 million with 61.3k posts. The compiled data for Fox determines that this account clearly dominates in terms of incivility, with 72% of its content exemplifying at least one instance of incivility while carrying a mean incivility ratio of 1.56 instances per 50 words. The respective boxplot in Figure 6 illustrates a shared minimum and lower quartile value of 0, a median of 1.29, an upper quartile of 2.29, and a maximum of 5.7, with no outliers. When accounting for engagement variables within this section of sampled data, I calculated a mean value of 26,813 likes, 4,859 comments, 18,415 shares, and 592,387 views. Of the 100 posts sampled relating to Fox, only 31 of them were in video format and had a mean of 85 words across all posts.

CNN leads with the highest performance values with 20.4 million followers but only 18.4k posts (Ibid). Incivility for CNN accounts for only 39% of all sampled posts, resting at a minimal 0.25 instances for every 50 words with a shared minimum and lower quartile value of 0, a median of 0, an upper quartile of 0.32, and a maximum of 0.79, with 9 outliers. Engagement variables for this program rest at mean values of 37,211 likes, 5,678 comments, 5,364 shares, and 1,827,926 views (surpassing Fox by every figure save for share count), and publish primarily videos with 55 out of the 87 sampled posts accounting for this format type. Content on CNN offered an average of 214 words in general.

Finally, MSNBC represents the left-leaning program with only a fraction of followers and posted content to its counterparts, 1.7 million and 14k posts respectively (Ibid). It displayed incivility within 49% of its posts, scoring an incivility mean value of a moderate 0.53 instances for every 50 words, with a shared minimum and lower quartile value of 0, a median of 0, an upper quartile of 0.79, and a maximum of 1.6, with 9 outliers. Engagement variables across MSNBC content are far more modest than its counterparts, with mean values of 7,601 likes, 1,312 comments, 740 shares, and 224, 223 views. Video content dominates this account with 89 out of its 100 sampled media classified as reels, with a mean word count of 217 words between all content.

Figure 6: Incivility Boxplots Between Each News Network



5.2 Trends Across The General Sample Population

Across the general sampled population, my engagement variables appear to differ in frequency based on the prevalence of incivility in Tables 1 and 2. The bivariate regression for like count demonstrated a 0.11% increase in the amount of likes for every 1% increase in the incivility ratio for all sampled posts. This slope coefficient fell to 0.085% when controlling for news program, topic, and the type of content (photo or video) in multivariate regression, as demonstrated in Figure 7. I found both relationships to be statistically significant with more than a 95% confidence level. As for comments, my analysis indicated no relationship with a coefficient of negative 0.024% in the bivariate regression and 0.033% in the multivariate regression, both offering predictably insignificant p values. The share count variable produced a negligible 0.006% coefficient as a bivariate regression but a 0.188% coefficient for the multivariate regression, though only statistically significant at a 90% confidence interval. Finally, view count boasted a negative 0.241% coefficient with a statistically significant p value as a bivariate regression but is reduced to a 0.011% slope with no statistical significance when controlled between the other categorical variables in the multivariate test. Importantly, these metrics appear to be diminished by content related to the Trump Trials or belonging to Fox News and MSNBC, as each of these controls experience lower engagement overall compared to their counterparts (the Israel-Palestine Conflict and CNN). I therefore fail to reject the null hypothesis for our engagement variables across the general sampled population with the exception of likes, which interestingly proves to have a robust positive relationship with incivility.

Table 1 Bivariate Regression

Incivility Across The General Sample Population

	Likes	Comments	Shares	Views
Incivility	0.110**	-0.024	0.006	-0.241**
Std. Error	0.048	0.044	0.108	0.094
Constant	9.579***	7.544***	6.485***	12.329***
Std. Error	0.080	0.073	0.184	0.159
Observations	287	287	182	173
R^2	0.018	0.001	0.00002	0.037
Adjusted R^2	0.015	-0.002	-0.006	0.031
Residual Std. Error	1.107 (df = 285)	1.010 (df = 285)	1.802 (df = 180)	1.544 (df = 171)
F Statistic	5.260** (df = 1; 285)	0.296 (df = 1; 285)	0.003 (df = 1; 180)	6.502** (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2 Multivariate Regression[11]

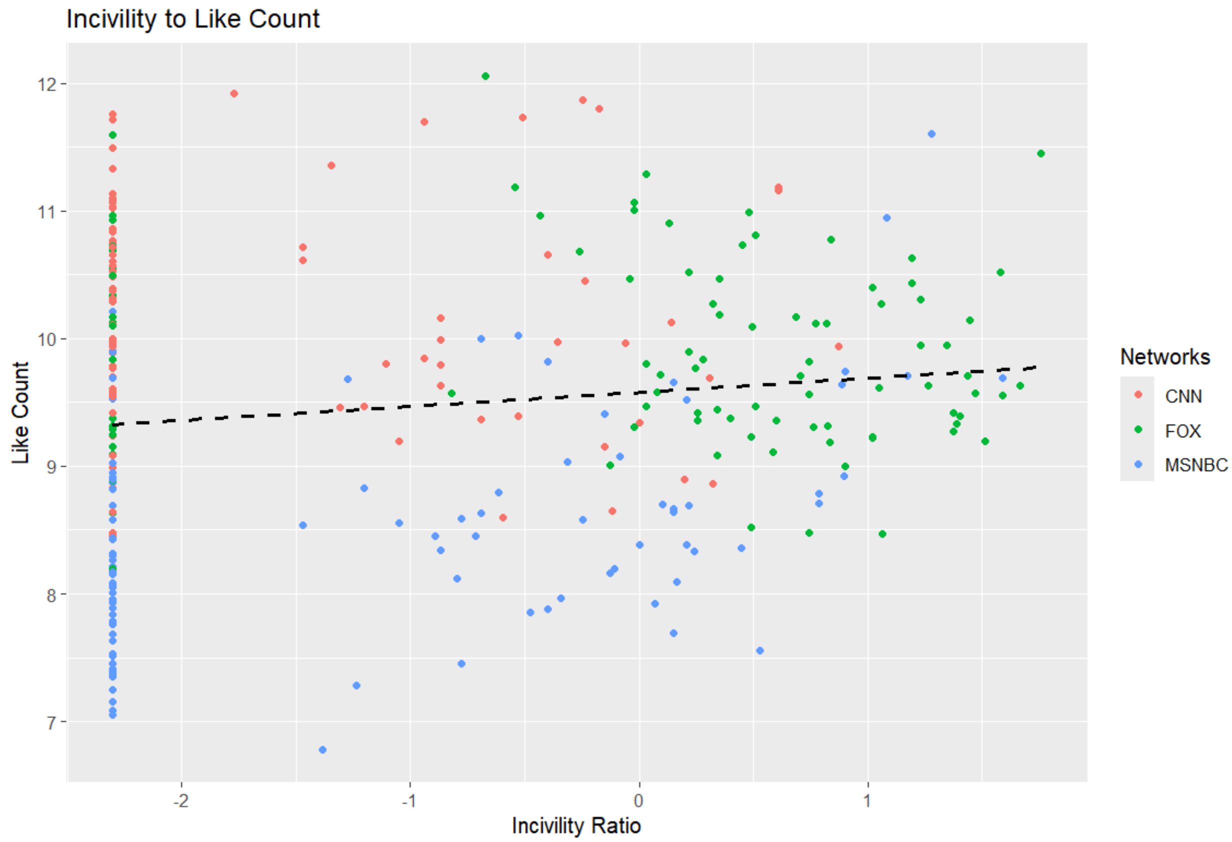
Engagement Variables Across The General Sample Population

	Likes	Comments	Shares	Views
Incivility	0.085**	0.033	0.188*	-0.011
Std. Error	0.041	0.039	0.110	0.066
Trump Trials	-0.041	-0.250**	-0.806***	-1.312***
Std. Error	0.100	0.097	0.247	0.147
FOX News	-0.472***	-0.721***	-0.800**	-0.739***
Std. Error	0.138	0.133	0.367	0.224
MSNBC	-1.623***	-1.547***	-2.086***	-2.322***
Std. Error	0.124	0.120	0.251	0.153
Video Content	-0.349***	0.007	-0.607	NA
Std. Error	0.114	0.110	0.572	NA
Constant	10.517***	8.504***	8.826***	14.496***
Std. Error	0.146	0.140	0.616	0.179
Observations	287	287	182	173
R^2	0.476	0.404	0.347	0.700
Adjusted R^2	0.467	0.393	0.328	0.693
Residual Std. Error	0.814 (df = 281)	0.785 (df = 281)	1.473 (df = 176)	0.869 (df = 168)
F Statistic	51.124*** (df = 5; 281)	38.071*** (df = 5; 281)	18.664*** (df = 5; 176)	98.043*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01

[11] Note that the network CNN, the Israel-Palestine Conflict, and Non-Video Content are being used as factor variables hereafter.

Figure 7: Incivility To Like Count Linear Regression Across The General Sample Population



5.3 Findings By News Topic

When examining these same engagement variables across topics, I derive similar results. In testing for the relationship between incivility and audience engagement across Israel and Palestine-related content, I find a weaker correlation across my bivariate and multivariate regressions. For like count, my bivariate again finds a positive coefficient value of 0.104%, but with no indication of statistical significance. This relationship is reduced to a 0.051% slope with an even less significant p value when tested with a multivariate regression. Comments again indicate a negative coefficient of 0.022% in the bivariate regression before shifting positive to 0.007% within the multivariate test, with no statistical significance. As for shares, the bivariate model returns a 0.048% coefficient while the multivariate produces a 0.22% slope, neither meeting any standard of statistical significance. View count again shows no significant results with negative coefficients of 0.13% and 0.048% across bivariate and multivariate tests respectively.

Content discussing the Trump Trials indicates stronger relationships amongst like count in particular, as demonstrated in Tables 3 and 4. Although the bivariate test for likes produces a 0.136% coefficient that initially falls just outside of the scope of a 95% confidence interval, this relationship matures to a 0.131% coefficient that meets our 95% confidence interval when examined through the multivariate regression, signifying a notable positive slope as examined in Figure 8. Comment count indicates a 0.031% coefficient in the bivariate regression and then 0.061% in the multivariate regression, but without any statistical significance. Shares initially produces a 0.324% coefficient value that is statistically significant within a 95% confidence interval when tested in the bivariate regression model, though this finding is degraded to a statistically insignificant slope of 0.191% in the multivariate regression. Finally, view count demonstrates a 0.171% coefficient within the bivariate regression with no statistical significance, which then falls to 0.009% with an even higher p value when examined through the multivariate model. Although the data fluctuates at slightly higher levels, I similarly fail to reject the null hypothesis for comment, share, and view count across the multivariate models, but again accept my positive relationship hypothesis when accounting for likes.

