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Journal of Social Media Research (JSOMER) is a multidisciplinary, blind peer-reviewed, open-access, free-of-charge, international scientific academic journal published twice a year (June, December) focusing on the social, cultural, educational, psychological, economic, technological, and sociological dimensions of social media. JSOMER is an interdisciplinary journal with a broad scope that includes social sciences, humanities, arts, health, medicine, psychiatry, psychology, computational social sciences, artificial intelligence, and natural sciences, focusing on, or related to social media. We are pleased to publish current and innovative research articles, reviews, and argumentative essays focusing on social media. Articles published in JSOMER are expected to raise issues related to social media in various fields, open discussions about these issues, and propose different methods to address these issues or solve related problems. It is also hoped that the papers published in JSOMER will provide a basis for current debates on various areas of social media and guide innovative research and practice. JSOMER welcomes a variety of theoretical paradigms and methodologies and considers this as a scientific enrichment. JSOMER aims to contribute to scientific accumulation by including original and qualified studies written by academic standards, copyrights, and ethical rules and to be among the first reference sources for those doing research in the field of social media.

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RESEARCH ARTICLE OPEN ACCESS

Disinformation and democratic threats: Insights from the 2019 Canadian federal election

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Highlights:

- Exposure to disinformation has a significant relationship to changes in voting decisions.
- Instagram exposure correlates strongly with changes in participant voting decisions.
- Real news has a limited impact on shifts in voting decisions compared to fake news.
- Believing fake news increases the likelihood of voting decision changes among participants.

Abstract

News and social media shape voter decisions by influencing which political issues receive attention and how they are presented. This study examines how exposure to social media and disinformation impacted voter behaviour during the 2019 Canadian federal election. A survey was designed and delivered via various social media channels to collect data from Canadians who voted in the 2019 election (N = 182). Participants were presented with a mix of real and fake news headlines, and their responses were analyzed using binary logistic regression to assess the impact of media exposure on voting decisions. The results highlight that time spent on social media, particularly Instagram, significantly increased the likelihood of participants changing their voting decisions. Even when not widely circulated, exposure to fake news profoundly influenced voting decisions among respondents. Interestingly, real news headlines showed no statistically significant effect on voting behaviour, suggesting a reduced impact of credible journalism compared to other media types. This study emphasizes the necessity to create well-informed strategies to mitigate the spread of fake news and enhance media literacy to safeguard democratic processes in the digital age. This research contributes to theoretical advancements in understanding disinformation's impacts and provides relevant insights for policymakers, educators, and media platforms working to mitigate the influence of disinformation.

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1. Introduction

Social media platforms have emerged as an influential tool for shaping public discourse and political behaviour. Social media has provided benefits through the democratization of political communication, offering political actors direct channels to interact with voters, mobilize support, and disseminate electoral messaging without having to navigate through bureaucratic controls and gatekeeping structures (Lachapelle & Maarek, 2015; Pruitt-Santos, 2023; Towner & Muñoz, 2018). However, alongside its benefits, the proliferation of digital platforms has also raised concerns about social media's role in amplifying disinformation and influencing public opinion (Bradshaw et al., 2021; Johnson & Kaye, 2015).

Through a quantitative analysis of survey data collected from Canadian voters after the 2019 Canadian federal election, this research explores the relationship between exposure to disinformation, shifts in voting intentions, and perceptions of political trustworthiness. By analyzing voter responses and behaviours in the context of exposure to disinformation, this study aims to contribute to the broader discourse on the intersection of media influence, political communication, and democratic integrity. Applying agenda-setting theory (McCombs & Shaw, 1972), this study examines how misleading narratives gain prominence, shaping voter concerns and ultimately influencing political attitudes and electoral decisions. Understanding how disinformation shapes voter perceptions and influences electoral outcomes is critical to developing research-informed strategies safeguarding democratic processes.

1.1. Social Media and Political Communication

Social media has become an integral form of political communication (Lachapelle & Maarek, 2015; Towner & Muñoz, 2018). Political figures have increasingly turned to social media platforms such as Facebook, Twitter, and Instagram as a method of communicating political topics to large audiences, mobilizing supporters, shaping their public image, fostering dialogue with citizens, and publicizing their views on politically relevant issues (Klinger & Russmann, 2017; Towner & Muñoz, 2018; Vuckovic, 2023). By communicating directly with social media users through social media networks, political parties can directly influence political public discourse and manage political narratives more effectively (Yang, Chen, Maity, & Ferrara, 2016). The accessibility and low cost associated with social media political communications also allow political parties to communicate information while saving on time, resources, and labour (Klinger & Russmann, 2017; Lachapelle & Maarek, 2015).

In the age of social media, the power that traditional media has in setting the news agenda has drastically reduced. Independent platforms allow the average citizen more influence, challenging the historical monopoly of traditional media (Harder et al., 2017; Meraz, 2009). Mainstream news media delivered through television and newspapers tend to be slower in circulating information as their publication schedule limits them. Social media platforms have no fixed schedule and can publish new information as it occurs. Despite the rise of social media, traditional outlets still play a crucial role in legitimizing news topics, albeit with delayed speed compared to online platforms (Harder et al., 2017).

While the growth of social media has brought forth many advantages in delivering need-to-know political information, it has drawbacks. The immediacy of political communication delivered via social networks can present challenges in managing the rapid spread and potentially inaccurate or misleading information (Lipschultz, 2021). The quality of information delivered via non-journalistic bodies is not bound to the same level of journalistic integrity as conventional news sources. As a result, the political information delivered through social media networks tends to be less credible and more biased (Johnson & Kaye, 2015). Information delivered by non-journalistic sources also lacks transparency and accountability. With the ability to create fake accounts, or cloned accounts of trusted sources, it is possible to spread false political narratives without the same fear of public backlash or legal punishment that a legitimate news source would be subject to (McKay & Tenove, 2021). While social media has democratized political communication, it has also increased the ease of spreading false information.

1.2. Agenda-Setting Theory

Agenda-setting theory explains how media influence extends beyond simply reporting information to shaping which issues the public perceives as most important; this concept is known as issue salience (McCombs & Shaw, 1972). Traditionally, mainstream news organizations controlled this process by selecting, emphasizing, and framing certain topics while downplaying or omitting others. However, the rise of social media has disrupted this dynamic, shifting agenda-setting power from journalists and editors to algorithms and user-driven engagement metrics (Tsfati et al., 2020). Social media platforms prioritize content that generates high engagement, often amplifying emotionally charged, polarizing, or misleading information over fact-based reporting (Bennett & Livingston, 2018). As a result, the prominence of certain political narratives in digital spaces may be determined more by their ability to provoke reactions than by their factual accuracy, meaning that the issues receiving the most attention may not reflect objective reality (McCombs & Shaw, 1972).

1.3. Disinformation and Fake News

Disinformation and misinformation, though often used interchangeably, represent distinct concepts. Misinformation refers to inaccurate information that is not intentionally created to be misleading or serve any malicious purpose (Derakhshan & Wardle, 2017; Lewandowsky et al., 2013). Disinformation is often created and disseminated to achieve politically desired ends (Bennett & Livingston, 2018). Disinformation may also take on the form of political propaganda, where inaccurate, biased, or misleading information is purposefully created and circulated to influence public opinion, decrease support for an enemy state, justify violence and war, or increase support from allies (Evans, 2014; Murphy & White, 2007; Schudson & Zelizer, 2017).

Fake news represents one of the most recognizable forms of disinformation. It is often crafted to discredit political opponents, sway public opinion, or reinforce ideological divisions (Bader, 2019). This form of disinformation has flourished in an era of declining journalistic trust and the amplification of hyper-partisan voices (Bradshaw et al., 2021; Carlson, 2020). It can take multiple forms, including memes, viral videos, manipulated news articles, misleading social media posts, and algorithmically generated content. No matter what form it takes, the information disseminated is meant to mimic reality in a way that influences political beliefs (Ali & Zain-ul-abdin, 2021).

Disinformation is often used to influence large segments of the population strategically. These strategic initiatives to use disinformation as a weapon are often referred to as influence operations or influence campaigns. Influence operations are planned purposefully and strategically to influence how people perceive the world (Jackson, 2023, July 27). These campaigns can be organized by a single actor or a group of actors who may be state-sponsored or acting independently (Hoffman, 2022, October 20). Influence operations are frequently linked to state-sponsored geopolitical tactics, political warfare, and hybrid conflict strategies that blend cyberattacks, coercive economic measures, and social engineering to destabilize democratic institutions (Sazonov et al., 2022). Starbird et al. (2019) emphasize the need to examine disinformation beyond factual accuracy, recognizing that its true power lies in its ability to reshape political reality and influence electoral decisions.

1.4. Impacts

Disinformation campaigns can polarize entire populations by decreasing respect and admiration for various social groups, discrediting important voices from political conversation, and misrepresenting the views of different communities, often in a way that reduces public support for the group (McKay & Tenove, 2021). The 2016 United States (US) Presidential Election highlights these dangers. After the election, a sophisticated disinformation campaign was discovered and attributed to the Russian Internet Research Agency (IRA). The goal of the IRA's campaign was to sow discord in the US, influence voter support for Donald Trump, and capitalize on the political divide between left- and right-wing political supporters (Ali & Zain-ul-abdin, 2021; Serafino et al., 2024).

The tactics employed by IRA campaigns involved spreading unsubstantiated claims and promoting polarizing conspiracy theories. Additionally, the IRA spread social media posts using politically charged language in attempts to reduce moral support for specific individuals and groups, including political candidates, journalists, political parties, and various social groups (McKay & Tenove, 2021). Many of the narratives associated with previous disinformation campaigns include rhetoric on already polarized issues, including immigration, socially progressive policies, climate change, sexual reproductive rights, and LGBTQ+ rights. These narratives are manipulated to create further polarizing content (Bridgman et al., 2022). Disinformation campaigns sow discord, polarize the population, and reduce sympathy and support for different groups, posing a significant threat to social cohesion.

An ill-informed citizen guided by disinformation may vote differently in elections as unreliable facts direct their inspiration. Citizens make decisions about key social and democratic issues through the information they interact with (Bridgman et al., 2022; McKay & Tenove, 2021). Disinformation can also threaten the democratic process by stoking social unrest around issues that may not require immediate social reaction

(Carlson, 2020). Far-reaching, deceptive facts delivered through disinformation campaigns hold the power to impact democratic outcomes significantly.

1.5. Threats

Canada faces significant threats from foreign disinformation campaigns driven by its NATO membership, global influence, and involvement in geopolitical conflicts. While Russia is well known for using disinformation to undermine trust among NATO states and Western democracies (Sazonov et al., 2022; Tuttle, 2019), the People's Republic of China (PRC) has been the most active foreign actor targeting Canada's democratic systems (Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions, 2025). The 2025 Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions found that China used disinformation and covert tactics to further its interests by spreading partisan narratives, supporting specific candidates during nominations, and influencing ethnic media and community networks. The report found no clear evidence that these interference attempts affected the election outcome. However, it noted that the attacks significantly damaged public trust in Canada's democratic institutions and posed ongoing risks to the country's information security.

Beyond direct foreign interference, domestic vulnerabilities in Canada's information environment further amplify the risks posed by disinformation. The public's increasing reliance on untrustworthy sources for political information, driven by mistrust in mainstream media, undermines Canada's democratic systems (Bridgman et al., 2022). Social media platforms often provide information reinforcing pre-existing beliefs, creating echo chambers that limit exposure to diverse perspectives and hinder critical evaluation (Kumar & Krishna, 2014). This dynamic mirrors trends observed in countries like Hungary, where polarization and distrust in public institutions have created fertile ground for fake news, fueling the formation of polarized echo chambers (Szebeni et al., 2021). These online environments inflate disinformation's impact, posing significant challenges to democratic integrity.