Table 3 Bivariate Regression

Incivility Across Topics: Trump Trials

	Likes	Comments	Shares	Views
Incivility	0.136*	0.031	0.324**	0.171
Std. Error	0.070	0.064	0.161	0.145
Constant	9.544***	7.430***	6.180***	11.836***
Std. Error	0.102	0.094	0.213	0.194
Observations	137	137	79	78
R^2	0.027	0.002	0.050	0.018
Adjusted R^2	0.020	-0.006	0.038	0.005
Residual Std. Error	1.082 (df = 135)	0.993 (df = 135)	1.715 (df = 77)	1.546 (df = 76)
F Statistic	3.782* (df = 1; 135)	0.239 (df = 1; 135)	4.063** (df = 1; 77)	1.391 (df = 1; 76)

Note: *p<0.1; **p<0.05; ***p<0.01

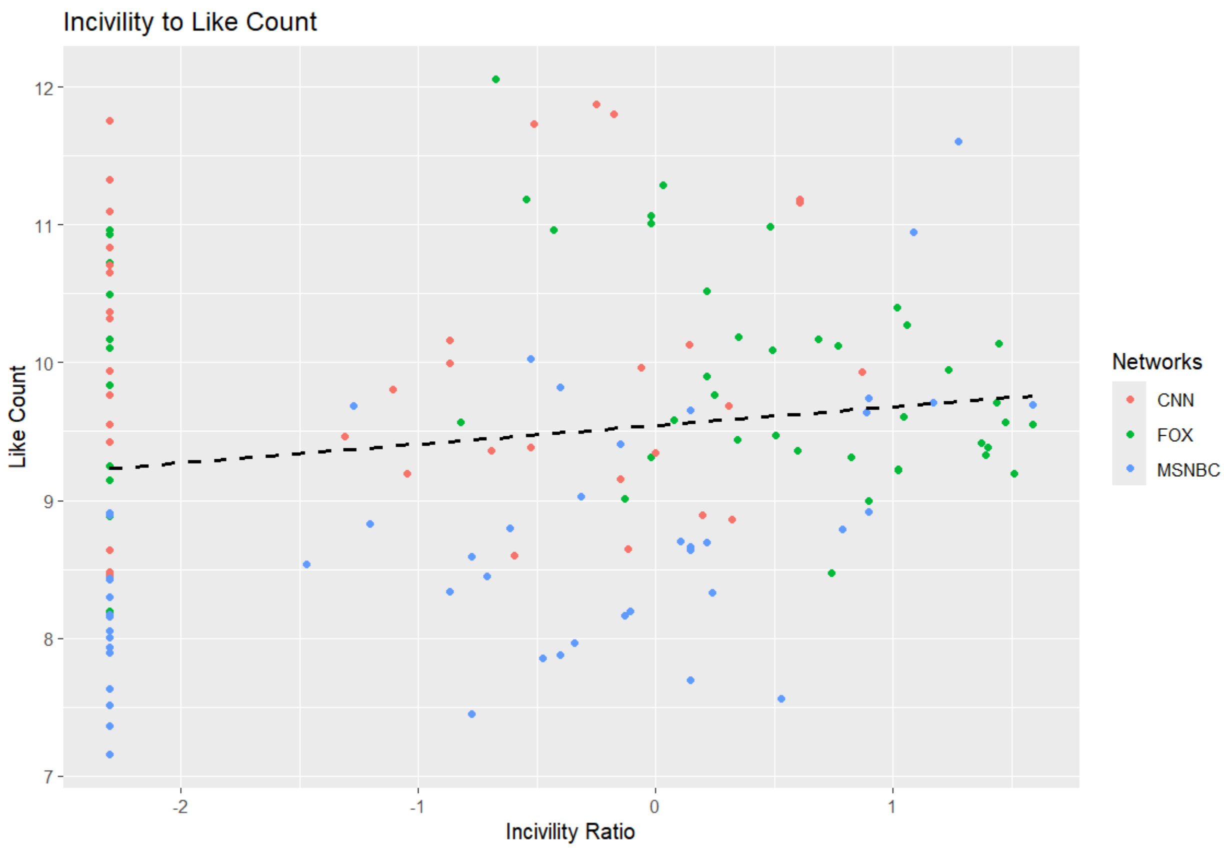
Table 4 Multivariate Regression

Engagement Variables Across Topics: Trump Trials

	Likes	Comments	Shares	Views
Incivility	0.131**	0.061	0.191	0.009
Std. Error	0.058	0.057	0.172	0.090
FOX News	-0.271	-0.695***	-0.096	-0.924***
Std. Error	0.195	0.190	0.600	0.314
MSNBC	-1.169***	-1.305***	-1.407***	-3.017***
Std. Error	0.196	0.192	0.463	0.242
Video Content	-0.587***	-0.190	0.244	NA
Std. Error	0.166	0.162	1.667	NA
Constant	10.401***	8.287***	6.652***	13.620***
Std. Error	0.175	0.171	1.613	0.223
Observations	137	137	79	78
R^2	0.411	0.315	0.192	0.716
Adjusted R^2	0.393	0.294	0.149	0.704
Residual Std. Error	0.851 (df = 132)	0.832 (df = 132)	1.613 (df = 74)	0.843 (df = 74)
F Statistic	23.012*** (df = 4; 132)	15.162*** (df = 4; 132)	4.406*** (df = 4; 74)	62.085*** (df = 3; 74)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 8: Incivility To Like Count Linear Regression Across Trump Trials



5.4 Findings By News Network

Across the partisan lenses of the different news networks, incivility offers its own unique impact across these metrics within the sample population. For all content related to Fox News, I find mostly insignificant negative correlations between incivility and engagement for a program ordinarily criticized for its extremist rhetoric. The like count coefficients take a negative slope of 0.044% and 0.037% across the bivariate and multivariate tests depicted in Tables 5 and 6, though this time failing to meet any acceptable confidence interval. Comment count similarly produces a negative 0.075% coefficient in the bivariate regression and negative 0.088% in the multivariate regression, with no sufficient indication of statistical significance. Share count also indicates a negative 0.288% coefficient with no statistical significance within the bivariate test, and a similarly insignificant coefficient of negative 0.399% across the multivariate regression. View count is the only engagement variable in this model that produces statistically significant findings at a 95% confidence interval across both tests, indicating negative slopes of 0.366% and 0.288% for the bivariate and multivariate models respectively and illustrated within Figure 9. Nevertheless, I fail to reject the null hypothesis across all variables with the exception of view count, to which I instead accept alternative hypothesis 2.[12]

Table 5 Bivariate Regression

Incivility Across News Sources: FOX News

	Likes	Comments	Shares	Views
Incivility	-0.044	-0.075	-0.288	-0.366***
Std. Error	0.053	0.059	0.286	0.113
Constant	9.896***	7.644***	7.006***	13.038***
Std. Error	0.075	0.083	0.332	0.125
Observations	100	100	32	31
R^2	0.007	0.016	0.033	0.266
Adjusted R^2	-0.003	0.006	0.001	0.241
Residual Std. Error	0.748 (df = 98)	0.827 (df = 98)	1.877 (df = 30)	0.690 (df = 29)
F Statistic	0.671 (df = 1; 98)	1.621 (df = 1; 98)	1.018 (df = 1; 30)	10.531*** (df = 1; 29)

Note: *p<0.1; **p<0.05; ***p<0.01

[12] Recall that only 31% of the sampled posts by Fox have a view count feature since they are in video format, so even this finding is largely inconclusive.

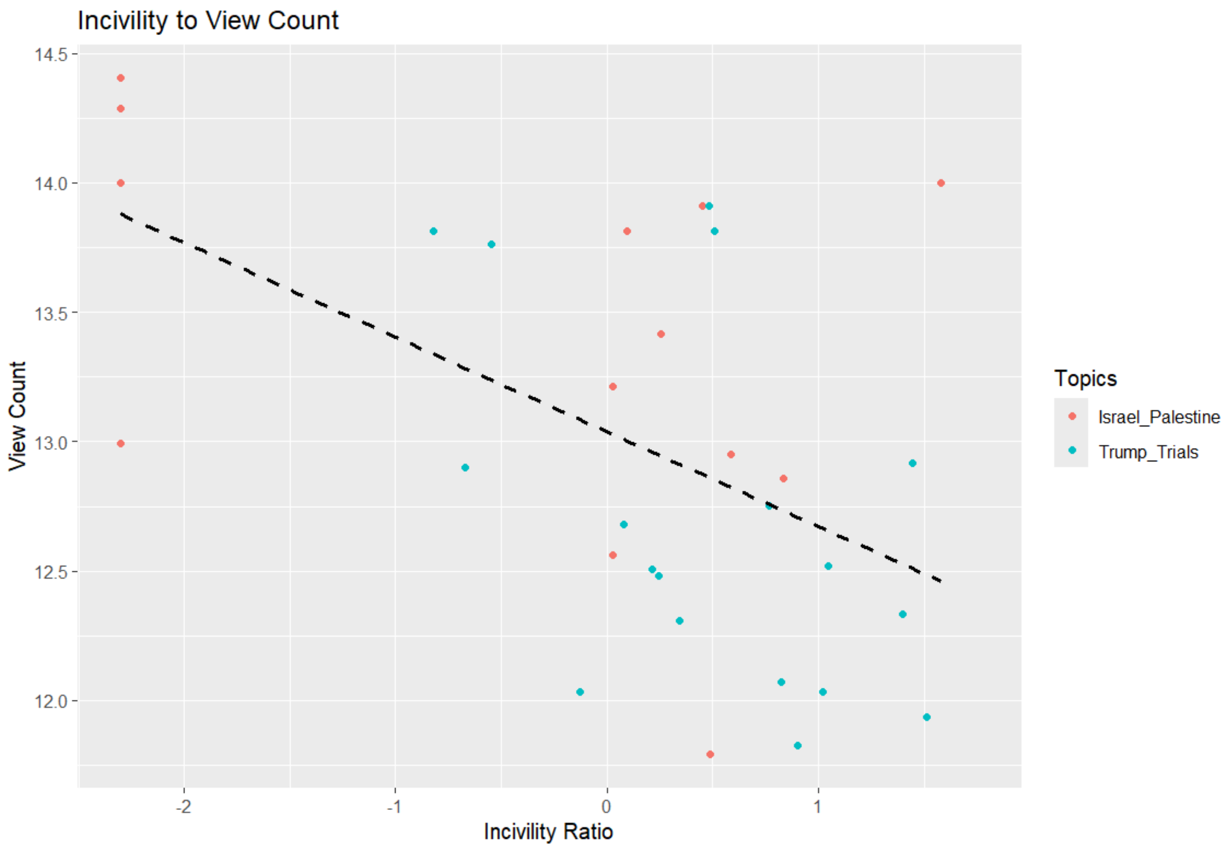
Table 6 Multivariate Regression

Engagement Variables Across News Sources: FOX News

	Likes	Comments	Shares	Views
Incivility	-0.037	-0.088	-0.399	-0.288**
Std. Error	0.054	0.058	0.338	0.118
Trump Trials	0.027	-0.307*	0.020	-0.454*
Std. Error	0.151	0.161	0.754	0.263
Video Content	-0.174	0.407**	1.971	NA
Std. Error	0.165	0.176	2.089	NA
Constant	9.938***	7.670***	5.090**	13.292***
Std. Error	0.116	0.124	2.065	0.190
Observations	100	100	32	31
R^2	0.018	0.093	0.063	0.337
Adjusted R^2	-0.012	0.065	-0.038	0.289
Residual Std. Error	0.752 (df = 96)	0.802 (df = 96)	1.913 (df = 28)	0.668 (df = 28)
F Statistic	0.594 (df = 3; 96)	3.288** (df = 3; 96)	0.626 (df = 3; 28)	7.111*** (df = 2; 28)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 9: Incivility To View Count Linear Regression Across FOX News



For CNN, my tests find no significant results. The like count coefficient fluctuates between a negative 0.046% and positive 0.041% coefficient across the bivariate and multivariate test with no statistical significance. For comments, I also start and end with negative and positive slopes of 0.032% and 0.076% between the bivariate and multivariate models with no statistical significance. Share count again touts a negative 0.369% coefficient that is statistically significant within a 90% confidence interval, but changes direction to a 0.014% slope with no statistical significance for the multivariate regression. Finally, view count produces a similar negative 0.208% coefficient with statistical significance within a 90% confidence interval but also falls to a negative 0.038% slope with no statistical significance when accounting for the multivariate regression model. Engagement indicators within CNN fluctuate between positive and negative coefficients or have weak ones altogether without statistically significant findings, so I thereby fail to reject the null hypothesis across all engagement variables.