American media and political disinformation also shape Canadian public opinion, influencing how citizens perceive political and social issues. Disinformation campaigns in the US have contributed to deep political polarization and growing mistrust in both government and mainstream media (Bridgman et al., 2022; McKay & Tenove, 2021). Narratives from the US have influenced Canadian discourse, fueling polarization and raising doubts about election integrity and claims of electoral fraud (Bridgman et al., 2022). By targeting democratic institutions, election infrastructure, media industries, and citizens, foreign actors can significantly damage a democratic system (Henschke et al., 2020).

1.6. Defences

The 2019 Canadian federal election exposed Canada's weaknesses in countering foreign disinformation and election interference. In response, Bill C-76 limited foreign contributions and increased transparency in digital advertising, while the Critical Election Incident Public Protocol (CEIPP) set guidelines for publicly disclosing credible threats (Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions, 2025). However, covert influence tactics, such as those seen in 2019, often bypass regulations by spreading through organic content, community networks, and indirect financial support (Dawood, 2021; Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions, 2025).

Addressing these gaps requires a multifaceted approach. Dawood (2021) highlights three key areas for improvement: tightening campaign finance laws, strengthening regulations on disinformation, and expanding media literacy programs to improve public resilience. This includes mandatory disclosure laws, targeted regulations on harmful content, and voluntary agreements discouraging political parties from using misleading or illegally obtained information. Additionally, securing voter data, preventing unauthorized access, and improving coordination between security agencies remain critical cybersecurity priorities.

Disinformation campaigns are not confined to election cycles but are long-term efforts to erode trust in institutions and social cohesion (Bridgman et al., 2022). The 2019 election revealed how foreign actors exploited social divisions, using social media and ethnic media networks to amplify partisan narratives and election-related misinformation (Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions, 2025). To counter these tactics, Canada must strengthen coordination between intelligence agencies, digital platforms, and media organizations to enhance real-time disinformation detection. International models, such as the EU's East StratCom Task Force, show how centralized monitoring and rapid response efforts can limit the spread of false information (Vasu et al., 2018). Introducing a similar framework in Canada could be effective in raising public awareness of foreign influence operations and improving early detection of election-related disinformation.

Public education is also key to reducing the impact of political disinformation, particularly in vulnerable communities. Research suggests misinformation in the 2019 election spread widely through private messaging apps and alternative media, where fact-checking efforts had limited reach (Bridgman et al., 2022; Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions, 2025). Expanding media literacy initiatives, especially within communities targeted by foreign influence operations, could help voters critically assess the accuracy of political information (Mourão & Robertson, 2019). Lessons on disinformation should also integrate emotional intelligence training, which has been shown to improve a person's ability to identify manipulative content (Preston et al., 2021).

As social media users navigate an overwhelming volume of content, the ability to critically assess accuracy and legitimacy diminishes, increasing the risk of disinformation shaping voter perceptions (Bermes, 2021). The 2019 election highlighted these risks, as certain foreign influence campaigns relied on organic content and social networks rather than direct political advertising to circumvent regulations (Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions, 2025). When this information is used to inform political decision-making, the integrity of democracy is threatened (Tenove, 2020). This research aims to provide insight into the impact of disinformation on the sample of Canadian voters represented in this study during the 2019 Canadian Federal election. By increasing our understanding of how Canadian social media users interact with different forms of political disinformation, evidence-based responses that aim to reduce the damage of disinformation narratives can be developed. The insights provided by this study can provide significant value to policymakers and the Canadian government in the ongoing effort to increase Canadian resilience against disinformation campaigns.

2. Method

This study is grounded in the theory of agenda-setting and media effects, which posits that the media plays a critical role in shaping public perception and behaviours by highlighting certain issues over others. Central to this theory is the concept that the prominence given to issues in the media influences the importance these issues hold in the public's mind (Harder et al., 2017; Meraz, 2009). The research also draws on theories of disinformation and its impact on democratic processes, highlighting how fake news can distort and manipulate public opinion and decision-making (Bridgman et al., 2022; Carlson, 2020; McKay & Tenove, 2021). These theories are pertinent given the role of social media platforms in reinforcing or challenging these dynamics through algorithms that curate content aligning with users' preconceptions.

This study operationalizes several constructs through measurable variables to empirically test these theoretical frameworks. A series of binary logistic regressions are used to quantify the influence of media exposure on the survey respondent's voter behaviour. This approach models the likelihood of changes in voting decisions based on exposure to different types of media content and different forms of social media. The choice of logistic regression is informed by the dichotomous nature of the dependent variable (change in voting decision).

2.1. Ethics

Simon Fraser University approved the research on February 2, 2020 (decision #20200038). The survey, recruitment method, and method of survey delivery were approved by the REB. All procedures followed were in accordance with the ethical standards of the responsible institutional and national committees on human research ethics and the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2). Informed consent was obtained from all participants included in the study.

2.2. Survey Design and Delivery

This study utilized a quantitative design, analyzing data from a post-election survey distributed to Canadian citizens aged over 18 who voted in the 2019 Canadian Federal Election. Participants were recruited through a criterion sampling strategy, targeting Twitter, Reddit, and Facebook to reach individuals fitting the study criteria. The survey ran from February 6th, 2020, to June 26th, 2020, and garnered 308 responses, with a final analytical sample of 182 respondents after excluding incomplete and non-qualifying submissions.

The survey was modelled after Allcott and Gentzkow's (2017) post-election survey, which examined fake news during the 2016 Presidential election. The current study adapted the survey to generate similar data surrounding fake news delivered during the 2019 Canadian Federal election. Questions were asked regarding their demographics, political affiliation, and media usage habits. Further, the survey respondents were exposed to 9 headline-related questions (see Table 1). Each respondent was presented with four headlines consisting of real news articles distributed by reputable journalistic news sources in the month leading up to the election. Additionally, four fake news headlines were included in the survey. The news stories corresponding to these headlines were fictitious and contained unverified facts, speculation without merit, and/or extreme exaggeration of real facts; further, they were delivered through actual "news" articles on unreputable websites. Finally, one headline was included as a placebo to control for false recall on survey responses (Allcott & Gentzkow, 2017). The researcher created the placebo headline. In crafting this headline, the researcher aimed to ensure that it was a headline that depicted a story that did not happen but was not far outside the realm of possibility. To prevent bias, the headlines included all parties involved in the election. However, all fake headlines uncovered during the search for fake news headlines relevant to the election were found to be targeting the Liberal Party of Canada. In searching for fake headlines, there appeared to be no available fake news headlines that focused on a political party other than the Liberals.

2.3. Analytic Strategy

Data analysis was conducted using Python in Jupyter Notebook. For this study, four binary logistic regressions were conducted to address four research questions systematically centred around the impact of disinformation on voter behaviour in the Canadian context. Given the relatively small sample size, each question was explored through a separate regression model to ensure clarity and specificity in our findings and to prevent overfitting.

Prior to conducting the logistic regressions, a series of assumption tests were carried out for all variables included in the models. This included checking for multicollinearity using Variance Inflation Factors, calculated with the Pandas and Statsmodels libraries, to ensure that no independent variable was a linear combination of other variables. We also tested for the independence of errors and linearity in the log odds. Gender was systematically included as a control variable across all models in an attempt to reduce the presence of omitted variable bias. Robust standard errors, implemented using Statsmodels, were used in each regression analysis to safeguard against potential violations of standard regression assumptions, such as heteroscedasticity. Additionally, Scipy.stats was used for chi-square tests to examine relationships between categorical variables, and Numpy facilitated the calculation of odds ratios from regression coefficients. This analytic strategy is designed to isolate the effects of disinformation on political decision-making while also addressing the challenges posed by the small sample size. The limitations section details any limitations inherent to this approach.

2.4. Variables

The independent variable used in this study is Change of Vote (CV). CV is derived from responses to whether media exposure influenced participants to switch political parties. Treated as a dichotomous variable (changed/not changed). The independent variables examined in this study were chosen to isolate specific effects and interactions within the broader context of media influence on political decision-making. These variables include:

- *Media Exposure:* This variable comprises a mix of real news, fake news, and a placebo headline, as detailed in Table 2. Survey respondents were asked to recall whether they had encountered these headlines during the election period. Responses were binary and were categorized as 'seen' or 'not seen'.
- *Perceived Truth:* This measure evaluates the authenticity of the headlines as perceived by participants at the time of the election. The responses were classified into three categories: 'true', 'not true', or 'did not see'.
- *Demographic Variables:* The study incorporated several demographic factors as control variables, including age, gender, education level, household income, and self-identified political affiliation.
- *Media Usage Habits:* Participants provided time estimates on various social media platforms. These variables are treated as continuous and represent the time spent on different social media channels.
- *Primary Source of Information:* This variable identifies the main source of election-related information used by participants during the election period.

Table 1. Real News and Fake News Headlines

Headline	Source	Date	News Type	Variable Name
"Singh says NDP would form coalition with the Liberals to stop Tories"	CTV News	13-Oct-19	Real	Real News 1
"NDP Brampton-Centre candidate apologizes for offensive tweet from 2012"	Global News	17-Oct-19	Real	Real News 2
"Scheer won't say if Conservatives hired consultant to 'destroy' People's Party"	CTV News	19-Oct-19	Real	Real News 3
"Edmonton Strathcona Green Party candidate drops out, asks supporters to vote NDP"	The National Post	16-Oct-19	Real	Real News 4
"Justin Trudeau is trying to rig the election through controlling the Canadian news media"	Canada Proud (Facebook Page)	12-Oct-19	Fake	Fake News 1
"RCMP plans to charge Trudeau with obstruction in SNC Lavalin affair, following federal elections"	The Buffalo Chronicle	17-Oct-19	Fake	Fake News 2
"RCMP source says 'security risk' against Trudeau was contrived by PMO staffers"	The Buffalo Chronicle	15-Oct-19	Fake	Fake News 3
"Elections Canada attempts to combat huge number of non-Canadians on voting register"	The Post Millennial	06-Oct-19	Fake	Fake News 4
"Trudeau's visit to Cuba – PM promises to provide financial aid to the country as US embargo discussions persist"			Placebo	Placebo

3. Results

This research highlights key relationships between media exposure, voter behaviour, and individual characteristics during the 2019 Canadian federal election. First, descriptive statistics are examined to explore trends in demographics, political affiliation, and media usage, while subsequent logistic regression analyses identify significant predictors of voting behaviour changes. These findings reveal how election-related media influenced participant voting behaviours during the 2019 Canadian federal election.

3.1. Descriptive Statistical Analysis

Table 2 presents the demographic characteristics of the survey respondents (N = 190) and their relationship to the dependent variable, Change of Vote (CV). Within the sample, 22% of respondents reported changing their vote based on media influence (n = 40). None of the demographic variables appears to be significantly correlated with CV.

Table 3 illustrates descriptive statistics for political affiliation. This table also reveals information about the relationship between self-identified political alignments and each respondent's vote status change. Political alignment has no significant relationship to CV. Most respondents identify as having a very liberal political alignment (n = 79), followed by slightly liberal (n = 37) and slightly conservative (n = 27). Respondents who report very conservative political alignments make up the second smallest political orientation in the sample (n = 21). Those with political alignments somewhere in between accounted for the smallest political affiliation group (n = 18); however, they represented the group with a higher percentage of people who changed their voting decision. Notably, the distribution of political affiliations represented in this sample does not necessarily represent Canada's voting population.

Table 2. Descriptive Statistics for Demographic Variables

	Change of Vote Status						
	Vote Not Changed	Vote Changed	Mean	SD	χ2 (p)	df	Cramer's V
Gender					6.64	2	0.19
Man	98 (82.4%)	21 (17.6%)					
Woman	39 (67.2%)	19 (32.8%)					
Non-Binary	3 (100.0%)	0 (0.0%)					
Prefer not to say	2 (100.0%)	0 (0.0%)					
Age[a]			33.86	11.34	4.46	5	4.43
18 – 25	41 (80.4%)	10 (19.6%)					
26 – 34	43 (74.1%)	15 (25.9%)					
35 – 43	28 (75.7%)	9 (24.3%)					
44 – 52	17 (94.4%)	1 (5.6%)					
53+	12 (70.6%)	5 (29.4%)					
Prefer not to say	1 (100.0%)	0 (0.0%)					
Level of Education					5.14	5	0.17
High School	48 (81.4%)	11 (18.6%)					
Trade School	25 (80.6%)	6 (19.4%)					
Undergraduate	45 (72.6%)	17 (27.4%)					
Graduate	19 (76.0%)	6 (24.0%)					
Prefer Not to Say	5 (100.0%)	0 (0.0%)					
Household Income[a]			89,906.83	66,136.63	2.34	5	2.33
Less than $24,999	23 (79.3%)	6 (20.7%)					
$25,000 - $49,999	19 (70.4%)	8 (29.6%)					
$50,000 - $99,999	48 (76.0%)	12 (24.0%)					
$100,000 - $199,999	36 (81.8%)	8 (18.2%)					
More than $200,000	8 (72.7%)	3 (27.3%)					
Prefer Not to Say	18 (85.7%)	3 (14.3%)					
Number of Languages					0.98	3	0.07
One	91 (79.8%)	23 (20.2%)					
Two	42 (75.0%)	14 (25.0%)					
Three or More	8 (72.7%)	3 (27.3%)					
Prefer Not to Say	1 (100.0%)	0 (0.0%)					

Note. A Variable with a subscript contains Kruskal Wallace test results
DV: Change of Vote, *p < 0.05

Table 3. Descriptive Statistics for Political Affiliation

	Change of Vote Status				
	Vote Not Changed	Vote Changed	χ2 (p)	df	Cramer's V
Political Affiliation			4.70	4	0.16
Very Liberal	66 (83.5%)	13 (16.5%)			
Slightly Liberal	29 (78.4%)	8 (21.6%)			
Neutral	11 (61.1%)	7 (38.9%)			
Slightly Conservative	20 (74.1%)	7 (25.9%)			
Very Conservative	16 (76.2%)	5 (23.8%)			

DV: Change of Vote

The primary source of election information provides insight into which respondents primarily used information source types to keep up to date on election-related information. Overall, there are no significant relationships between primary source of information and CV (Table 4). The internet (not including social media) is the most common source of information among the survey's respondents; 62.1% of respondents report using this as their primary source of election-related information (n = 113). Social media is the second most frequent primary source; 23.6% of respondents (n = 43) identified that social media platforms are where they primarily go to access election-related information. Family and friends, radio, printed newspapers, in-mail brochures, and political party emails account for the least commonly used forms of political communication.

Table 4. Descriptive Statistics for Primary Source of Election Information.

	Change of Vote Status				
	Vote Not Changed	**Vote Changed**	***χ2 (p)***	**df**	**Cramer's V**
Primary Source of Information			6.46	7	0.19
Television	8 (72.7%)	3 (27.3%)			
Social Media	34 (79.1%)	9 (20.9%)			
Internet (not including social media)	88 (77.9%)	25 (22.1%)			
Radio	2 (66.7%)	1 (18.6%)			
Newspaper (printed)	2 (66.7%)	1 (18.6%)			
Family and Friends	0 (0.00%)	1 (100.0%)			
Brochures in Mail	3 (100.0%)	0 (0.0%)			
Emails Sent on Behalf of Political Party	5 (100.00%)	0 (0.00%)			

DV: Change of Vote

Table 5 represents descriptive information for all social media usage habit variables. The platforms examined are Twitter, Facebook, Reddit, and Instagram. The use of Facebook is significantly associated with changes in voting decisions among survey respondents ($\chi2(4) = 11.06$, $p = .03$, $H = 5.11$). Among the Facebook user group, one-quarter of respondents reported changing their voting decision based on something they saw in the media (n = 32). Instagram and CV are also significantly correlated ($\chi2(4) = 15.94$, $p = .003$, $H = 4.97$). Together, the significance of Facebook and Instagram highlights the influence of social media on political voting behaviours among respondents.

Table 6 provides descriptive information for all headline variables (real and fake) and their association with changes in political voting decisions. Exposure to specific fake news headlines shows significant associations with changes in voting decisions. Notably, demonstrating a significant relationship with voting changes ($\chi2(1) = 0.91$, $p = .03$, $V = 0.17$), and even more pronounced is the influence of fake news headline 4 ($\chi2(1) = 6.61$, $p = .01$, $V = 0.19$). Fake news headlines 3 and 4 suggest a relationship between a respondent's exposure to these sources of false election-related information and a change in political voting decision.

The most common headline observed by survey respondents during the election was real news 1 (n = 113), as 62.1% of all respondents recalled seeing this news item reported. The least common headline recalled by survey respondents during the time of the election is fake news 3. Only 13.2% of respondents (n = 24) remember this headline. Despite being the least commonly recalled headline, it shows a significant relationship with CV, suggesting that even when fake news is not widely circulated, it can still have a significant negative impact on political minds.

Table 7 provides descriptive information for the perceived truth of headline variables and their association with a change in voting decisions due to information observed in the media. No significant relationships exist between the perceived truth of any headline variables (real or fake). Among those who reported seeing fake news headlines, most participants could discern fact from fiction. 79.2% of those who recall seeing fake news headline 3 were able to identify the information as fictitious, making it the most correctly identified in terms of validity (n = 19). The truth assessment of fake news headline 1 was the least correctly identified, with only 55.9% of respondents correctly assessing it as untrue (n = 33). The findings in Table 7 also highlight that some respondents perceived the real news headlines as untrue, suggesting a lack of trust in mainstream media sources among the survey's respondents.

Table 5. Descriptive Statistics for Social Media Usage Habits

	Change of Vote Status						
	Vote Not Changed	Vote Changed	Mean	SD	*χ2 (p)*	df	Kruskal-Wallis
Time Spent on Twitter			0.96	0.84	1.39	4	0.78
Less than 1 hour	51 (76.1%)	16 (23.9%)					
1 to 2 hours	17 (81.0%)	4 (19.0%)					
2 to 3 hours	4 (80.0%)	1 (20.0%)					
3 to 4 hours	3 (100.0%)	0 (0.0%)					
More than 4 hours	1 (100.0%)	0 (0.0%)					
Time Spent on Facebook			1.22	1.01	11.06*	4	5.11
Less than 1 hour	57 (82.6%)	12 (17.4%)					
1 to 2 hours	21 (61.8%)	13 (38.2%)					
2 to 3 hours	8 (72.7%)	3 (27.3%)					
3 to 4 hours	6 (75.0%)	2 (25.0%)					
More than 4 hours	0 (0.0%)	2 (100.0%)					
Time Spent on Reddit			1.94	1.16	4.74	4	2.04
Less than 1 hour	23 (82.1%)	5 (17.9%)					
1 to 2 hours	57 (89.1%)	7 (10.9%)					
2 to 3 hours	26 (74.3%)	9 (25.7%)					
3 to 4 hours	10 (71.4%)	4 (28.6%)					
More than 4 hours	7 (77.8%)	2 (22.2%)					
Time Spent on Instagram			1.16	0.96	15.94**	4	4.97
Less than 1 hour	51 (76.1%)	16 (23.9%)					
1 to 2 hours	21 (84.0%)	4 (16.0%)					
2 to 3 hours	7 (53.9%)	6 (46.1%)					
3 to 4 hours	1 (16.7%)	5 (83.3%)					
More than 4 hours	0 (0.0%)	1 (100.0%)					

DV: Change of Vote.
*p < 0.05, **p < 0.01.

Table 6. Descriptive Statistics for Headline Variables

	Change of Vote Status				
	Vote Not Changed	Vote Changed	*χ2 (p)*	df	Cramer's V
Real News 1			0.38	1	0.05
No	56 (81.2%)	13 (18.8%)			
Yes	86 (76.1%)	27 (23.9%)			
Real News 2			0.79	1	0.07
No	108 (80.0%)	27 (20.0%)			
Yes	34 (72.3%)	13 (27.7%)			
Real News 3			0.11	1	0.02
No	86 (76.8%)	26 (23.2%)			
Yes	56 (80.0%)	14 (20.0%)			
Real News 4			0.03	1	0.01
No	107 (78.7%)	29 (21.3%)			
Yes	35 (76.1%)	11 (23.9%)			
Fake News 1			0.94	1	0.07
No	99 (80.5%)	24 (19.5%)			
Yes	43 (72.9%)	16 (27.1%)			

Fake News 2			1.96	1	0.10
No	94 (81.2%)	21 (18.8%)			
Yes	48 (71.6%)	19 (28.4%)			
Fake News 3			5.00*	1	0.17
No	128 (81.0%)	30 (19.0%)			
Yes	14 (58.3%)	10 (41.7%)			
Fake News 4			6.61**	1	0.19
No	123 (82.0%)	27 (18.0%)			
Yes	19 (59.4%)	13 (40.6%)			

DV: Change of Vote.
*p < 0.05, **p < 0.01.

Table 7. Descriptive Statistics for Perceived Truth of Headlines Variables

	Change of Vote Status				
	Vote Not Changed	**Vote Changed**	***χ2 (p)***	***df***	***Cramer's V***
Perceived Truth of Real News 1			0.00	1	0.00
Did Not Believe	18 (78.3%)	5 (21.7%)			
Believed	68 (75.6%)	22 (24.4%)			
Perceived Truth of Real News 2			0.00	1	0.00
Did Not Believe	4 (80.0%)	1 (20%)			
Believed	30 (71.4%)	12 (28.6%)			
Perceived Truth of Real News 3			0.05	1	0.03
Did Not Believe	12 (85.7%)	2 (14.3%)			
Believed	44 (78.6%)	12 (21.4%)			
Perceived Truth of Real News 4			0.41	1	0.09
Did Not Believe	12 (85.7%)	2 (14.3%)			
Believed	23 (71.9%)	9 (28.1%)			
Perceived Truth of Fake News 1			0.07	1	0.03
Did Not Believe	25 (75.8%)	8 (24.2%)			
Believed	18 (69.2%)	8 (30.8%)			
Perceived Truth of Fake News 2			2.89	1	0.21
Did Not Believe	35 (79.5%)	9 (20.5%)			
Believed	13 (56.5%)	10 (43.5%)			
Perceived Truth of Fake News 3			2.09	1	0.30
Did Not Believe	13 (68.4%)	6 (31.6%)			
Believed	1 (20.0%)	4 (80.0%)			
Perceived Truth of Fake News 4			0.03	1	0.03
Did Not Believe	12 (63.2%)	7 (36.8%)			
Believed	7 (53.8%)	6 (46.2%)			

DV: Change of Vote.

3.2. Binary Logistic Regression Analysis

The first research question examines the relationship between social media usage and changes in voting behaviour. The research question is: Does time spent on social media influence whether a participant decides to change their vote? To address this question, the following hypotheses were proposed:

H_1: Increased time spent on social media is predicted to raise the likelihood of a participant changing their political voting decision.

H_{1_null}: Time spent on social media does not have a statistically significant relationship with the likelihood of a participant changing their political voting decision.

A binary logistic regression was conducted to examine the effects of time spent on various social media platforms on the likelihood that respondents will change their voting decision due to information conveyed through the media. The logistic regression model was statistically significant ($p \leq .001$). Additionally, the model's goodness of fit was assessed using the Hosmer-Lemeshow test, which indicated a good fit to the data ($\chi^2 = 0.00$, $p = 1.000$). This suggests that the model adequately fits the observed data.