Unlike its counterparts, MSNBC poses multiple statistically significant correlations within the engagement variables which collectively point toward a positive relationship regarding incivility. Across Tables 7 and 8, the bivariate regression for likes produces a substantial 0.315% coefficient while the multivariate regression indicates a similar 0.299% coefficient, both of which are statistically significant at a 99.9% confidence interval! The comment count variable similarly incurs a 0.139% coefficient for the bivariate test and a 0.158% coefficient within the multivariate test, reaching statistical significance within a 95% confidence interval. Share count has a bivariate coefficient of 0.308% with statistical significance within a 95% confidence interval before enlarging to a 0.41% slope under the multivariate regression with statistical significance under a 99% confidence interval. These three positive relationships are illustrated in Figures 10 to 12. Finally, the bivariate model for views instead results in a negative slope of 0.218 % under a 90% confidence interval but dilutes to a positive 0.069% coefficient with no statistical significance value under the multivariate test. There is a particularly strong deterrent regarding content focusing on the Trump trials, as this content is associated with a 0.628% decrease in shares and almost a 2% decrease in views compared to coverage on the Israel-Palestine conflict. Video content in general also experiences a reduction in engagement regarding comments (-0.612%) and shares (-1.58%), likely indicating that users show a keen interest within the image post headlines of MSNBC rather than their actual commentary. Given that I accept alternative hypothesis 1 for every engagement variable within MSNBC (except views, to which I instead fail to reject the null hypothesis), this finding may indicate that smaller news networks on Instagram may benefit more from the use of incivility amongst its smaller partisan supporter base.

Table 7 Bivariate Regression

Incivility Across News Sources: MSNBC

	Likes	Comments	Shares	Views
Incivility	0.315***	0.139**	0.308**	-0.218*
Std. Error	0.064	0.067	0.124	0.118
Constant	8.846***	6.969***	5.930***	11.271***
Std. Error	0.110	0.116	0.214	0.202
Observations	100	100	92	88
R^2	0.199	0.042	0.064	0.038
Adjusted R^2	0.191	0.032	0.053	0.027
Residual Std. Error	0.773 (df = 98)	0.813 (df = 98)	1.373 (df = 90)	1.289 (df = 86)
F Statistic	24.410*** (df = 1; 98)	4.288** (df = 1; 98)	6.140** (df = 1; 90)	3.405* (df = 1; 86)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8 Multivariate Regression

Engagement Variables Across News Sources: MSNBC

	Likes	Comments	Shares	Views
Incivility	0.299***	0.158**	0.410***	0.069
Std. Error	0.069	0.070	0.127	0.090
Trump Trials	0.045	-0.233	-0.628**	-1.914***
Std. Error	0.166	0.170	0.298	0.210
Video Content	-0.376	-0.612**	-1.580**	NA
Std. Error	0.248	0.255	0.784	NA
Constant	9.138***	7.653***	7.882***	12.568***
Std. Error	0.271	0.278	0.780	0.203
Observations	100	100	92	88
R^2	0.219	0.109	0.162	0.514
Adjusted R^2	0.195	0.081	0.134	0.503
Residual Std. Error	0.771 (df = 96)	0.792 (df = 96)	1.314 (df = 88)	0.922 (df = 85)
F Statistic	8.979*** (df = 3; 96)	3.920** (df = 3; 96)	5.676*** (df = 3; 88)	44.946*** (df = 2; 85)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 10: Incivility To Like Count Linear Regression Across MSNBC

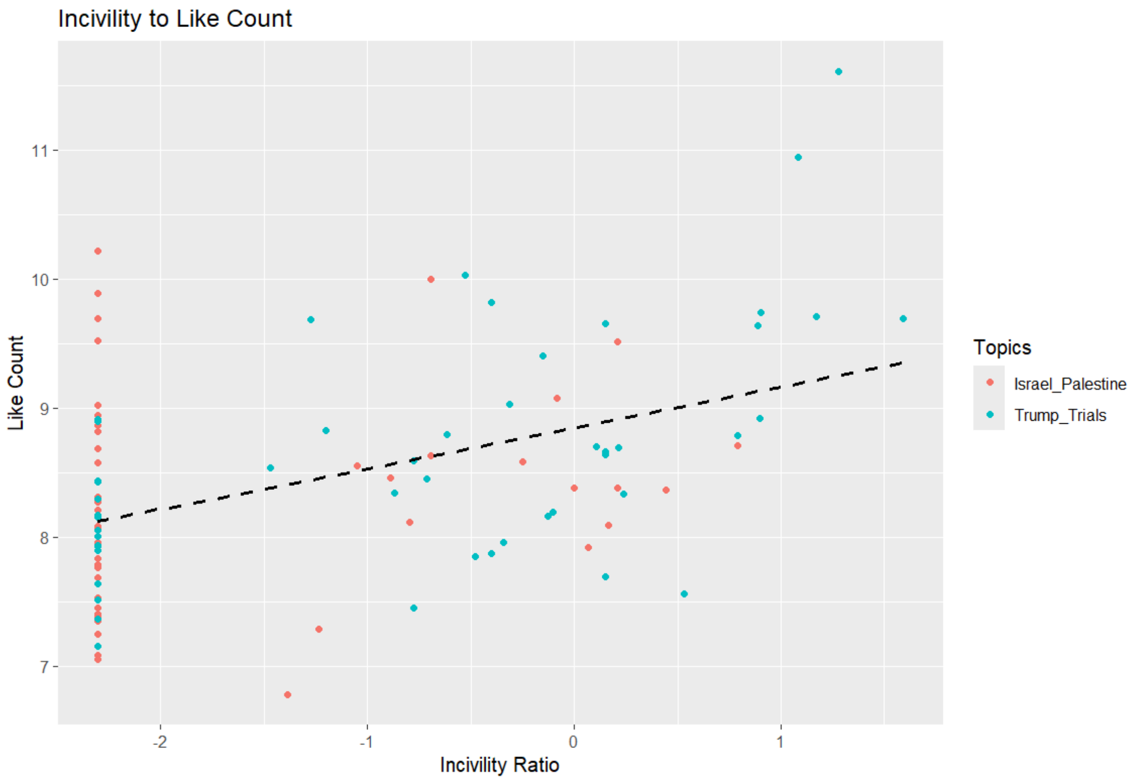


Figure 11: Incivility To Comment Count Linear Regression Across MSNBC

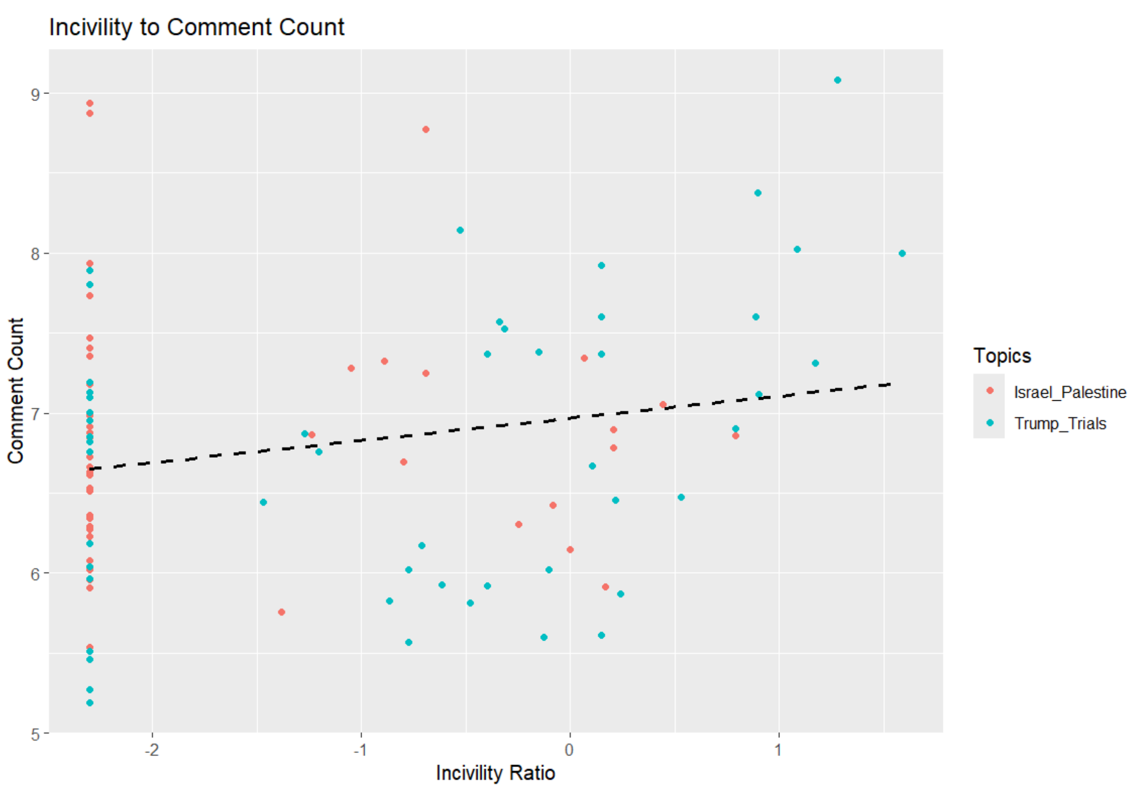
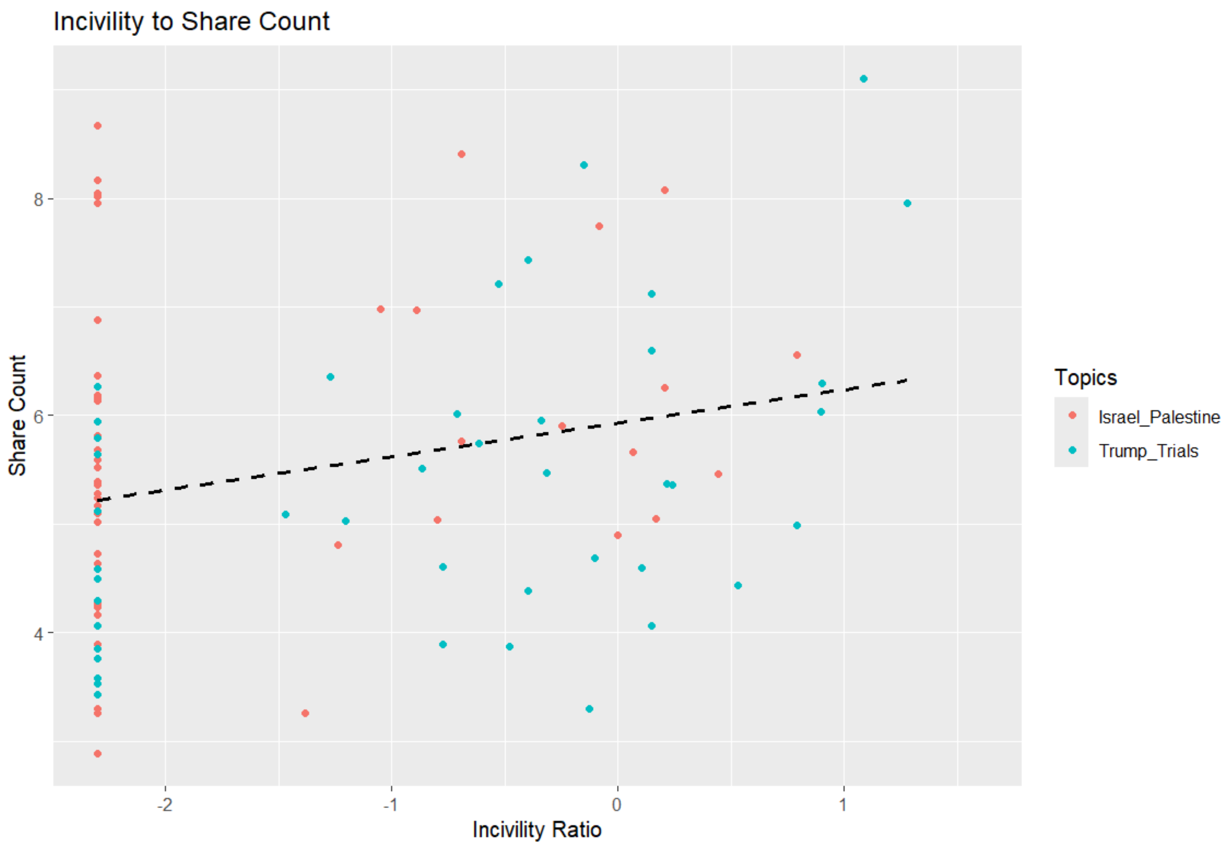