Time on Instagram is shown to have a significant association with changes in voting behaviours ($\beta = 0.62$, $p \leq .001$). This implies that increased time on Instagram is strongly associated with an increased likelihood of changing one's vote. For each unit increase in the time spent on Instagram (from none to less than one hour, one hour to two hours, etc.), the odds of changing one's vote increase by 86.58% ($\exp(\beta) = 1.87$), assuming all other factors in the model are held constant. Thus, the null hypothesis for RQ1 is rejected. As Instagram is a statistically significant predictor of voting decision changes, social media has the potential to influence political decision-making.

Table 8. Social Media Usage Predicting Change of Vote

Variable	Coefficient	OR	Std. Err	z-value	95% CI (Lower, Upper)
Time on Facebook	0.31	1.37	0.17	1.88	(0.99, 1.90)
Time on Twitter	-0.36	0.70	0.22	-1.61	(0.46, 1.08)
Time on Reddit	-0.08	0.92	0.15	-0.57	(0.69, 1.23)
Time on Instagram	0.62***	1.87	0.16	3.89	(1.36, 2.56)
Gender	0.12	1.13	0.25	0.49	(0.70, 1.83)

*$p \leq .001$

The second research question examines the relationship between exposure to real news and changes in voting behaviour. The specific research question guiding this regression is: Does exposure to real news have an effect on whether a participant will change their vote? To address this question, the following hypotheses were proposed:

H_2: Greater exposure to real news is predicted to increase the likelihood of a participant changing their voting decision.
H_{2_null}: Exposure to real news has no statistically significant relationship with changes in a participant's voting decision.

A second binary logistic regression was conducted to examine the exposure to real news headlines on the likelihood that respondents will change their voting decision due to information conveyed through the media. While the model is an overall good fit based on the Hosmer-Lemeshow test ($\chi^2 = 0.00$, $p = 1.000$)., the logistic regression model is not statistically significant ($p = .75$). This suggests that, despite the model’s good fit, the real news headlines included in this analysis were not impactful in vote changing behaviours.

As indicated in Table 9, there are no statistically significant findings within any of the real news predictors. The null hypothesis is accepted. The real news headlines included in this study do not increase or decrease the chance that a participant will be influenced to change their voting decision. This could suggest that accurate news reporting is less powerful in its effect on a respondent’s voting decisions. The inclusion of more real news variables may prove valuable for further analysis.

Table 9. Exposure to Real News Predicting Change of Vote

Variable	**Coefficient**	**OR**	**Std. Err**	**z-value**	**95% CI (Lower, Upper)**
Real News 1	0.35	1.42	0.40	0.88	(-0.43, 1.14)
Real News 2	0.41	1.51	0.40	1.03	(-0.37, 1.20)
Real News 3	-0.23	0.80	0.37	-0.61	(-0.95, 0.50)
Real News 4	0.02	1.02	0.43	0.05	(-0.82, 0.86)
Gender	0.19	1.21	0.22	0.87	(-0.25, 0.63)

Reference category = Did not see

The third research question investigates the relationship between exposure to fake news and changes in voting behaviour. The research question asked is: Does exposure to fake news influence whether a participant will change their vote? To address this question, the following hypotheses were proposed:

H_3: Exposure to fake news is hypothesized to increase the likelihood of a participant changing their voting decision.
H_{3_null}: Exposure to fake news does not have a statistically significant impact on a participant's voting decision.

A third binary logistic regression was conducted to examine the effects of exposure to fake news on the likelihood that respondents will change their voting decision due to information conveyed through the media. The logistic regression model itself did not show conventional statistical significance ($p = .06$). This indicates that the model's predictors, as a whole, may not reliably distinguish between those who change their voting decisions and those who do not. However, the model's proximity to conventional significance levels suggests that it is still worthwhile examining the results. While individual predictors may not have strong effects, their collective influence could be relevant in specific contexts or subsets of the data. The Hosmer-Lemeshow test, used to assess the model's goodness of fit, indicated a good fit to the data ($\chi2 = 0.00$, $p = 1.000$), suggesting that the model adequately fits the observed data.

As indicated in Table 10, participants who recall reading a fake news headline 4 are likelier to change their vote than participants who did not see fake news 4 ($\beta = 0.98$, $p = 0.05$). Exposure to this specific fake news headline increases the likelihood of changing one's vote by approximately 166% compared to unexposed ($exp(\beta) = 2.66$). Based on this finding, the null hypothesis is rejected. Fake news headlines may influence readers to change their political voting decisions depending on the article.

Table 10. Exposure to Fake News Predicting Change of Vote

Variable	Coefficient	OR	Std. Err	z-value	95% CI (Lower, Upper)
Fake News 1	-0.20	0.82	0.49	-0.41	(-1.15, 0.75)
Fake News 2	0.12	1.13	0.41	0.30	(-0.68, 0.92)
Fake News 3	0.85	2.33	0.50	1.70	(-0.13, 1.82)
Fake News 4	0.98*	2.66	0.50	1.95	(-0.01, 1.97)
Gender	0.24	1.26	0.21	1.14	(-0.17, 0.64)

*p < .05, Reference category = Did not see

The fourth research question explores the impact of belief in fake news on changes in voting behaviour. The research question is: Does believing fake news affect whether a participant will change their vote? To address this question, the following hypotheses were proposed:

H_4: It is hypothesized that those who believe fake news articles to be true are more likely to change their voting decision.
H_{4_null}: Perceiving fake news as true has no statistically significant impact on political voting decisions.

A final binary logistic regression was conducted to examine the likelihood that believing that fake news is true affects respondents' voting decisions due to information conveyed through the media. The logistic regression model was statistically significant ($p = .05$). Based on the Hosmer-Lemeshow test, the model is deemed a good fit for the data ($\chi^2 = 0.00$, $p = 1.000$).

As indicated in Table 11, a negative and significant relationship is found between those who were not exposed to fake news 3 (compared to those who both saw and believed the headline) and a change in voting decision ($\beta = -2.82$, $p = .02$). The odds of changing one's voting decision are 94% lower for individuals who did not see Fake News 3 compared to those who believed it ($exp(\beta) = 0.06$). In this case, not seeing the fake news stabilizes voters' existing decisions significantly, preventing shifts that might occur if they believed the fake news. Based on this finding, the null hypothesis is rejected. Believing that fictitious news is accurate can predict whether a respondent may change their vote due to the influence of the media.

Table 11. The Perceived Truth of Fake News Predicting Change of Vote

Variable	Coefficient	OR	Std. Err	z-value	95% CI (Lower, Upper)
Perceived Truth of Fake News 1					
Did not believe vs. Believed	0.28	1.32	0.71	0.39	(-1.11, 1.67)
Did not see vs. Believed	0.52	1.70	0.58	0.90	(-0.61, 1.66)
Perceived Truth of Fake News 2					
Did not believe vs. Believed	-0.94	0.39	0.63	-1.50	(-2.16, 0.29)
Did not see vs. Believed	-0.75	0.47	0.57	-1.31	(-1.88, 0.37)
Perceived Truth of Fake News 3					
Did not believe vs. Believed	-2.20	0.11	1.28	-1.72	(-4.72, 0.31)
Did not see vs. Believed	-2.82*	0.06	1.21	-2.33	(-5.19, -0.45)
Perceived Truth of Fake News 4					
Did not believe vs. Believed	-0.10	0.91	0.85	-0.11	(-1.80, 1.57)
Did not see vs. Believed	-0.92	0.40	0.75	-1.23	(-2.38, 0.54)
Gender	0.21	1.24	1.00	-0.05	(-0.21, 0.63)

*p < .05

4. Discussion

This study provides insight into how media, particularly social media, shapes political behaviour and democratic processes. A key concern is that disinformation can significantly influence voter decision-making, even when its direct impact on election outcomes remains unclear. For at least some Canadians who participated in this survey, exposure to false or misleading information influenced their voting choices. This underscores the importance of analyzing how media platforms influence which political issues voters prioritize and the broader role of agenda-setting in political discourse.

Our findings indicate that Instagram is the platform most strongly associated with changes in voting decisions. Social media plays a pivotal role in modern political communication, allowing political parties to engage directly with the public and shape discourse (Lachapelle & Maarek, 2015; Towner & Muñoz, 2018; Yang et al., 2016). While this democratization of information can enhance voter awareness, it also facilitates the spread of low-quality and misleading content (Lipschultz, 2021). Agenda-setting theory suggests that media influence extends beyond merely informing the public; it determines which issues receive the most attention and, in turn, shape voter priorities (McCombs & Shaw, 1972). This study highlights a critical concern, showing that exposure to fake news, even when not believed, can significantly influence voting behaviour by amplifying certain political narratives over others. In an algorithm-driven media environment, disinformation exploits agenda-setting mechanisms by elevating misleading content, reinforcing selective issue salience, and shaping electoral decision-making in ways that may not align with objective realities (Bennett & Livingston, 2018; Tsfati et al., 2020). Although changing one's vote based on reliable information is part of informed decision-making, the risk arises when these shifts are driven by disinformation rather than factual reporting.

This analysis has also shown that even infrequently viewed fake news can influence political decision-making. Fake news headline 3, the least recalled by respondents, was the strongest predictor of voting changes, suggesting that social media echo chambers amplify disinformation's effects. By circulating within insular networks, these chambers reinforce biases and accelerate the spread of inaccuracies (Szebeni et al., 2021). Even limited exposure can shape political priorities by repeatedly surfacing certain issues, making them seem more pressing than they are. Echo chambers further intensify this effect by limiting diverse perspectives, amplifying misleading narratives, and suppressing counterarguments (Kumar & Krishna, 2014). This self-reinforcing cycle strengthens the agenda-setting power of disinformation, keeping select topics prominent in public discourse while pushing fact-based discussions to the margins.

The study highlights a significant trend of skepticism among participants toward mainstream media despite its role in providing more reliable and less partisan information. This distrust points to broader challenges within the information ecosystem. Even when presented with factual content, a substantial portion of the public questions its authenticity. Disinformation campaigns exploit this process by undermining trust in traditional media, allowing misleading or partisan narratives to fill the informational void. Over time, such campaigns erode public confidence in media integrity, leaving individuals more vulnerable to alternative narratives, regardless of their factual accuracy. As disinformation gains visibility and repetition within algorithm-driven platforms, it strengthens agenda-setting effects, amplifying certain narratives, deepening polarization, and reshaping perceptions of institutional legitimacy (Bridgman et al., 2022; McKay & Tenove, 2021; Szebeni et al., 2021). This dynamic heightens the risk of voters becoming trapped in echo chambers, adopting increasingly polarized views, and further distancing themselves from fact-based reporting.

Another potential explanation for this finding provides a far more optimistic outlook on Canadian media literacy. The rise of disinformation and the resulting skepticism toward media sources may encourage individuals to evaluate even factual reports critically. While this heightened caution can lead to distrust of credible sources and rejection of valid information, it may serve as a defence against accepting false narratives. Such vigilance, though potentially obstructive to recognizing truthful content, helps safeguard against the influence of disinformation. However, this over-cautious approach can also hinder the ability of accurate, well-reported news to penetrate divisive ideological bubbles and mitigate polarization. These findings highlight the need for media literacy initiatives that not only enhance critical evaluation skills to detect misinformation but also rebuild trust in traditional journalism as a foundation of informed democratic discourse (Mourão & Robertson, 2019; Preston et al., 2021; Vasu et al., 2018).

The observation that real news headlines did not significantly influence voting decisions in this study suggests that accurate news reporting may have a diminished impact on electoral behaviour compared to other forms of media content. Several factors could explain this phenomenon. First, the saturation of information in digital media environments may dilute the impact of individual news stories, regardless of their veracity, making it harder for any single piece of real news to influence opinions or voting behaviour significantly. Mainstream journalism publishes information at a significantly lower speed than information disseminated through social media platforms. As a result, information circulated with less rigour and critique can reach more media consumers faster, ultimately dominating the digital information environment (Harder et al., 2017). In this landscape, agenda-setting power is often dictated by visibility rather than credibility, allowing sensationalized or emotionally charged content to overshadow fact-based discourse (Tsfati et al., 2020).

Forms of non-journalistic political information delivered through social networks can be tainted with inaccuracy and bias but reach intended audiences more frequently and consistently (Lipschultz, 2021). The constant exposure to a high volume of media content might lead to information overload, where the ability of voters to process and evaluate new information effectively is compromised. This overload can cause real news to be lost amidst the noise of sensationalist or fake news, which is often designed to be more engaging and emotionally charged (Harder et al., 2017; Meraz, 2009). Implementing stricter regulations on social media platforms to curb the spread of misinformation can help ensure that factual content is not overshadowed by fake news. This includes holding platforms accountable for actively monitoring and labelling or removing false information and enhancing the algorithms prioritizing content to ensure quality over sensationalism (Dawood, 2021).

This study also shows that individuals who were not exposed to fake news headline 3 were significantly less likely to change their vote compared to those who believed the misleading content. This finding underscores the stabilizing effect of avoiding exposure to fake news, as it greatly reduces the likelihood of such information influencing voting decisions. This outcome highlights the risks of disinformation in political contexts, where fake news can be a powerful tool for manipulating public opinion and electoral outcomes (Bradshaw et al., 2021). Preventing the circulation of fake news is more effective than relying on post-hoc damage control strategies. However, implementing stricter regulations on social media content raises concerns about infringing on freedom of speech protections. Striking a balance between removing harmful disinformation and preserving legitimate discourse is essential. While beyond the scope of this study, the complexities of this balance must be carefully considered to avoid unintended consequences when formulating media regulation policies.

Disinformation campaigns intended to create polarization within a democratic body do not happen overnight. Rather, these campaigns are a slow and coordinated effort that steadily erodes social cohesion and trust in public institutions over time (Bridgman et al., 2022). Given the findings of this study, disinformation is a threat to Canadian democracy. Canada's national security must respond to disinformation threats promptly and decisively. We must examine how all attacks against Canada's democracy fit together to help us understand whether these attacks work together to serve a larger intended purpose (Starbird et al., 2019). Proactive measures against disinformation not only protect democratic processes but also reinforce national resilience against political disinformation designed to undermine social stability. Agenda-setting theory provides a framework for understanding why these efforts must extend beyond fact-checking alone; disrupting the mechanisms that give misleading narratives their influence is essential to safeguarding electoral integrity.

5.1. Implications for Theory and Practice

This study offers significant implications for theory and practice by advancing our understanding of the relationship between disinformation, social media, and democratic processes. The findings highlight how exposure to disinformation, even at low levels, can disproportionately influence voter behaviours. The diminished impact of real news on electoral decisions suggests a need to refine traditional frameworks, particularly given the role of social media in amplifying content that aligns with users' biases (Kumar & Krishna, 2014). Echo chambers and algorithmic curation exacerbate these dynamics, limiting exposure to diverse perspectives and reinforcing polarization (Szebeni et al., 2021).

Practically, this research underscores the urgent need to address the proliferation of disinformation through media literacy initiatives and regulatory measures. Social media platforms have democratized political communication, allowing for faster and more direct engagement between political actors and the electorate (Lachapelle & Maarek, 2015; Yang et al., 2016). However, this accessibility has also lowered the barriers to disseminating misleading and harmful information, which poses a significant threat to democratic integrity (Lipschultz, 2021; McKay & Tenove, 2021). Efforts to enhance public media literacy should include critical evaluation skills and emotional intelligence, as these have been shown to improve individuals' ability to detect disinformation (Preston et al., 2021). Additionally, fostering trust in credible journalism is essential to counter the erosion of confidence caused by disinformation campaigns (Bridgman et al., 2022).

The evidence that even low-visibility fake news can significantly influence voter decisions highlights the critical role of regulatory and collaborative efforts. Disinformation campaigns thrive within echo chambers, where repeated exposure amplifies their impact (Kumar & Krishna, 2014). To combat this, policymakers and social media platforms must implement content moderation practices, transparency in algorithmic prioritization, and mechanisms to identify and label false information swiftly (Dawood, 2021). International examples, such as the European Union's East StratCom Task Force, demonstrate the value of coordinated efforts to detect and challenge disinformation while promoting public resilience through education (Vasu et al., 2018). The findings emphasize the importance of a sustained and proactive approach to safeguarding democratic processes (Starbird et al., 2019).

5.2. Limitations and Directions for Future Research

This study has several limitations, primarily due to its small, non-random sample size, which increases the likelihood of a type II error and limits generalizability to the broader Canadian voting population. The reliance on social media, particularly Reddit, for recruitment further reduces representativeness. Additionally, a more diverse set of real and fake news articles could enhance the findings by capturing headlines with greater potential to influence political decision-making. Potential misclassification of news items, where real news may not be fully accurate or fake news may contain elements of truth, also poses a challenge.

Despite these limitations, the study demonstrates that fake news can influence voting decisions, though these effects likely interact with other factors such as upbringing, peer influence, and psychological variables. Future research should increase sample size, adopt randomized sampling, include a wider range of news content, and examine additional social and psychological factors to improve the validity and reliability of findings.

5. Conclusion & Practical Implications

This research highlights how disinformation and social media shape voting behaviours within the Canadian voter sample. Our findings reveal that politically charged content on social media platforms significantly influences voting decisions, while the impact of real news is notably weaker. This suggests that the rapid dissemination of information through digital channels may dilute the influence of credible journalism. Agenda-setting theory suggests that media influence extends beyond simply providing information; it also shapes public priorities by determining which issues receive the most attention (McCombs & Shaw, 1972). In social media, this process is no longer controlled by traditional news outlets but by algorithm-driven platforms that amplify content based on engagement rather than accuracy. This study demonstrates how disinformation takes advantage of these dynamics, repeatedly surfacing in digital environments and reinforcing selective issue salience. As misleading narratives dominate online spaces, they shift voter concerns from fact-based discussions to exaggerated or polarizing topics. Even minimal exposure to fake news influences voting decisions, emphasizing how disinformation misleads voters and dictates which political issues seem most urgent or relevant.

Protecting democratic integrity requires a multifaceted approach from policymakers and social media platforms. Strategies should include curbing the spread of fake news, promoting media literacy education, enhancing transparency, and swiftly addressing false claims to rebuild public trust. Given that agenda-setting effects are amplified in algorithm-driven media spaces, interventions must also focus on disrupting the visibility and dominance of misleading narratives while ensuring fact-based reporting remains accessible and prioritized. This study identifies the challenges posed by the current information ecosystem and calls for sustained vigilance and proactive measures to safeguard democratic engagement in the digital age.

Statement of Researchers

Researchers' contribution rate statement:

Conceptualization (RL, RF), Data curation (RL, RF), Formal analysis (RL), Investigation (RL), Methodology (RL), Project administration (RF), Software (RF), Supervision (RF), Validation (RL, RF), Visualization (RL), Writing – original draft (RL), Writing – review & editing (RL, RF)

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The authors declare that they have no conflict of interest.

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6. References

Ali, K., & Zain-ul-abdin, K. (2021). Post-truth propaganda: Heuristic processing of political fake news on Facebook during the 2016 U.S. presidential election. *Journal of Applied Communication Research*, *49*(1), 109–128. https://doi.org/10.1080/00909882.2020.1847311

Allcott, H., & Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of Economic Perspectives*, 31(2), 211–236. https://doi.org/10.1257/jep.31.2.211

Bader, M. (2019). Disinformation in elections. *Security and Human Rights*, *29*(14), 24–35. https://doi.org/10.1163/18750230-02901006

Bennett, L. & Livingston, S. (2018). The disinformation order: Disruptive communication and the decline of democratic institutions. *European Journal of Communication*, *33*(2), 122–139. https://doi.org/10.1177/0267323118760317

Bermes A. (2021). Information overload and fake news sharing: A transactional stress perspective exploring the mitigating role of consumers' resilience during COVID-19. *Journal of Retailing and Consumer Services*, *61*, 102555. https://doi.org/10.1016/j.jretconser.2021.102555

Bradshaw, S., Bailey, H., & Howard, P. (2021). *Industrialized disinformation: 2020 Global inventory of organized social media manipulation.* Computational Propaganda Project at the Oxford Internet Institute. https://demtech.oii.ox.ac.uk/wp-content/uploads/sites/12/2021/02/CyberTroop-Report20-Draft9.pdf

Bridgman, A., Lavigne, M., Baker, M., Bergeron, T., Bohonos, D., Burton, A., McCoy, K., Hart, M., Lavault, M., Liddar, R., & Peng, P. (2022). Mis-and disinformation during the 2021 Canadian federal election. *Media Ecosystem Observatory*. https://osf.io/preprints/ubfmx

Carlson, M. (2020). Fake news as an informational moral panic: The symbolic deviancy of social media during the 2016 US presidential election. *Information, Communication & Society*, *23*(3), 374–388. https://doi.org/10.1080/1369118X.2018.1505934

Dawood, Y. (2021). Combatting foreign election interference: Canada's electoral ecosystem approach to disinformation and cyber threats. *Election Law Journal*, *20*(1), 10–31. https://doi.org/10.1089/elj.2020.0652

Derakhshan, H. & Wardle, C. (2017). Information disorder: Definitions. In *Understanding and Addressing the Disinformation Ecosystem*. Annenberg School for Communication.

Evans, G. (2014). Propaganda: World War 1 usages. *History Class Publications*. 10. https://scholarlycommons.obu.edu/cgi/viewcontent.cgi?article=1030&context=history

Graham, T. (2024, May 16). What does Putin really want in Ukraine? *Council on Foreign Relations*. https://www.cfr.org/expert-brief/what-does-putin-really-want-ukraine

Harder, R. A., Sevenans, J., & Van Aelst, P. (2017). Intermedia agenda setting in the social media age: How traditional players dominate the news agenda in election times. *The International Journal of Press/Politics*, *22*(3), 275–293. https://doi.org/10.1177/1940161217704969

Henschke, A., Sussex, M., & O'Connor, C. (2020). Countering foreign interference: Election integrity lessons for liberal democracies. *Journal of Cyber Policy*, 5(2), 180–198. https://doi.org/10.1080/23738871.2020.1797136

Hoffman, M. (2022, October 10). *Fighting disinformation, malinformation, and misinformation in influence operations campaigns*. North Atlantic Treaty Organization. https://www.sto.nato.int/publications/STO%20Meeting%20Proceedings/STO-MP-MSG-197/MP-MSG-197-22P.pdf

Jackson, J. (2023, July 27). *What are influence operations and why are we investigating them?* The Bureau of Investigative Journalism. https://www.thebureauinvestigates.com/stories/2023-07-27/what-are-influence-operations-and-why-are-we-investigating-them/

Jacobs, C. S., & Carley, K. M. (2024). WhatIsDemocracy: Finding key actors in a Chinese influence campaign. *Computational and Mathematical Organization Theory*, 30(2), 127–147. https://doi.org/10.1007/s10588-023-09380-9

Johnson, T. J., & Kaye, B. K. (2015). Reasons to believe: Influence of credibility on motivations for using social networks. *Computers in Human Behavior*, 50, 544–555. https://doi.org/10.1016/j.chb.2015.04.002

Klinger, U., & Russmann, U. (2017). "Beer is more efficient than social media" - Political parties and strategic communication in Austrian and Swiss national elections. *Journal of Information Technology & Politics*, *14*(4), 299–313. https://doi.org/10.1080/19331681.2017.1369919

Kumar, K. & Krishna, G. (2014). Detecting misinformation in online social networks using cognitive psychology. *Human-Centric Computing and Information Sciences*, *4*(1), 1–22. https://doi.org/10.1186/s13673-014-0014-x

Lachapelle, G., & Maarek, P. J. (2015*). Political parties in the digital age: The impact of new technologies in politics*. ProQuest Ebook Central.