Figure 12: Incivility To Share Count Linear Regression Across MSNBC



5.5 Findings By Content Type:

When accounting for the different format style of posts within my sampled data, I find noticeable differences in how incivility impacts engagement across video reels and photo posts. Since CNN and MSNBC almost exclusively use video reels to publish their content, my findings for video content apply largely to them, while non-video figures are more indicative of FOX. Across all video content, the like count coefficient is 0.116% with statistical significance within a 90% confidence interval for the bivariate regression within Table 9. This relationship matures to an 0.143% coefficient with statistical significance within a 95% confidence interval across the multivariate regression in Table 10 and illustrated in Figure 13. The comment engagement variable offers a negative 0.022% coefficient within the bivariate test and a positive 0.039%

coefficient across the multivariate model, both lacking statistical significance. Share count is associated with a 0.027% and an 0.181% coefficient in the bivariate and multivariate analyses but ultimately offers no statistical significance. Across view counts, I find a negative 0.241% slope that is statistically significant within a 95% confidence interval when testing the bivariate relationship, though the multivariate test results in only a negative 0.011% coefficient that lacks statistical significance. Across Instagram reels, I ultimately reject the null hypothesis only for like count in adopting hypothesis 1 and fail to reject the null hypothesis for the other engagement variables.

Table 9 Bivariate Regression

Incivility Across Content Type: Video Content

	Likes	Comments	Shares	Views
Incivility	0.116*	-0.022	0.027	-0.241**
Std. Error	0.069	0.070	0.110	0.094
Constant	9.277***	7.422***	6.473***	12.329***
Std. Error	0.116	0.119	0.187	0.159
Observations	175	175	175	173
R^2	0.016	0.001	0.0004	0.037
Adjusted R^2	0.011	-0.005	-0.005	0.031
Residual Std. Error	1.130 (df = 173)	1.159 (df = 173)	1.817 (df = 173)	1.544 (df = 171)
F Statistic	2.855* (df = 1; 173)	0.099 (df = 1; 173)	0.061 (df = 1; 173)	6.502** (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

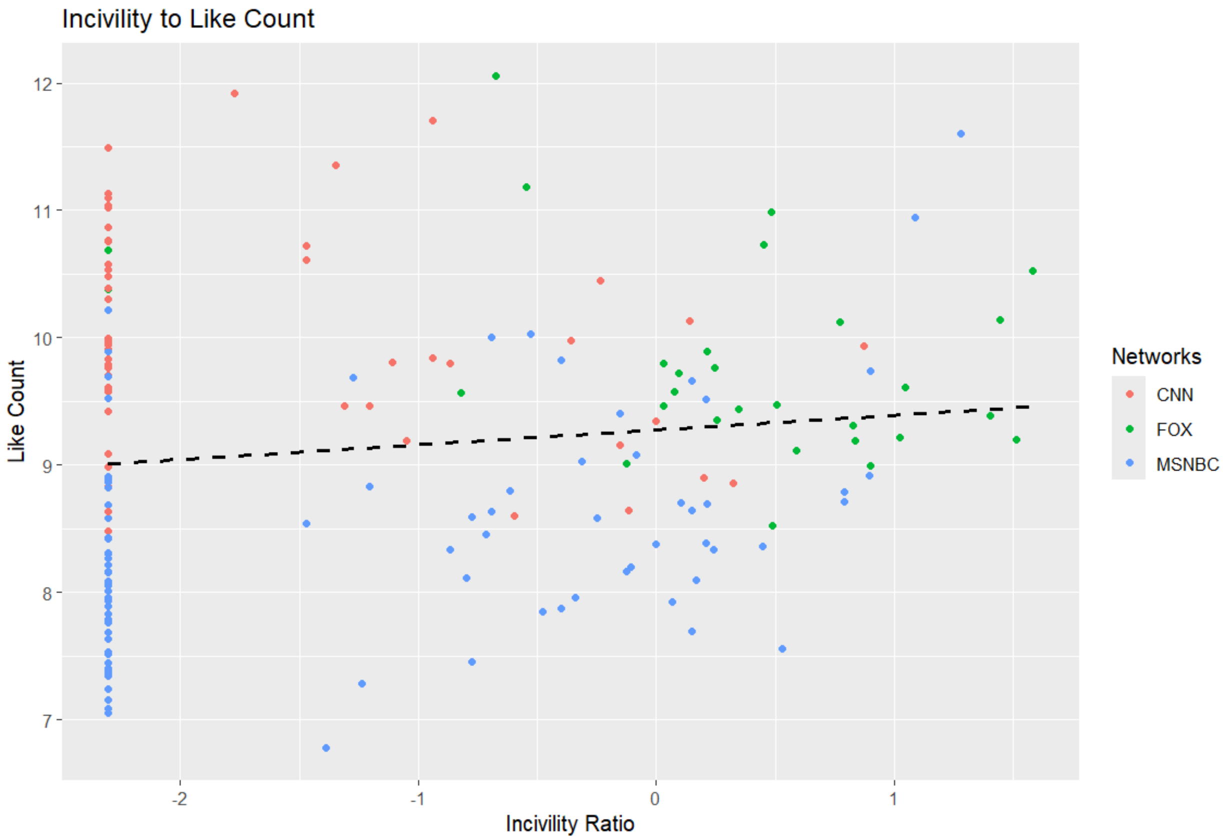
Table 10 Multivariate Regression

Engagement Variables Across Content Type: Video Content

	Likes	Comments	Shares	Views
Incivility	0.143**	0.039	0.181	-0.011
Std. Error	0.064	0.067	0.113	0.066
Trump Trials	-0.185	-0.354**	-0.767***	-1.312***
Std. Error	0.143	0.148	0.251	0.147
FOX News	-0.413*	-0.450**	-0.764**	-0.739***
Std. Error	0.217	0.225	0.381	0.224
MSNBC	-1.604***	-1.591***	-2.135***	-2.322***
Std. Error	0.147	0.152	0.259	0.153
Constant	10.278***	8.538***	8.213***	14.496***
Std. Error	0.174	0.180	0.305	0.179
Observations	175	175	175	173
R^2	0.461	0.443	0.346	0.700
Adjusted R^2	0.449	0.429	0.331	0.693
Residual Std. Error	0.843 (df = 170)	0.873 (df = 170)	1.482 (df = 170)	0.869 (df = 168)
F Statistic	36.402*** (df = 4; 170)	33.748*** (df = 4; 170)	22.505*** (df = 4; 170)	98.043*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 13: Incivility To Like Count Linear Regression Across Video Content



For non-video content, I fail to find any statistically significant trends altogether. The coefficient for like count under the bivariate model is particularly trivial at virtually 0% with no statistical significance, while the multivariate regression offers little additional info with another statistically insignificant coefficient of 0.043%. For comments, I find a negative 0.067% coefficient with no statistical significance under the bivariate test, and the multivariate model finds a 0.018% coefficient that also lacks statistical significance. Finally, the share count regression models provide inconclusive findings based on the mere 7 sampled posts that include this metric value. From these findings, I fail to reject the null hypothesis for any of these variables in concluding that the most significant relationship between incivility and likes is related to audience behaviors concerning Instagram reels.

5.6 Accounting for Types of Political Incivility

When accounting for the type of incivility that best explains the aforementioned relationships (or in many cases, the lack of a relationship), I find that some prove to be more salient in how they impact the data than others. Across the 15 sampled posts that include at least one instance of blame, the bivariate regression indicates a negative coefficient of 0.077% with no statistically significant p-value, similar to the multivariate test which produces a coefficient of negative 0.02% with no statistical significance. Comments also indicated statistically insignificant trends, as the bivariate and multivariate regressions produced negative coefficients of 0.139% and 0.077% respectively. Share count similarly experienced negative coefficients of 0.085% and 0.056% amongst the bivariate and multivariate regressions respectively with no statistically significant p values. Finally, the findings for view count also failed to achieve any statistically significant relationship, with a negative 0.023% coefficient across the bivariate regression and a positive 0.06% coefficient for the multivariate regression. Given the low sample count of this variable, failing to reject the null hypothesis across the engagement variables for this type of incivility isn't surprising.

Hyperbole, an incivility type accounting for almost half of the entire sample population, ultimately has little impact on incivility by itself. For like count, the bivariate regression indicates a negative 0.01% coefficient with no statistical significance, whereas the multivariate model reveals a positive 0.051% coefficient with a p value just below the threshold for a 90% confidence interval. Comment count yielded a negative 0.071% coefficient for the bivariate regression that was statistically significant at a 95% confidence interval, but this finding failed to remain significant in the multivariate test with a mere 0.009% slope. Share count indicated a slope of negative 0.029% that originally lacked any statistical significance until it was controlled for in the multivariate regression, becoming a positive coefficient of 0.142% with statistical significance within a 90% confidence interval. Lastly, view count shows a statistically significant negative coefficient of 0.25% in the bivariate regression within a 99.9% confidence interval, though this effect loses significance in the multivariate regression, where the coefficient drops to a negative 0.025%. In sum, I fail to reject the null hypothesis amongst all engagement variables when using a 95% confidence interval. It should be mentioned that evaluating hyperbolic incivility on its face did reveal some positive correlations, though they are largely inconsistent results.

Accusations of lying, the least common incivility type within the sample population exemplified by a mere 5 posts, is incapable of producing any conclusive results.

When examining name-calling, the second most frequent incivility category accounting for more than 20% of our sampled population, the positive correlation with likes becomes better understood. I found this sub-category of incivility to be associated with a 0.118% slope coefficient across likes in the bivariate regression under Table 11, a statistically significant finding within a 95% confidence interval. When accounting for controls through the multivariate regression in Table 12, I derive a similar coefficient of 0.095% that retains the same degree of statistical significance. Across comments, the coefficient value sits at 0.034% for the bivariate regression with no statistical significance, while the multivariate model produces a similarly insignificant 0.05% coefficient. Share count poses a 0.06% coefficient with no statistical significance in the bivariate regression, while the multivariate test reveals a 0.096% coefficient with no statistical significance either. View count starts with a bivariate regression coefficient of 0.022% with no statistical significance, though the multivariate regression instead indicates a 0.119% coefficient that is statistically significant within a 95% confidence interval. The positive relationships among likes and views are shown in Figures 14 and 15. Based on these results, I fail to reject the null hypothesis across comments and shares while adopting hypothesis 1 for likes and views. Interestingly, name-calling appears to primarily increase passive engagement metrics, giving credence to the theory that such flagrant instances of incivility can be captivating to a general audience at a superficial level.

Table 11 Bivariate Regression

Name-Calling Across The General Sample Population

	Likes	Comments	Shares	Views
Name-Calling	0.118**	0.034	0.060	0.022
Std. Error	0.056	0.051	0.112	0.098
Constant	9.676***	7.625***	6.585***	12.641***
Std. Error	0.116	0.106	0.238	0.209
Observations	287	287	182	173
R^2	0.015	0.002	0.002	0.0003
Adjusted R^2	0.012	-0.002	-0.004	-0.006
Residual Std. Error	1.108 (df = 285)	1.009 (df = 285)	1.800 (df = 180)	1.572 (df = 171)
F Statistic	4.463** (df = 1; 285)	0.438 (df = 1; 285)	0.287 (df = 1; 180)	0.049 (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12 Multivariate Regression

Engagement Variables Across Incivility Types: Name-Calling

	Likes	Comments	Shares	Views
Name-Calling	0.095**	0.050	0.096	0.119**
Std. Error	0.042	0.041	0.100	0.058
Trump Trials	-0.018	-0.245***	-0.680***	-1.378***
Std. Error	0.098	0.094	0.232	0.137
FOX News	-0.399***	-0.699***	-0.615*	-0.871***
Std. Error	0.126	0.122	0.344	0.205
MSNBC	-1.596***	-1.536***	-2.042***	-2.325***
Std. Error	0.123	0.119	0.251	0.150
Video Content	-0.362***	-0.001	-0.624	NA
Std. Error	0.114	0.110	0.576	NA
Constant	10.561***	8.550***	8.684***	14.769***
Std. Error	0.153	0.147	0.628	0.175
Observations	287	287	182	173
R^2	0.478	0.406	0.339	0.707
Adjusted R^2	0.469	0.395	0.320	0.700
Residual Std. Error	0.813 (df = 281)	0.784 (df = 281)	1.481 (df = 176)	0.858 (df = 168)
F Statistic	51.442*** (df = 5; 281)	38.346*** (df = 5; 281)	18.074*** (df = 5; 176)	101.528*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01

Figure 14: Name-Calling To Like Count Linear Regression Across The General Sample Population

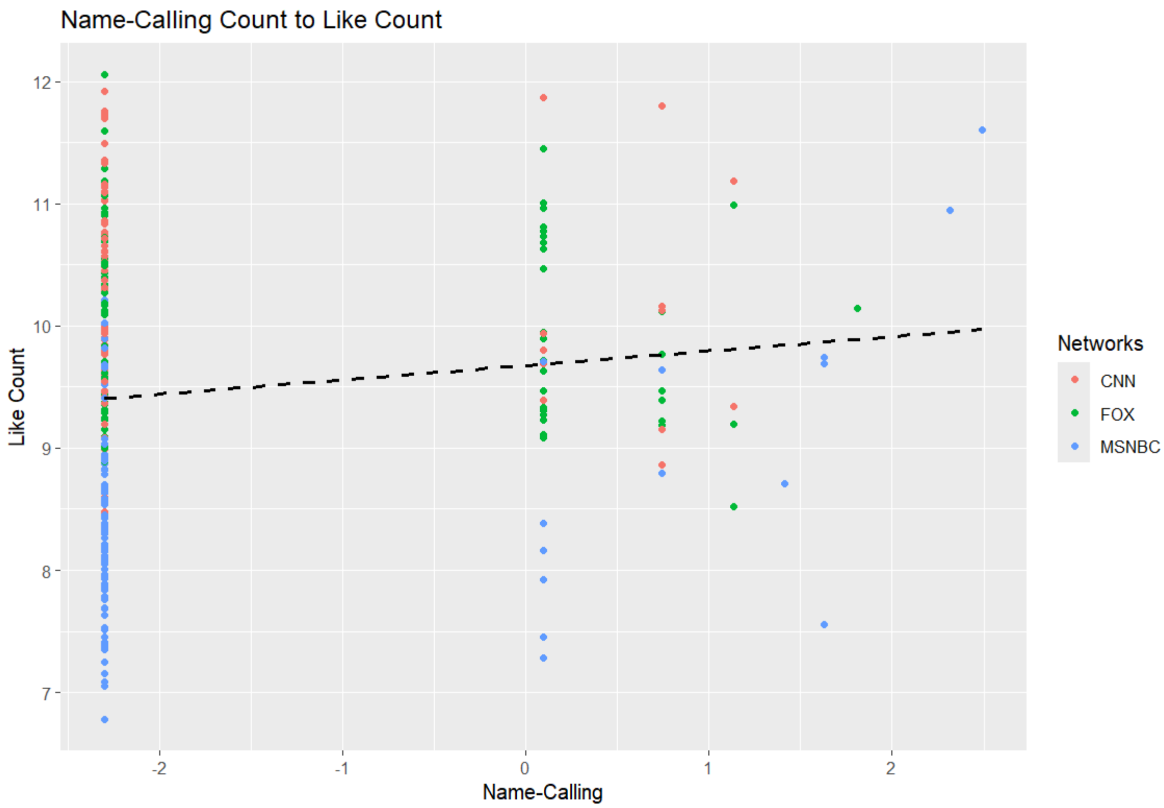
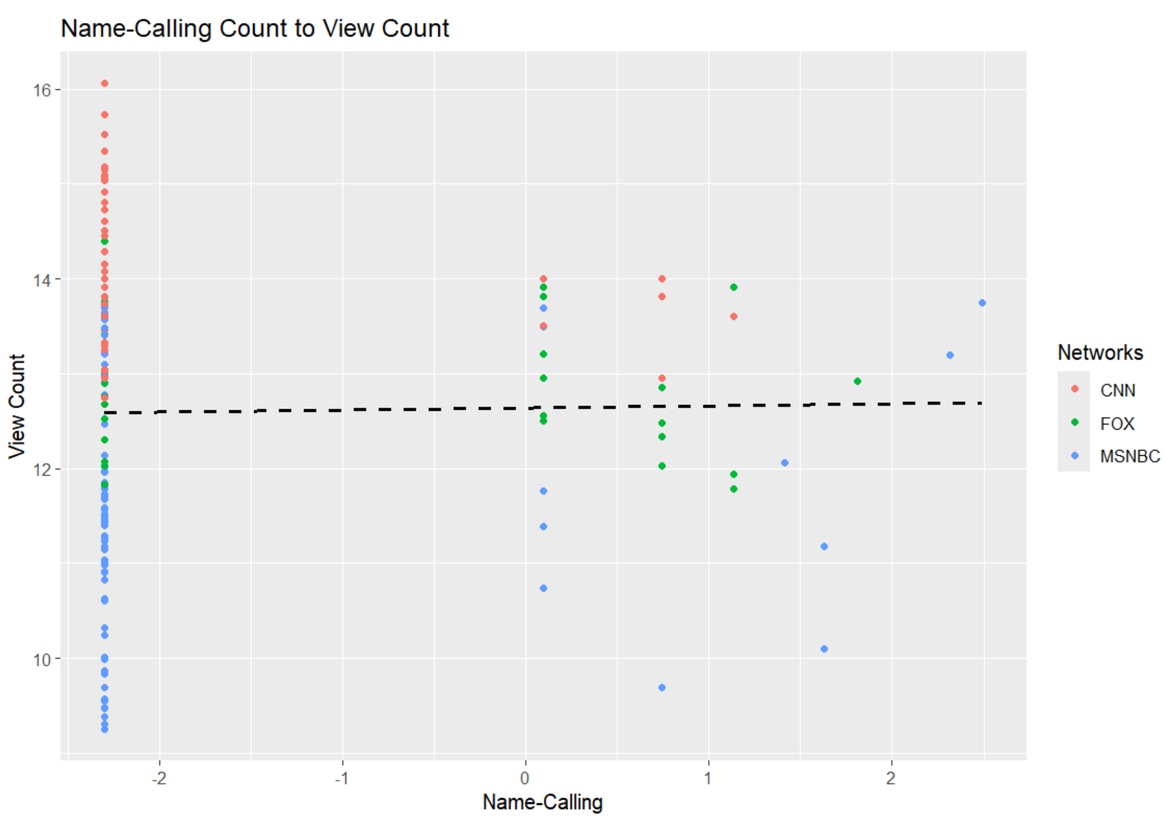


Figure 15: Name-Calling To Like Count Linear Regression Across The General Sample Population



Lastly, Threatens American Values offers only 14 sampled posts, and poses no statistically significant findings. Across likes, my bivariate test offers an insignificant coefficient of 0.14% that is reduced to 0.06% in the multivariate regression. My comments variable features a negligible 0.001% coefficient that shifts to a negative 0.003% value between the bivariate and multivariate regression. Share count produces a statistically insignificant bivariate coefficient of 0.305% that experiences little differentiation when compared to the 0.273% value within the multivariate model. Finally, view count is also hardly impacted by this relatively infrequent subcategory of incivility, incurring a coefficient of 0.122% and 0.159% across the bivariate and multivariate tests respectively. I therefore fail to reject the null hypothesis across all engagement variables when considering this incivility type.

VI. CONCLUSION

This study seeks to unravel the various confounding factors that relate to the phenomenon of political incivility by individually accounting for differences across research models ("generalized" and "operationalized"), media formats, issue topics, and classification of such uncivil discourse. Additionally, I attempt to associate both the prevalence of incivility and its existing trends to a particular ideological faction based on prior research. Although these findings can effectively represent the total population of Instagram posts that fall within the parameters of this study (287 posts out of the 1,549 found within the sampled networks and topics), my intention is to also compare these findings across other social networks.

Throughout the general sample population, we find that incivility impacts user engagement in relatively consistent ways. There exists a positive correlation between incivility and likes across the general population (0.085% slope), content referring to the Trump trials

(0.13%), posts within MSNBC (0.30%), and video content (0.14%). Although comments and shares also tend to increase with the presence of incivility, this is only statistically significant for the latter at a 90% confidence interval across the general population (0.19%). View count oddly tends to have a negative correlation but is only statistically significant in the case of FOX News, likely due to the lack of video-based content throughout their Instagram account. When considering different categories of incivility, my limited results conclude that only name-calling is responsible for a statistically significant increase in like count and view count by 0.10% and 0.12% respectively. This suggests that insults directed towards a particular person or group could captivate audiences more effectively across passive engagement metrics than indirect attacks or sensationalism. Taken together, these results support the predominant theory across literature that political incivility fosters audience engagement, as its captivating qualities attract users between passive and active engagement options.

When attributing these findings to a particular ideological group, I discover that such a process becomes rather sophisticated. Fox News, the most popular conservative news network on Instagram, leads by far in perpetuating incivility with 72% of its posts categorized as uncivil with a mean incivility ratio of 1.56 instances for every 50 words. However, it remains the only tested network that features a statistically significant decrease in views by 0.29% and a negative relationship across the other engagement variables (to an insignificant degree) as incivility becomes more prevalent. Rather, it is the less popular liberal network MSNBC that earns statistically significant increases in likes (0.30%), comments (0.16%), and shares (0.41%) for every 1% increase in the use of uncivil commentary. This reality turns the conflicting narrative of political incivility on its head in demonstrating that a major political actor on Instagram who perpetuates incivility actually faces reduced audience engagement while smaller actors that use substantially less benefit, dismissing partisan affiliation altogether. Hence, I cautiously adopt aspects of both alternative hypotheses 1 and 2 for this research question (i.e. the conservative network produces more incivility, though only the liberal network earns more engagement when using such discourse), while acknowledging within my incivility-engagement theory that such a positive relation exists only to a certain extent.