Lewandowsky, S., Stritzke, W. G. K., Freund, A. M., Oberauer, K., & Krueger, J. I. (2013). Misinformation, disinformation, and violent conflict. *American Psychologist*, *68*(7), 487–501. https://doi.org/10.1037/a0034515

Lipschultz, J. H. (2021). StopTheSteal on Twitter: Social media and political communication. *Advances in Social Sciences Research Journal*, *8*(6), 56–70. https://doi.org/10.14738/assrj.86.10309

Meraz, S. (2009). Is there an elite hold? Traditional media to social media agenda setting influence in blog networks*. Journal of Computer-Mediated Communication*, 14(3), 682–707. https://doi.org/10.1111/j.1083-6101.2009.01458.x

McCombs, M. E., & Shaw, D. L. (1972). The agenda-setting function of mass media. *Public Opinion Quarterly*, *36*(2), 176–187. https://doi.org/10.1086/267990

McKay, S., & Tenove, C. (2021). Disinformation as a threat to deliberative democracy. *Political Research Quarterly*, 74(3), 703–717. https://doi.org/10.1177/1065912920938143

Mourão, R. R., & Robertson, C. T. (2019). Fake news as discursive integration: An analysis of sites that publish false, misleading, hyperpartisan and sensational information.

Journalism Studies, 20(14), 2077–2095. https://doi.org.proxy.lib.sfu.ca/10.1080/1461670X.2019.1566871

Murphy, D. M., & White, J. F. (2007). Propaganda: Can a word decide a war? *The US Army War College Quarterly: Parameters*, 37(3), 15–27. doi:10.55540/0031-1723.2383.

Preston, S., Anderson, A., Robertson, D. J., Shephard, M. P., & Huhe, N. (2021). Detecting fake news on Facebook: The role of emotional intelligence. *PLoS One*, 16(3) https://doi.org/10.1371/journal.pone.0246757

Pruitt-Santos, G. M. (2023). The role of social media in political communication: How alternative journalists illuminate information in Central America's declining democracies. *Atlantic Journal of Communication*, 1–16. https://doi.org/10.1080/15456870.2023.2292217

Public Inquiry into Foreign Interference in Federal Electoral Processes and Democratic Institutions. (2025). *Final report*. Government of Canada. https://foreigninterferencecommission.ca/fileadmin/report_volume_1.pdf

Sazonov, V., Ploom, I., & Veebel, V. (2022). The Kremlin's information influence campaigns in Estonia and Estonian response in the context of Russian-Western relations. *TalTech Journal of European Studies*, 12(1), 27–59. https://doi.org/10.2478/bjes-2022-0002

Schudson, M., & Zelizer, B. (2017). Fake news in context. In *Understanding and Addressing the Disinformation Ecosystem*. Annenberg School for Communication.

Serafino, M., Zhou, Z., Andrade, J. S., Bovet, A., & Makse, H. A. (2024). Suspended accounts align with the Internet Research Agency misinformation campaign to influence the 2016 US election. *EPJ Data Science*, 13(1), 29–19. https://doi.org/10.1140/epjds/s13688-024-00464-3

Starbird, K., Arif, A., & Wilson, T. (2019). Disinformation as collaborative work: Surfacing the participatory nature of strategic information operations. *Proceedings of the ACM on Human-Computer Interaction*, *3*, 1–26. https://doi.org/10.1145/3359229

Szebeni, Z., Lönnqvist, J.-E., & Jasinskaja-Lahti, I. (2021). Social psychological predictors of belief in fake news in the run-up to the 2019 Hungarian elections: The importance of conspiracy mentality supports the notion of ideological symmetry in fake news belief. Frontiers in Psychology, 12, 1-17. https://doi.org/10.3389/fpsyg.2021.790848

Tenove, C. (2020). Protecting democracy from disinformation: Normative threats and policy responses. *The International Journal of Press/Politics,* 25(3), 517-537. https://doi.org/10.1177/1940161220918740

Towner, T. L., & Muñoz, C. L. (2018). Picture perfect? The role of Instagram in issue agenda setting during the 2016 presidential primary campaign. Social Science Computer Review, 36(4), 484-499. https://doi-org.proxy.lib.sfu.ca/10.1177/0894439317728222

Tsfati, Y., Boomgaarden, H. G., Strömbäck, J., Vliegenthart, R., Damstra, A., & Lindgren, E. (2020). Causes and consequences of mainstream media dissemination of fake news: Literature review and synthesis. Annals of the International Communication Association, 44(2), 157–173. https://doi.org/10.1080/23808985.2020.1759443

Tuttle, D. (2019). *Campaigns of disinformation: Modern warfare, electoral interference, and Canada's security environment.* [Master's Capstone Project, University of Alberta] http://hdl.handle.net/1880/111834

Vasu, N., Ang, B., Teo, T.A., Jayakumar, S., Faizal, M., & Ahuja, J. (2018). *Fake news: National security in the post-truth era.* (Policy Report 2018). S. Rajaratnam School of International Studies. https://www.rsis.edu.sg/wp-content/uploads/2018/01/PR180313_Fake-News_WEB.pdf

Vuckovic, M. (2023). Politicizing, personalizing, and mobilizing in online political communication: Drivers and killers of users' engagement. *International Journal of Communication*, 17, 3033-3053. https://doi.org/1932–8036/20230005

Yang, X., Chen, B.-C., Maity, M., & Ferrara, E. (2016). Social politics: Agenda setting and political communication on social media. In E. Spiro, & Y. Ahn (Eds.), *Social Informatics* (pp. 330–344). Springer International Publishing. https://doi.org/10.1007/978-3-319-47880-7_20

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Adaptation of perceived social media literacy scale to Turkish culture: The case of educators

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Highlights:

- The Perceived Social Media Literacy Scale (PSMLS) was adapted and validated for use among Turkish educators and school administrators.
- Utilizing both first- and second-order confirmatory factor analyses, the PSMLS's structural validity and theoretical alignment were confirmed.
- The Turkish version demonstrated strong internal consistency, construct reliability, and criterion validity.
- No significant gender differences were found, but younger educators (≤ 40 years) reported higher levels of social media literacy.
- The scale, having undergone validation, provides a reliable basis for formulating educational policies to enhance digital and media literacy competencies among educators.

Abstract

Social media has become an integral component of contemporary digital interactions, influencing education, communication, and information access. As social media usage continues to rise, social media literacy (SML) has gained increasing attention as a crucial competency for individuals to critically assess online information, manage digital interactions, and navigate algorithmic content. While several scales have been developed to measure SML, there remains a gap in assessing the construct among educators, particularly within non-Western cultural contexts such as Türkiye. Addressing this gap, this study aims to adapt and validate the Perceived Social Media Literacy Scale (PSMLS) for use among Turkish educators and school administrators. The research sample consisted of 571 teachers and 293 school administrators, and the adaptation process involved translation, cultural adaptation, and psychometric validation. Both first- and second-level confirmatory factor analyses (CFA) were conducted to examine the structural validity of the scale. The first-level CFA confirmed the original factor structure and achieved cultural fit, while the second-level CFA supported the hierarchical structure of the scale, demonstrating strong alignment with the theoretical model. Additionally, criterion validity correlations, construct reliability, Cronbach's Alpha, and McDonald's Omega coefficients confirmed the scale's reliability. While gender differences in SML scores were not statistically significant, teachers aged 40 and below exhibited significantly higher SML scores than their older counterparts. The findings establish the PSMLS as a valid and reliable instrument for assessing social media literacy among educators and school administrators in Türkiye. This study contributes to the literature by providing a culturally adapted and psychometrically robust tool, enabling further research on digital literacy, media education, and social media engagement within educational contexts.

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1. Introduction

With the expansion of digital technologies, social media has become a dominant force shaping personal, social, and professional interactions (Brown & Duguid, 2017). As individuals engage with this ever-evolving digital landscape, social media literacy (SML)—which encompasses the skills, knowledge, and attitudes required for critical engagement with social media platforms—has emerged as a key area of academic inquiry. Developing SML is essential for promoting responsible and effective use of digital media while mitigating risks such as misinformation, cyberbullying, and privacy violations (Samala et al., 2024). Research instruments must be carefully adapted to specific cultural contexts to ensure accurate measurement of SML across different populations. The Perceived Social Media Literacy Scale (PSMLS), originally designed to assess individuals' ability to analyze and interact with social media content critically, requires a thorough cultural adaptation to reflect the distinctive social dynamics of Turkish society accurately. SML, which entails the ability to access, interpret, evaluate, and produce digital media content, is increasingly regarded as a crucial competence in the digital age (Özel, 2023). In Türkiye, educational policies have increasingly emphasized the integration of digital and media literacy into curricula, acknowledging its role in equipping students with essential critical thinking skills for engaging with digital media (Hobbs & Tuzel, 2017). Given the significant influence of social media on public discourse and daily communication, developing SML among students and educators alike is more important than ever (Solmaz & Reinhardt, 2024).

The adaptation of the PSMLS extends beyond mere linguistic translation; it requires cultural modification to ensure that the scale adequately captures the specific ways social media is used and perceived within the Turkish context. Research has repeatedly emphasized the importance of psychometric validation when adapting media literacy instruments to different cultural settings (e.g., Ak & Arslantaş, 2024). For instance, adapting the Algorithmic Media Content Awareness Scale for Turkish learners involved comprehensive validity and reliability testing to confirm its effectiveness in assessing algorithmic literacy (Ak & Arslantaş, 2024). A similar methodological approach is necessary to adapt the PSMLS, ensuring it undergoes rigorous translation, cultural alignment, and psychometric evaluation to establish its applicability and validity in Türkiye.

As digital platforms become increasingly embedded in educational environments, educators play a fundamental role in fostering social media literacy among students. However, a significant research gap remains regarding how educators perceive and engage with social media, particularly within the Turkish educational system. In addressing this gap, the present study seeks to adapt and validate the Perceived Social Media Literacy Scale (PSMLS) specifically for educators, thus providing a reliable tool for assessing their digital competencies.

The present study focuses on adapting the PSMLS for the Turkish educational context, ensuring its linguistic, conceptual, and psychometric suitability for Turkish-speaking educators. The adaptation process entails rigorous translation, cultural alignment, and validation techniques, including confirmatory factor analysis (CFA), to establish the scale's reliability and construct validity. By localizing the PSMLS, this research contributes to the expanding body of scholarship on SML while offering educators, researchers, and policymakers in Türkiye a reliable instrument for assessing and enhancing digital literacy skills. The subsequent sections explore the theoretical foundations of SML, outline the methodological framework of the adaptation process, and discuss the implications of the adapted scale for research and practice in Türkiye. This study addresses a significant gap in the literature and highlights the importance of culturally responsive assessment tools in advancing digital literacy on a global scale.

1.1. Literature Review

Social media literacy (SML), a fundamental aspect of digital literacy, involves interpreting, critically assessing, and actively engaging with content on social media platforms (Meyers et al., 2013). Prior research has demonstrated a positive relationship between SML and several beneficial outcomes, including improved critical thinking, responsible digital engagement, and enhanced communication abilities (Tommasi et al., 2023). However, since digital engagement is shaped by cultural, societal, and technological factors, localized investigations and tailored measurement tools are essential for ensuring the validity and applicability of research findings. Scholars have widely recognized the significance of SML as a vital skill in today's digital landscape. For example, Buckingham (2013) emphasized its role in addressing contemporary issues such as misinformation, digital manipulation, and disparities in online participation. Similarly, Livingstone (2008) explored the function of digital literacy in enabling individuals to assess online information and interact responsibly and critically with digital platforms. Jenkins (2007), in turn, examined how participatory culture within social media necessitates educational interventions that encourage critical engagement and collaborative competencies among users.

In Türkiye, equipping individuals with the skills required to navigate complex digital spaces has gained increasing prominence. Ugurhan et al. (2020) highlighted the urgent need for comprehensive media literacy education to counteract misinformation and bridge the digital divide. Additionally, incorporating media literacy into the Turkish educational curriculum has strengthened students' analytical and evaluative skills (Tüzel, 2012).

The Perceived Social Media Literacy Scale (PSMLS) is a comprehensive instrument for measuring SML, encompassing various dimensions such as information verification, privacy management, and digital participation. The successful adaptation of similar instruments underscores the necessity of psychometric validation and cultural sensitivity when localizing scales. For instance, previous studies have successfully adapted the Digital Competence Scale (Toker et al., 2021) and the Media and Information Literacy Assessment (Ugurhan et al., 2020) to diverse cultural settings. Additionally, cross-cultural research highlights how media literacy assessments must be tailored to reflect local sociocultural nuances. Du Preez et al. (2024), for example, examined the influence of cultural and socioeconomic factors on digital engagement in South Africa, while Park (2012) analyzed SML in East Asia, emphasizing the impact of collectivist values on online behavior and participation.

Beyond being an individual competency, SML is increasingly recognized as a critical pedagogical skill (Williams, 2024). Educators play a central role in fostering students' digital literacy by guiding them in assessing online content, promoting responsible social media practices, and integrating digital tools into their teaching methodologies (Livingstone & Helsper, 2007; Greenhow & Lewin, 2016). However, as students increasingly rely on digital platforms as primary sources of information, they become more vulnerable to misinformation, privacy threats, and unethical content consumption (Tandoc et al., 2018). Without sufficient SML skills, educators may struggle to equip students with the necessary competencies to navigate digital environments critically (Selwyn, 2012).

Despite the widespread integration of digital technologies into education, research indicates that many educators receive minimal formal training in social media literacy (Koltay, 2011; Erstad, 2015). As a result, there remains a significant knowledge gap regarding how educators perceive their SML abilities and their preparedness to teach these competencies.

Previous studies examining educators' use of social media have primarily focused on their attitudes toward its implementation in classrooms (Carpenter & Krutka, 2014; Manca & Ranieri, 2017). However, research specifically investigating teachers' competencies in evaluating the credibility of online content, understanding social media algorithms, and managing digital privacy remains limited. Moreover, many of the existing SML measurement tools are designed for general users, failing to account for the unique instructional responsibilities of educators (Lankshear & Knobel, 2008). Recent research has underscored concerns regarding educators' ability to analyze digital information critically. Studies suggest teachers frequently struggle to detect misinformation and may inadvertently reinforce digital biases in classroom discussions (Tandoc et al., 2018). Moreover, Kahne and Bowyer (2017) assert that digital literacy education must extend beyond technical competencies to include critical engagement with digital content. These findings emphasize the necessity of an SML assessment tool specifically designed for educators, as their digital competencies directly shape students' media literacy development. With the rapid pace at which digital environments evolve, assessing educators' SML competencies is crucial for understanding their ability to navigate and integrate digital technologies into teaching effectively. Implementing the PSMLS in an educational context will yield valuable insights into educators' digital competencies, highlight areas requiring professional development, and contribute to ongoing policy discussions surrounding digital education (Greenhow & Lewin, 2016). In Türkiye, adapting the PSMLS is particularly relevant, as national education policies increasingly prioritize digital literacy initiatives. The present study aims to establish a reliable and culturally adapted instrument for assessing teachers' SML competencies by validating this scale among educator-specific populations. Findings from this research will inform teacher training programs and curriculum development, ultimately supporting educators in fostering responsible digital citizenship among students (Selwyn, 2012).

1.2. Significance of the Study

The present study is significant for several reasons. Firstly, considering the paucity of validated instruments specifically designed for the Turkish context, adapting this scale into Turkish and subsequent analysis of its psychometric properties will provide researchers with a culturally relevant tool. This will, in turn, enable a more accurate and context-specific examination of teachers' instructional practices in Türkiye. Secondly, the findings will contribute to developing targeted educational strategies and policies to enhance digital literacy among diverse populations in Türkiye. Finally, adapting the PSMLS provides a model for similar efforts in other non-Western settings, promoting global equity in digital literacy research and practice. By adapting the PSMLS, this research underscores the importance of culturally relevant tools for understanding how individuals interact with digital environments. As social media continues to shape societal discourses and practices, a localized approach to assessing and fostering SML becomes increasingly critical.

1.3. Research Questions

The present study has two objectives. Firstly, it aims to examine the cultural appropriateness of a construct measured through an existing scale within the Turkish cultural context. Secondly, it aims to adapt the scale accordingly. To address this objective, the following research questions were investigated:

RQ1: How can the Perceived Social Media Literacy Scale (PSMLS) be linguistically and culturally adapted to align with the Turkish cultural context?

RQ2: What are the psychometric properties (e.g., reliability, construct validity) of the adapted PSMLS within the Turkish context?

Whilst the principal objective of this study is to adapt and validate the PSMLS in the Turkish context, an ancillary exploratory analysis was also conducted to examine its relationship with digital literacy and potential demographic influences. However, it should be noted that these analyses remain secondary and do not interfere with the primary objective of this research.

2. Method

The extant literature defines the process of adapting scales as translating measurement instruments into different languages and cultures and re-evaluating their psychometric properties (Deniz, 2007; Heggestad et al., 2019). The present study employs a cross-sectional design utilizing quantitative methods (Hall, 2008; Spector, 2019). During the adaptation process, linguistic equivalence of the scale was first ensured, followed by validity and reliability analyses.

2.1. Participants

The study's sample group comprises 864 voluntary participants selected through convenience sampling (Battaglia, 2008) from various urban centers across Türkiye. Five hundred and seventy-one of the participants are teachers, and 293 are school administrators. Detailed demographic information about the sample group is summarized in Table 1.

Table 1. Characteristics of participants (*n* = 864)

Variable	Category	Mean or N	SD or %
Age	21-30 years old	178	20.6%
	31-40 years old	339	39.2%
	41-50 years old	257	29.8%
	51 years and over	90	10.4%
Gender	Female	457	52.9%
	Male	407	47.1%
Type of school where the position is held	High School	398	46.1%
	Middle School	174	20.1%
	Primary School	236	27.3%
	Preschool	56	6.5%
Time on social media use (hours/day)		3.26	1.47
Marital Status	Married	634	73.4%
	Single	230	26.6%

Note. *SD* = standard deviation

As seen in Table 1, the participants' mean daily social media usage time was M = 3.26 and SD = 1.47 (range = 1-5 hours/day). The demographic profile of the participants reveals several notable patterns. Concerning age distribution, the largest group comprises individuals aged 31-40 (39.2%), followed by those aged 41-50 (29.8%). The 21-30 age group accounts for 20.6% of the sample, while the 51+ age group constitutes the most minor proportion (10.4%). The gender distribution is relatively balanced, with 52.9% of participants identifying as female and 47.1% as male, ensuring diverse representation. Concerning the institution type, most participants are employed in high schools (46.1%), followed by primary schools (27.3%), middle schools (20.1%), and preschools (6.5%). This finding suggests that a significant proportion of the sample comprises high school educators, while preschool educators constitute a comparatively smaller segment. The data on marital status reveals that most of the participants (73.4%) are married. The remaining 26.6% are single, consistent with the age distribution, as a substantial proportion of the sample falls within middle-aged groups. The findings provide a comprehensive demographic overview of the sample, which consists predominantly of middle-aged, highly educated educators with balanced gender representation and moderate daily social media use. This profile offers valuable context for interpreting their SML levels and related behaviors.

2.2. Scale Adaptation Process

The PSMLS, developed by Tandoc Jr. et al. (2021) and adapted to Turkish culture, consists of 14 items distributed across four subdimensions: Technical Competence (5 items), Social Relationships (3 items), Information Awareness (3 items), and Privacy and Algorithmic Awareness (3 items) (see Appendix). The adaptation process was conducted in accordance with the principles proposed by Hambleton et al. (2004). Initially, permission to adapt the scale to Turkish culture was obtained via email from the original scale's authors. Following this, ethical approval was obtained from the Ethics Committee of Niğde Ömer Halisdemir University (Ethics Number 608039, dated 14/01/2025). Following the procurement of these permissions, the translation and linguistic validation processes were conducted. Adapting the PSMLS to Turkish followed a rigorous methodological approach to ensure linguistic accuracy, cultural appropriateness, and psychometric validity. Initially, the English version of the scale was translated into Turkish by three independent bilingual linguists, each of whom was proficient in both languages and specialized in educational research. A fourth language expert conducted a comparative analysis to ensure consistency across translations, identifying any discrepancies between the translations. A consensus approach was then employed to finalize each item's most semantically and contextually appropriate translation. To further validate the linguistic integrity of the scale, a back-translation method was applied, wherein a separate group of bilingual experts translated the Turkish version back into English. The back-translated version was then compared to the original scale to assess whether the semantic integrity and conceptual equivalence had been preserved. It was established that minor discrepancies in meaning were present in a small number of items, particularly those involving colloquial expressions and culturally specific terminology. These discrepancies were resolved through expert discussions, ensuring that the final Turkish version accurately conveyed the intended meaning while remaining culturally appropriate. Following the translation phase, an expert panel comprising five specialists in educational sciences and digital literacy evaluated the Turkish version of the scale regarding content validity, assessing each item for relevance, clarity, and cultural appropriateness. Experts provided feedback on the alignment of items with the construct of social media literacy in the Turkish context, and minor modifications were made to improve clarity and ensure that the scale maintained its conceptual integrity within the target population.

A pilot study was conducted with a sample of 50 educators to examine the comprehensibility and usability of the Turkish version, with participants encouraged to provide qualitative feedback regarding any items that were unclear or difficult to interpret. Based on this feedback, two items underwent minor rewording to enhance clarity without altering their original meaning. During the adaptation process, several linguistic and cultural challenges were encountered. For instance, some terminology related to algorithmic awareness and digital privacy had no direct equivalents in Turkish and required contextual reinterpretation. Additionally, certain phrases with specific cultural connotations in English were adapted to ensure they were meaningful and relevant to Turkish educators. These challenges were addressed through an iterative review process, incorporating feedback from both linguists and subject matter experts.

The study's systematic and multi-step adaptation process ensures the PSMLS maintains its validity, reliability, and cultural appropriateness for assessing social media literacy among educators in Türkiye. The original five-point Likert scale (ranging from 1 [strongly disagree] to 5 [strongly agree]) was retained.

2.3. Materials Procedure

To examine the adapted PSMLS's concurrent validity, the Digital Literacy Scale subdimensions, developed by Bayrakcı and Narmanlıoğlu (2021), were used as a data collection instrument. The scale comprises six subdimensions: "Ethics and Responsibility, General Knowledge and Functional Skills, Daily Use, Professional Production, Privacy and Security, and Social Dimension". The scale consists of 29 items, rated on a five-point Likert scale (1- Strongly Disagree; 2- Disagree; 3- Neutral; 4- Agree; 5- Strongly Agree). In the present study, the internal consistency reliability of the scale was re-evaluated. The results obtained from the analysis revealed that Cronbach's α and McDonald's ω coefficients ranged between .79 and .93, indicating a high level of internal consistency.

2.4. Procedure Data Analysis

Following the ethics committee's approval, research data was collected over a period of two weeks between the 14th and 27th January 2025. An online research form, prepared using Google Forms, was utilized during this process. The form comprised two sections: the first included questions about participants' personal information and the informed consent form, while the second contained the scales used in the study. No financial compensation was provided to the voluntary participants. The access link to the research form was distributed to participants via social media platforms such as WhatsApp, Instagram, and email.