These results demonstrate significant parallels and deviations from previous literature, deposing conventional theories and suggesting novel approaches to our understanding of incivility patterns. Whereas Barry and Sobieraj evaluated Talk Radio transcripts that consistently employed incivility while 70% of Sydnor's sampled cable programs transcripts followed suit, my study accounts for even less between the three networks (54%). That said, the positive relationship heralded by these works and those particularly within the realm of Twitter (Brady, Kosmides and Theocharis) and the homogenization of communities within Reddit (Sun, Weld, and Nithyanand) is supported by a marked increase in engagement particularly in the form of likes. Keeping this in mind, such a trend falls into question when considering the concentration of uncivil discourse within each program, which instead echoes the parabolic association outlined by Kim's research within Facebook and invites further discussion as to how such a trend may deviate from conventional linear relationships. These findings also fail to reject the negative relationship expressed by Feinberg and Frimer outright and may explain the sporadic results expressed in studies related to Tiktok. Finally, Su's assessment within Facebook implies that these trends may become further compounded when incorporating the progressively uncivil dialogue found within local news media, a factor that will hopefully be accounted for in future research. The same can be said for differences in user anonymity and content moderation techniques between social media, as expressed by Sude and Rossini. Such conclusions call for additional comprehensive studies that are capable of testing multiple interrelated theories and controlling for lingering variables that may confound results.

Despite my efforts to address pre-existing limitations in prior research, this study includes its own respective assortment that prevents my findings from being taken at face value. For one, the limited pool of partisan cable networks sampled within Instagram fails to account for the entire population of political activity across the platform, as there are a variety of other dominant networks and even private users who also shape political commentary throughout Instagram. Although maintaining continuity with other operationalized research methods and keeping the focus on historically popular news outlets was a compelling reason to limit the scope of this work, such a decision should be considered when applying these findings outside the confines of my research model.

Secondly, although my quantitative content analysis on social media engagement metrics does incorporate some public perception based on the choice of engagement by online users, it lacks descriptive insights into such behaviors necessary in sufficiently postulating causation. Even when my data concludes that particular Instagram accounts "benefit" from their use of incivility compared to others, such an empirical finding alone fails to prove that an increase in engagement actually motivates news outlets in producing more incivility. Moreover, the motive behind an Instagram user's behavior in using one or multiple types of engagement on the platform over others remains fairly ambiguous outside of prevailing theories from independent works, as such engagement can represent a variety of behaviors from unwavering support in a content piece's message to vehement opposition. In light of these circumstances, such findings should only be observed as correlations best suited to support or challenge previous theories, and instead suggest that employing aspects of both a generalized and operationalized research approach is necessary in drawing such a comprehensive conclusion.

Nevertheless, this study is the first of its kind that evaluates the properties of political incivility within Instagram relative to other social media platforms and their research contributions to our understanding of the phenomenon. Previous studies differed in the media types that they analyzed, assessing broad categories of content using dissimilar research models. Although one work alone cannot possibly address each of these distinctive features and their respective disparities in current literature, this study hopes to encourage scholars to critically assess the mechanisms used to descriptively and empirically determine the consequences of uncivil language within the political realm. Such an endeavor is imperative to the statistical integrity of future research and our comprehension of productive political discourse within a democratic society as a whole.

6.1 Bibliography

Ahuja, Sunil, and Thomas Charles Sawyer, *Congress Behaving Badly: The Rise of Partisanship and Incivility and the Death of Public Trust*. Westport, Connecticut, Praeger, 2008. https://search.worldcat.org/title/179802449

Barberá, Pablo, "Social Media, Echo Chambers, and Political Polarization", *Social Media and Democracy*, Cambridge University Press. https://doi.org/10.1017/9781108890960.004.

Berry, Jeffrey M, and Sarah Sobieraj, *The Outrage Industry: Political Opinion Media and The New Incivility*, Oxford University Press, 2013. https://search-library.ucsd.edu/view/action/uresolver.do?operation=resolveService&package_service_id=17998607750006535&institutionId=6535&customerId=6530&VE=true

Blake, Aaron, "Ranking The Media From Liberal to Conservative, Based On Their Audiences", The Washington Post, 2014. https://www.washingtonpost.com/news/the-fix/wp/2014/10/21/lets-rank-the-media-from-liberal-to-conservative-based-on-their-audiences/

Bossetta, Michael, "The Digital Architectures of Social Media: Comparing Political Campaigning on Facebook, Twitter, Instagram, and Snapchat in the 2016 U.S. Election" *Journalism & Mass Communication Quarterly* 95, no. 2, 2018. https://doi.org/10.1177/1077699018763307

Brady, William & Wills, Julian & Jost, John & Tucker, Joshua & Van Bavel, Jay, "Emotion Shapes The Diffusion of Moralized Content In Social Networks" *Proceedings of the National Academy of Sciences* 114, 2017. https://doi.org/10.1073/pnas.1618923114

Breur, Tom, "US Elections: How Could Predictions Be So Wrong?", *Journal of Marketing Analytics* vol. 4, 2017. https://doi.org/10.1057/s41270-016-0010-2.

DeBois, Pierre, "Likes, Dislikes, Social Media and Mental Health", CMSWire.com, 2022. www.cmswire.com/digital-experience/changing-social-media-likes-as-mental-health-safety-changes/.

Dixon, Stacy J, "Topic: Social Media and Generation Z in the United States", Statista, 2024. https://www.statista.com/topics/10943/social-media-and-generation-z-in-the-united-states/.

Druckman, James N., S. R. Gubitz, Ashley M. Lloyd, and Matthew S. Levendusky, "How Incivility On Partisan Media (De)Polarizes The Electorate", *The Journal of Politics*, vol. 81, no. 1, 2019. https://doi.org/10.1086/699912

Eddy, Kirsten, "8 Facts about Americans and TikTok", Pew Research Center, 2024. www.pewresearch.org/short-reads/2024/12/20/8-facts-about-americans-and-tiktok/#:~:text=Almost%20all%20adults%20who%20use,on%20it%20%E2%80%9Calmost%20constantly.%E2%80%9D.

Feinberg, Matthew, and Jeremy A. Frimer, "Incivility Diminishes Interest In What Politicians Have To Say", *Social Psychological and Personality Science*, vol. 14, no. 7, 2023. https://doi.org/10.1177/19485506221136182

Fung, Brian, and Clare Duffy, “How a Single Year of Elon Musk Turned Twitter Into a Husk of Its Former Self” CNN Business, CNN, 2023. www.cnn.com/2023/10/27/tech/elon-musk-twitter-x-one-year-changes/index.html.

Gervais, Bryan T., "Rousing The Partisan Combatant: Elite Incivility, Anger, and Antideliberative Attitudes", Political Psychology 40, no. 3, 2019. https://doi.org/10.1111/pops.12532

Goldman, David, and Clare Duffy, “Elon Musk May Be On The Brink Of Achieving The Impossible: Salvaging His $44 Billion Investment In X”, CNN Business, CNN, 2025. www.cnn.com/2025/02/20/tech/elon-musk-x-valuation/index.html.

Goldstein, Susan B., “Construction and Validation of a Conflict Communication Scale” *Journal of Applied Social Psychology*, vol. 29, no. 9, 1999. https://doi.org/10.1111/j.1559-1816.1999.tb00153.x.

Goovaerts, Ine, “Highlighting Incivility: How the News Media’s Focus on Political Incivility Affects Political Trust and News Credibility”, *Journalism & Mass Communication Quarterly*, 2022. https://doi.org/10.1177/10776990221084608

Goovaerts, Ine, and Sofie Marien, “Uncivil Communication and Simplistic Argumentation: Decreasing Political Trust, Increasing Persuasive Power?”, *Political Communication*, vol. 37, no. 6, 2020. https://doi:10.1080/10584609.2020.1753868.

Gramlich, Michael Dimock and John, “How America Changed During Donald Trump’s Presidency” Pew Research Center, 2021. https://www.pewresearch.org/politics/2021/01/29/how-america-changed-during-donald-trumps-presidency/.

Granger, C W J., “Investigating Causal Relations by Econometric Models and Cross-Spectral Methods”, *Econometrica: Journal of the Econometric Society*, vol. 37, no. 3, 1969. https://doi.org/10.2307/1912791.

Grieco, Elizabeth, “Americans' Main Sources For Political News Vary By Party and Age”, Pew Research Center, 2020. https://www.pewresearch.org/fact-tank/2020/04/01/americans-main-sources-for-political-news-vary-by-party-and-age/

Halpern, Daniel, Jennifer Gibbs, “Social Media As a Catalyst For Online Deliberation? Exploring The Affordances of Facebook and YouTube For Political Expression”, *Computers in Human Behavior*, vol. 29, Issue 3, 2013. https://doi.org/10.1016/j.chb.2012.10.008.

Herbst, Susan, *Rude Democracy: Civility and Incivility in American Politics*. 1st edition, Temple University Press, 2010. https://www.jstor.org/stable/j.ctt14bt9vz

Hirsch, Lauren, and Sapna Maheshwari, “How A Sale Of TikTok Would Work And Who Might Buy It”, The New York Times, 2025. www.nytimes.com/2025/02/04/business/media/tiktok-sale-who-could-buy.html.

Instagram.com,”Instagram”, Instagram, 17 Feb. 2025. https://www.instagram.com/

Jurkowitz, Mark, et al. "Americans Are Divided By Party In The Sources They Turn To For Political News." *U.S. Media Polarization and the 2020 Election: A Nation Divided*, Pew Research Center, 2020. www.pewresearch.org/journalism/2020/01/24/americans-are-divided-by-party-in-the-sources-they-turn-to-for-political-news/.

Jones, CT, *How Social Media Platforms Are Courting The TikTok Crowd*, Rolling Stone, 2025. www.rollingstone.com/culture/culture-features/tiktok-ban-social-media-alternatives-1235239687/.

Kashyap, Ruchi, "What Counts As A View On Instagram Reels, Videos, Posts & Stories? (SPAM)", iGuideInsta, 2024. iguide-insta.com/faq/views-count-instagram-reels-videos-stories-post/.

Kim, Jin Woo, Andrew Guess, Brendan Nyhan, and Jason Reifler, "The Distorting Prism of Social Media: How Self-Selection and Exposure to Incivility Fuel Online Comment Toxicity." *Journal of Communication* vol. 71, no. 6, 2021. https://doi.org/10.1093/joc/jqab034

Kim, Youngju, and Hyunseo Hwang, "When Partisans See Media Coverage as Hostile: The Effect of Uncivil Online Comments on Hostile Media Effect" *Media Psychology*, vol. 22, no. 6, 2018. https://doi:10.1080/15213269.2018.1554492.

Massaro, Toni M, and Robin Stryker, "Freedom of Speech, Liberal Democracy, and Emerging Evidence on Civility and Effective Democratic Engagement", *Arizona Law Review*, vol. 54, 2012. https://heinonline.org/HOL/LandingPage?handle=hein.journals/arz54&div=17&id=&page=

Mutz, Diana C, *In-Your-Face Politics: The Consequences of Uncivil Media*, Princeton University Press, 2015. http://www.jstor.org/stable/j.ctt1djmhbx.

Mutz, Diana C. and Bryon Reeves, "The New Videomalaise: Effects of Televised Incivility on Political Trust" *American Political Science Review* 99, no. 1, 2005. https://doi.org/10.1017/S0003055405051452.

Neilson, "Traditional TV Top 10." Top 10, The Neilson Company, 2025. www.nielsen.com/data-center/top-ten/#television.

Nithyanand, Rishab, Brian Schaffner, and Phillipa Gill, "Online Political Discourse In The Trump Era" arXiv preprint, Cornell University, 2017. https://doi.org/10.48550/arXiv.1711.05303

Papacharissi, Zizi, "Democracy Online: Civility, Politeness, and The Democratic Potential of Online Political Discussion Groups" *New Media & Society*, vol. 6, no. 2, 2004. https://doi.org/10.1177/146144480404F4

Perloff, Catherine, "Instagram Quietly Makes Share Counts Public", Adweek, 2023, www.adweek.com/media/instagram-quietly-makes-share-counts-public/.

RedSocial, "Instagram Showing Share Count: A New Way To Track Engagement", RedSocial, 2024. https://www.redsocial.com/blog/instagram-showing-share-count/#:~:text=your%20immediate%20circle.-,How%20Instagram%20Counts%20Shares,and%20one%20for%20the%20recipient.

Roseman, Ira J., and Craig A. Smith, "Appraisal Theory", *Appraisal Processes In Emotion: Theory, Methods, Research*, Oxford University Press, 2001. https://www.academia.edu/download/52846421/TEORIAS_DEL_APPRAISAL_CON PREGUNTAS_PRACTICAS.pdf

Rossini, Patrícia, "Beyond Incivility: Understanding Patterns of Uncivil and Intolerant Discourse in Online Political Talk", *Communication Research* vol. 49, no. 3, 2022. https://doi.org/10.1177/0093650220921314.

Sidoti, Olivia, and Wyatt Dawson, *Social Media Fact Sheet*, Pew Research Center, 2024. www.pewresearch.org/internet/fact-sheet/social-media/.

Singh, Spandana, "Everything In Moderation" Open Technology Institute, New America, 2019. www.newamerica.org/oti/reports/everything-moderation-analysis-how-internet-platforms-are-using-artificial-intelligence-moderate-user-generated-content/.

Skytte, Rasmus, "Dimensions of Elite Partisan Polarization: Disentangling the Effects of Incivility and Issue Polarization" *British Journal of Political Science*, vol. 51, no. 4, 2021. https://doi.org/10.1017/S0007123419000760.

Skytte, Rasmus, "Why Politicians Seem So Rude and How It Affects Citizens", Forlaget Politica, 2019. http://politica.dk/fileadmin/politica/Dokumenter/ph.d.-afhandlinger/rasmus_skytte.pdf.

Sonnenberg, Anna, "Which One's Better? Instagram Reels vs. Posts", Agorapulse, 2024. www.agorapulse.com/blog/instagram/instagram-reels-vs-posts/#:~:text=An%20Instagram%20post%20is%20a,individual%20videos%20are%20now%20Reels.

Spyros Kosmidis, Yannis Theocharis, "Can Social Media Incivility Induce Enthusiasm? Evidence from Survey Experiments", *Public Opinion Quarterly*, vol. 84, no. 1, 2020. https://doi.org/10.1093/poq/nfaa014.

Stelter, Brian, "Trump's Return to Power Raises Serious Questions about the Media's Credibility", CNN Business", CNN, 2024. https://www.cnn.com/2024/11/06/media/trump-reelection-media-credibility-trust/index.html.

Stryker, Robin, Bethany Anne Conway, and J. Taylor Danielson, "What Is Political Incivility?" *Communication Monographs*, vol. 83, no. 4, 2016. https://doi.org/10.1080/03637751.2016.1201207.

Sude, Daniel J and, Shira Dvir-Gvirsman, "Different Platforms, Different Uses: Testing The Effect of Platforms and Individual Differences On Perception of Incivility and Self-Reported Uncivil Behavior" *Journal of Computer-Mediated Communication*, vol. 28, no. 2, 2023. https://doi.org/10.1093/jcmc/zmac035

Sun, Qiusi, Magdalena Wojcieszak, and Sam Davidson, "Over-Time Trends In Incivility On Social Media: Evidence From Political, Non-Political, and Mixed Sub-Reddits Over Eleven Years", *Frontiers in Political Science*, vol. 3, 2021. https://www.frontiersin.org/journals/political-science/articles/10.3389/fpos.2021.741605/full

Sydnor, Emily, "*Disrespectful Democracy: The Psychology of Political Incivility"*, Columbia University Press, 2019. https://doi.org/10.7312/sydn18924-005

Sydnor, Emily, “Fighting Words and Fiery Tone: The Interaction of Political Incivility and Psychological Conflict Orientation”, University of Virginia, 2015. http://www.emily-sydnor.com/s/Sydnor-dissertation-LIBRA.pdf

Tiktok, “Content Moderation”, Tiktok, 2025. www.tiktok.com/euonlinesafety/en/content-moderation/.

Uslaner, Eric M., *The Decline of Comity in Congress*, University of Michigan Press, 1993. https://babel.hathitrust.org/cgi/pt?id=mdp.39015032490800&seq=1

Weld, Galen, Maria Glenski, and Tim Althoff, “Political Bias and Factualness in News Sharing Across More Than 100,000 Online Communities”, *Proceedings of The International AAAI Conference On Web and Social Media*, vol. 15, 2021. https://doi.org/10.1609/icwsm.v15i1.18104

X, “X’s Private Information Policy And Doxxing” Private Content, X Help Center, 2025. help.x.com/en/rules-and-policies/personal-information.

X, “Counting Characters When Composing Tweets”, X Developer Program, 2025. 2025docs.x.com/resources/fundamentals/counting-characters.

270toWin.com, “2024 Presidential Election Forecast Maps”, 270toWin.com, 2024. https://www.270towin.com/2024-presidential-election-forecast-predictions/.

6.2 Codebook

INCIVILITY-Discourse that is designed to elicit emotional responses (e.g. anger, fear, moral indignation) from its audiences by attacking the reputation or credibility of another individual or entity, often for the benefit of their own reputation (trust and support) and at the expense of the latter.

CATEGORICAL VARIABLES OF INCIVILITY (measured as binary):

- BLAME: present " if a source placed blame on his or her opponents" in an arbitrary or unreasonable way (Sydnor 2015, 43).

- HYPERBOLE: present if a source "used hyperbolic language to characterize his or her opponent ('outrageous')" (Sydnor 2015, 43). For my study, this also includes dramatic language used to characterize an opponent or an opponent's actions.

- ACCUSATIONS OF LYING: present if a source unjustly accuses an opponent or other entity of making a false/misinformative statement (Sydnor 2015, 43).

- NAME-CALLING: present if a source "used pejorative language ('racist,' 'liar')" or "described the opposition with a derogatory adjective ('reckless', 'weird')' (Sydnor 2015, 43). For my study, this also includes expressions with a negative connotation or inferences to name-calling.

- THREATENS AMERICAN VALUES: present if a source "suggests that the opponents' policies are going to destroy or fundamentally alter American values or institutions in a negative way" (Sydnor 2015, 43).

    - QUOTES OR REFERENCES TO INCIVILITY ARE CODED AS THEIR OWN INCIVILITY INSTANCES.
    - Disregard peripheral conversations, headlines, or phrases that aren't the focus of the posted content.
    - Incivil language produced in chants or protest slogans counts as a single incident

Include all posts "that make [an] explicit reference to one of the established topics" (Israel-Palestine Conflict or the Criminal Trials of Donald Trump) within the sample population (1,541 total posts), and sample 50 posts for each topic between the three networks (287 total due to the insufficient sample size of CNN's coverage of the Trump criminal trials).

FOR EACH INSTAGRAM POST AND REEL:

- Copy all available text from the post (including video closed captions) and record the total word count, the name of the network that the post is from, the date of the post, the topic discussed (Israel-Palestine Conflict or Trump Trials), the current like count, and the current share count.
- List the frequency of variable BLAME, variable HYPERBOLE, variable ACCUSATIONS OF LYING, variable NAME-CALLING, and variable THREATENS AMERICAN VALUES.
  *Repeated phrases such as chants or will be counted as a collective instance of incivility if the incident can be categorized within one of the aforementioned variables and isn't shown for purely educational purposes. Interjections, indecipherable language, peripheral discourse, and other insignificant dialogue will be omitted
- Using the total word count of the post and the total number of incivility instances present, calculate the ratio of incivility per 50 words (round to the nearest tenth) by using the following formula:

(50/(total word count of sampled post)) * (total number of incivility instances)

6.3 Supplementary Materials

Instagram Total Content Population:

https://docs.google.com/document/d/e/2PACX-1vQYXiGMRmMFqWowLYxGFqeepMj6eHzB
AFE8lHtFrcQXKw1HI6hkKv-wvi_HEQDCQOofg5Mi7k5H0DT8/pub

Instagram Post and Reel Transcripts:

https://docs.google.com/document/d/e/2PACX-1vSQvXVkwtmVm8b5nIEXWGXaFmdmVvnA
mX4kyfksRRwiovMTQB0L-KyUC2GONI-88K9T16Pu2jYEaWVc/pub

Political Incivility Spreadsheet:

https://docs.google.com/spreadsheets/d/e/2PACX-1vRgdqlDKGrfJMST2K8fxVB75ebnUf0Ep6S
eoGP79tSCMq-fmYPDn2OHT8zfu6krlCvQ6DXoGhL33QWA/pubhtml?gid=654692674&singl
e=true

R Studio Code:

https://docs.google.com/document/d/e/2PACX-1vQk2b5KIs5Ba5NLIlplIa4OQxqlpxiOsdauXF1j
y6qLHSK3M5qIbRKZFp6K3V6_Z4kH-9WXUWpa2NEp/pub

6.4 Appendices

6.5 Appendix A: Israel-Palestine Conflict

Table 13 Bivariate Regression

Incivility Across Topics: Israel-Palestine Conflict

	Likes	Comments	Shares	Views
Incivility	0.104	-0.022	0.048	-0.130
Std. Error	0.070	0.063	0.167	0.114
Constant	9.618***	7.682***	6.926***	13.103***
Std. Error	0.130	0.115	0.322	0.219
Observations	150	150	103	95
R^2	0.015	0.001	0.001	0.014
Adjusted R^2	0.008	-0.006	-0.009	0.003
Residual Std. Error	1.134 (df = 148)	1.009 (df = 148)	1.761 (df = 101)	1.183 (df = 93)
F Statistic	2.197 (df = 1; 148)	0.121 (df = 1; 148)	0.083 (df = 1; 101)	1.316 (df = 1; 93)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14 Multivariate Regression

Engagement Variables Across Topics: Israel-Palestine Conflict

	Likes	Comments	Shares	Views
Incivility	0.051	0.007	0.220	-0.048
Std. Error	0.058	0.057	0.142	0.089
FOX News	-0.542***	-0.629***	-1.352***	-0.848***
Std. Error	0.198	0.193	0.467	0.299
MSNBC	-1.948***	-1.717***	-2.495***	-1.856***
Std. Error	0.154	0.151	0.290	0.183
Video Content	-0.193	0.199	-0.886	NA
Std. Error	0.159	0.156	0.566	NA
Constant	10.504***	8.373***	9.412***	14.230***
Std. Error	0.196	0.192	0.661	0.221
Observations	150	150	103	95
R^2	0.573	0.479	0.438	0.541
Adjusted R^2	0.561	0.465	0.415	0.526
Residual Std. Error	0.754 (df = 145)	0.736 (df = 145)	1.341 (df = 98)	0.815 (df = 91)
F Statistic	48.675*** (df = 4; 145)	33.315*** (df = 4; 145)	19.112*** (df = 4; 98)	35.817*** (df = 3; 91)

Note: *p<0.1; **p<0.05; ***p<0.01

6.6 Appendix B: CNN

Table 13 Bivariate Regression

Incivility Across News Sources: CNN

	Likes	Comments	Shares	Views
Incivility	-0.046	-0.032	-0.369*	-0.208*
Std. Error	0.098	0.078	0.201	0.111
Constant	10.069***	8.298***	7.076***	13.756***
Std. Error	0.183	0.145	0.382	0.211
Observations	87	87	58	54
R^2	0.003	0.002	0.057	0.063
Adjusted R^2	-0.009	-0.010	0.040	0.045
Residual Std. Error	0.884 (df = 85)	0.701 (df = 85)	1.413 (df = 56)	0.752 (df = 52)
F Statistic	0.222 (df = 1; 85)	0.173 (df = 1; 85)	3.381* (df = 1; 56)	3.506* (df = 1; 52)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14 Multivariate Regression

Engagement Variables Across News Sources: CNN

	Likes	Comments	Shares	Views
Incivility	0.041	0.076	0.014	-0.038
Std. Error	0.106	0.085	0.220	0.120
Trump Trials	-0.476**	-0.474***	-1.443***	-0.675***
Std. Error	0.217	0.175	0.440	0.239
Video Content	-0.576***	-0.095	-0.327	NA
Std. Error	0.197	0.159	0.778	NA
Constant	10.775***	8.733***	8.470***	14.250***
Std. Error	0.291	0.235	0.876	0.264
Observations	87	87	58	54
R^2	0.114	0.084	0.216	0.190
Adjusted R^2	0.082	0.051	0.172	0.159
Residual Std. Error	0.843 (df = 83)	0.679 (df = 83)	1.312 (df = 54)	0.706 (df = 51)
F Statistic	3.558** (df = 3; 83)	2.538* (df = 3; 83)	4.948*** (df = 3; 54)	5.995*** (df = 2; 51)

Note: *p<0.1; **p<0.05; ***p<0.01

6.7 Appendix C: Non-Video Content

Table 15 Bivariate Regression[13]

Incivility Across Content Type: Non-Video Content

	Likes	Comments	Shares
Incivility	0.001	-0.067	-0.554
Std. Error	0.055	0.043	0.446
Constant	9.988***	7.709***	6.515***
Std. Error	0.090	0.071	0.811
Observations	112	112	7
R^2	0.00000	0.021	0.236
Adjusted R^2	-0.009	0.012	0.083
Residual Std. Error	0.866 (df = 110)	0.680 (df = 110)	1.012 (df = 5)
F Statistic	0.0002 (df = 1; 110)	2.381 (df = 1; 110)	1.542 (df = 1; 5)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16 Multivariate Regression

Engagement Variables Across Content Type: Non-Video Content

	Likes	Comments	Shares
Incivility	0.043	0.018	-0.732
Std. Error	0.052	0.040	0.452
Trump Trials	0.072	-0.172	-0.350
Std. Error	0.147	0.112	1.179
FOX News	-0.497***	-0.821***	-2.622**
Std. Error	0.178	0.135	0.605
MSNBC	-1.540***	-0.966***	-0.678
Std. Error	0.270	0.205	0.603
Constant	10.436***	8.458***	6.944**
Std. Error	0.184	0.140	1.097
Observations	112	112	7
R^2	0.236	0.303	0.927
Adjusted R^2	0.207	0.277	0.782
Residual Std. Error	0.767 (df = 107)	0.582 (df = 107)	0.494 (df = 2)
F Statistic	8.251*** (df = 4; 107)	11.607*** (df = 4; 107)	6.371 (df = 4; 2)

Note: *p<0.1; **p<0.05; ***p<0.01

[13] Recall that the view count feature isn't available for Instagram posts, so this variable is omitted within non-video content.

6.8 Appendix D: Incivility Type-Blame

Table 17 Bivariate Regression

Blame Across The General Sample Population

	Likes	Comments	Shares	Views
Blame	-0.077	-0.139	-0.085	-0.023
Std. Error	0.104	0.094	0.181	0.159
Constant	9.306***	7.267***	6.300***	12.555***
Std. Error	0.234	0.211	0.404	0.352
Observations	287	287	182	173
R^2	0.002	0.008	0.001	0.0001
Adjusted R^2	-0.002	0.004	-0.004	-0.006
Residual Std. Error	1.116 (df = 285)	1.006 (df = 285)	1.801 (df = 180)	1.573 (df = 171)
F Statistic	0.553 (df = 1; 285)	2.201 (df = 1; 285)	0.220 (df = 1; 180)	0.021 (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 18 Multivariate Regression

Engagement Variables Across Incivility Types: Blame

	Likes	Comments	Shares	Views
Blame	-0.020	-0.077	-0.056	0.060
Std. Error	0.079	0.076	0.156	0.091
Trump Trials	0.014	-0.222**	-0.630***	-1.326***
Std. Error	0.098	0.094	0.228	0.135
FOX News	-0.345***	-0.649***	-0.492	-0.790***
Std. Error	0.128	0.123	0.343	0.206
MSNBC	-1.596***	-1.535***	-2.036***	-2.331***
Std. Error	0.124	0.119	0.252	0.152
Video Content	-0.336***	0.032	-0.579	NA
Std. Error	0.117	0.112	0.577	NA
Constant	10.304***	8.248***	8.306***	14.652***
Std. Error	0.232	0.222	0.691	0.243
Observations	287	287	182	173
R^2	0.468	0.405	0.336	0.701
Adjusted R^2	0.459	0.394	0.317	0.694
Residual Std. Error	0.820 (df = 281)	0.785 (df = 281)	1.484 (df = 176)	0.868 (df = 168)
F Statistic	49.523*** (df = 5; 281)	38.183*** (df = 5; 281)	17.833*** (df = 5; 176)	98.378*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01

6.9 Appendix E: Incivility Type-Hyperbole

Table 19 Bivariate Regression

Hyperbole Across The General Sample Population

	Likes	Comments	Shares	Views
Hyperbole	-0.010	-0.071**	-0.029	-0.250***
Std. Error	0.040	0.036	0.078	0.067
Constant	9.464***	7.508***	6.458***	12.431***
Std. Error	0.074	0.066	0.145	0.124
Observations	287	287	182	173
R^2	0.0002	0.013	0.001	0.076
Adjusted R^2	-0.003	0.010	-0.005	0.070
Residual Std. Error	1.117 (df = 285)	1.003 (df = 285)	1.801 (df = 180)	1.512 (df = 171)
F Statistic	0.063 (df = 1; 285)	3.877** (df = 1; 285)	0.134 (df = 1; 180)	13.979*** (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 20 Multivariate Regression

Engagement Variables Across Incivility Types: Hyperbole

	Likes	Comments	Shares	Views
Hyperbole	0.051	0.009	0.142*	-0.025
Std. Error	0.032	0.031	0.074	0.044
Trump Trials	-0.037	-0.238**	-0.845***	-1.286***
Std. Error	0.102	0.098	0.250	0.149
FOX News	-0.407***	-0.684***	-0.680**	-0.726***
Std. Error	0.130	0.125	0.338	0.206
MSNBC	-1.621***	-1.542***	-2.098***	-2.315***
Std. Error	0.125	0.120	0.251	0.153
Video Content	-0.377***	0.003	-0.564	NA
Std. Error	0.116	0.112	0.571	NA
Constant	10.469***	8.462***	8.670***	14.473***
Std. Error	0.143	0.138	0.583	0.147
Observations	287	287	182	173
R^2	0.473	0.403	0.349	0.701
Adjusted R^2	0.464	0.392	0.331	0.693
Residual Std. Error	0.816 (df = 281)	0.786 (df = 281)	1.470 (df = 176)	0.868 (df = 168)
F Statistic	50.452*** (df = 5; 281)	37.865*** (df = 5; 281)	18.911*** (df = 5; 176)	98.289*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01

6.10 Appendix F: Incivility Type-Accusations of Lying

Table 21 Bivariate Regression

Accusations Of Lying Across The General Sample Population

	Likes	Comments	Shares	Views
Accusations of Lying	-0.089	-0.047	0.019	-0.076
Std. Error	0.188	0.170	0.305	0.267
Constant	9.273***	7.460***	6.520***	12.434***
Std. Error	0.430	0.389	0.694	0.605
Observations	287	287	182	173
R^2	0.001	0.0003	0.00002	0.0005
Adjusted R^2	-0.003	-0.003	-0.006	-0.005
Residual Std. Error	1.116 (df = 285)	1.010 (df = 285)	1.802 (df = 180)	1.572 (df = 171)
F Statistic	0.222 (df = 1; 285)	0.077 (df = 1; 285)	0.004 (df = 1; 180)	0.080 (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 22 Multivariate Regression

Engagement Variables Across Incivility Types: Accusations Of Lying

	Likes	Comments	Shares	Views
Accusations of Lying	0.092	0.076	0.155	0.107
Std. Error	0.139	0.134	0.252	0.148
Trump Trials	0.009	-0.231**	-0.643***	-1.327***
Std. Error	0.098	0.094	0.228	0.135
FOX News	-0.353***	-0.675***	-0.530	-0.759***
Std. Error	0.126	0.121	0.332	0.199
MSNBC	-1.600***	-1.539***	-2.047***	-2.329***
Std. Error	0.124	0.119	0.251	0.152
Video Content	-0.349***	0.004	-0.596	NA
Std. Error	0.115	0.111	0.576	NA
Constant	10.570***	8.619***	8.803***	14.759***
Std. Error	0.348	0.334	0.824	0.358
Observations	287	287	182	173
R^2	0.469	0.403	0.337	0.701
Adjusted R^2	0.460	0.392	0.318	0.694
Residual Std. Error	0.820 (df = 281)	0.786 (df = 281)	1.483 (df = 176)	0.868 (df = 168)
F Statistic	49.664*** (df = 5; 281)	37.944*** (df = 5; 281)	17.907*** (df = 5; 176)	98.458*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01

6.11 Appendix G: Incivility Type-Threatens American Values

Table 23 Bivariate Regression

Threatens American Values Across The General Sample Population

	Likes	Comments	Shares	Views
Threatens American Values	0.140	0.001	0.305	0.122
Std. Error	0.103	0.093	0.196	0.173
Constant	9.776***	7.570***	7.134***	12.864***
Std. Error	0.232	0.210	0.443	0.389
Observations	287	287	182	173
R^2	0.006	0.00000	0.013	0.003
Adjusted R^2	0.003	-0.004	0.008	-0.003
Residual Std. Error	1.113 (df = 285)	1.010 (df = 285)	1.790 (df = 180)	1.570 (df = 171)
F Statistic	1.863 (df = 1; 285)	0.0002 (df = 1; 285)	2.404 (df = 1; 180)	0.498 (df = 1; 171)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 24 Multivariate Regression

Engagement Variables Across Incivility Types: Threatens American Values

	Likes	Comments	Shares	Views
Threatens American Values	0.060	-0.003	0.273	0.159
Std. Error	0.080	0.077	0.175	0.102
Trump Trials	-0.001	-0.228**	-0.692***	-1.356***
Std. Error	0.099	0.095	0.229	0.136
FOX News	-0.373***	-0.672***	-0.667*	-0.841***
Std. Error	0.129	0.124	0.342	0.205
MSNBC	-1.591***	-1.537***	-2.023***	-2.313***
Std. Error	0.124	0.119	0.250	0.151
Video Content	-0.357***	0.010	-0.609	NA
Std. Error	0.117	0.112	0.573	NA
Constant	10.504***	8.434***	9.092***	14.883***
Std. Error	0.236	0.226	0.708	0.267
Observations	287	287	182	173
R^2	0.469	0.402	0.345	0.704
Adjusted R^2	0.460	0.392	0.326	0.697
Residual Std. Error	0.819 (df = 281)	0.786 (df = 281)	1.475 (df = 176)	0.863 (df = 168)
F Statistic	49.710*** (df = 5; 281)	37.835*** (df = 5; 281)	18.529*** (df = 5; 176)	100.045*** (df = 4; 168)

Note: *p<0.1; **p<0.05; ***p<0.01