2.5. Data Analysis

To verify the hypothesis that the original factor structure of the PSMLS was retained in its Turkish version, both first-order (n_1 = 500) and second-order CFA (n_2 = 364) were conducted. The discriminant validity of the scale was assessed using multiple criteria to ensure robustness. In addition to the Heterotrait-Monotrait (HTMT) ratio method, the Fornell-Larcker criterion was employed, comparing the square root of the Average Variance Extracted (AVE) values with inter-construct correlations. The results confirmed that each construct's AVE square root was greater than its highest correlation with any other construct, supporting the discriminant validity of the scale. Although Composite Reliability (CR) and Average Variance Extracted (AVE) values were not explicitly calculated, the Fornell-Larcker results indicate that the scale meets the recommended discriminant validity thresholds, as suggested in the literature (Yurt, 2023). Additionally, the following tests were performed: tests of internal consistency, tests of concurrent validity with external criteria, and gender differences. All analyses, including CFA, HTMT ratios, internal consistency, and other statistical evaluations, were conducted using Jeffreys's Amazing Statistics Program (JASP) version 0.19.2. The internal consistency of PSMLS with its sub-dimensions was analyzed using Cronbach's α and McDonald's ω. α and ω values higher than .70 indicate acceptable internal consistency (George & Mallery, 2019). It was considered more beneficial to use both reliability estimates together in this study (Soysal, 2023). The following fit indices, calculated from the CFA, were used to determine whether the original factor structure of the scale was validated in its Turkish version: Comparative Fit Index (CFI) > .90, Tucker-Lewis Index (TLI) > .90, Standardized Root Mean Square Residual (SRMR) < .08, and Root Mean Square Error of Approximation (RMSEA) < .08 (Byrne, 2011). The factor loadings obtained from the CFA were utilized in the HTMT method, where a ratio below .85 supports discriminant validity (Kline, 2023). The PSMLS and its subdimensions were also examined for concurrent validity with relevant external criteria (i.e., the subdimensions of the Digital Literacy Scale). Pearson correlations (r) were used to evaluate concurrent validity. Pearson correlation coefficients of $r < .30$ indicate weak correlations, while values of $r > .30$ suggest moderate to strong correlations (Cohen, 1988). Finally, the total PSMLS score and its subdimension scores were analyzed to determine whether they significantly differed across gender groups (i.e., male and female participants). To this end, an independent samples t-test was conducted to compare gender differences.

3. Results

In scale adaptation studies, it is imperative to ascertain the validity and consistency of the scale's subdimensions (first-order CFA) and its overall structure (second-order CFA) within the target culture. Suppose the first-order factor analysis results demonstrate that the items are appropriately loaded onto their respective factors. In that case, the subsequent step involves conducting a second-order factor analysis to test whether these subdimensions align with an overarching structure. This process is instrumental in ensuring the validity and compatibility of the scale at both the micro-level (items and subdimensions) and the macro-level (overall structure) (Arafat et al., 2016; Heggestad et al., 2019). In this context, a first-order CFA was initially conducted on the dataset (see Figure 1).

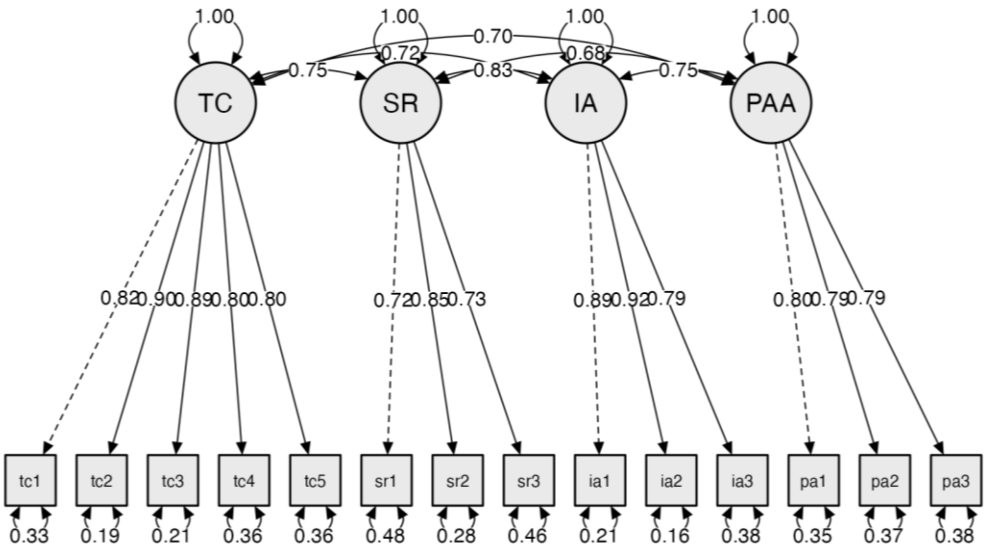

Figure 1. PSMLS 1st Level CFA Analysis Screen Output [TC=Technical Competency; SR=Social Relationships; IA=Information Awareness; PAA=Privacy and Algorithmic Awareness]

The model fit indices (χ^2/df = 8.31, TLI = .93, CFI = .94, SRMR = .04, RMSEA = .09) indicate an acceptable level of model fit, based on commonly used cutoff values (Hu & Bentler, 1999). Although the RMSEA slightly exceeds the conventional threshold of 0.08, previous research (e.g., MacCallum et al., 1996) suggests that values up to 0.10 can still be considered reasonable, particularly in the case of complex models with large datasets. The chi-square goodness-of-fit test yielded a relatively elevated ratio (χ^2/df = 8.31), which exceeds the commonly accepted limit of 5. Values below 3 generally indicate a robust model fit (Yurt, 2023). However, extensive literature highlights that chi-square values tend to be highly sensitive to sample size, often inflating the χ^2/df ratio, particularly in large-scale studies (Yurt, 2023). Given that this study includes 864 participants (571 teachers and 293 school administrators), the increased χ^2/df value is likely attributable to this sensitivity rather than an indication of model misspecification.

To address this concern, greater reliance was placed on alternative model fit indices that were less impacted by sample size. The Comparative Fit Index (CFI = .94) and Tucker-Lewis Index (TLI = .93) both surpass the recommended threshold of .90, indicating a good model fit (Hu & Bentler, 1999). Furthermore, the Standardized Root Mean Square Residual (SRMR = .04) falls within the optimal range ($\leq$ .08), while the Root Mean Square Error of Approximation (RMSEA = .09) remains within marginally acceptable levels. These indices suggest that the model adequately represents the underlying data structure despite the chi-square statistic being influenced by the large sample size. These values indicate that the model is generally consistent with the data. Furthermore, an examination of the factor loadings demonstrated that all items exhibited significant loading onto their respective factors, ranging from .72 to .92 ($p < .001$). The internal consistency values for each subdimension of the scale, calculated as Cronbach's Alpha and McDonald's Omega, are presented in Table 2. The values obtained were above .80, indicating that the subdimensions are reliable (Hayes & Coutts, 2020). These findings substantiate the predicted factor structure of the scale at the first-order level and affirm the scale's capacity for adequate measurement validity. Following the first-order CFA, it was determined that the scale items align well with the previously hypothesized factor structure, leading to the decision to conduct a second-order CFA. The objective of this analysis is to ascertain whether the subdimensions of the scale align with the overall structure of the scale. The results of the second-order CFA are presented in Figure 2.

A second-order CFA was conducted to evaluate the alignment of the scale's subdimensions with the overall structure. The model fit indices (χ^2/df = 6.17, CFI = .96, TLI = .95, RMSEA = .07, SRMR = .04) suggest an overall satisfactory model fit (Hu & Bentler, 1999). Although the chi-square/degree of freedom ratio (χ^2/df) remains above the conventional threshold, prior findings have demonstrated that this index is highly sensitive to sample size (Yurt, 2023). Therefore, in accordance with best practices in structural equation modelling, greater emphasis was placed on alternative fit indices to assess model adequacy. The results indicate that the Comparative Fit Index (CFI = .96) and the Tucker-Lewis Index (TLI = .95) both exceed the recommended threshold of .90, suggesting a strong model fit (Hu & Bentler, 1999). Furthermore, the Standardised Root Mean Square Residual (SRMR = .04) is within the optimal range ($\leq$ .08), and the Root Mean Square Error of

Approximation (RMSEA = .07) remains within acceptable limits. These indices collectively indicate that the model provides a theoretically sound and statistically robust representation of the data. These values suggest that the model is generally consistent with the data, with minor modifications (tc2 → tc3) further improving the model fit (Byrne, 2016). Furthermore, an examination of the factor loadings for the subdimensions demonstrated that all subdimensions were significantly and strongly loaded onto the overall structure, with factor loadings ranging from .82 to .90 ($p < .001$). These results indicate that the subdimensions of the scale exhibit an adequate level of fit with the overall structure proposed for the second-order CFA. Detailed results of this analysis are presented in Table 2.

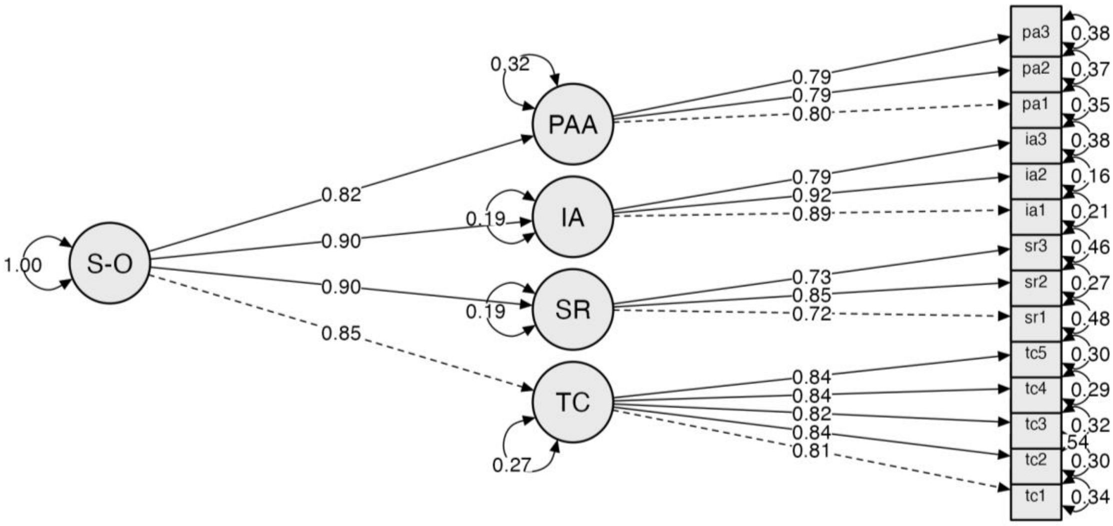

Figure 2. PSMLS 2nd Level CFA Analysis Screen Output

Table 2. The PSMLS' properties

	PSMLS	Technical Competency (TC)	Social Relationships (SR)	Informational Awareness (IA)	Privacy and Algorithmic Awareness (PAA)
Cronbach's α	.94	.92	.81	.90	.84
McDonald's ω	.95	.90	.81	.90	.84
2nd Level CFA					
$\chi 2$ (df)	444.19 (72)	–	–	–	–
p-value	<.001	–	–	–	–
CFI	.96	–	–	–	–
TLI	.95	–	–	–	–
RMSEA	.07	–	–	–	–
SRMR	.04	–	–	–	–
HTMT method					
TC	–	1.00			
SR	–	.78	1.00		
IA	–	.73	.84	1.00	
PAA	–	.72	.67	.77	1.00

Note. CFA=confirmatory factor analysis; CFI=comparative fit index; TLI=Tucker-Lewis's index; RMSEA=root mean square error of approximation; SRMR=standardized root mean square residual; HTMT= heterotrait-monotrait ratio.

The results of the second-order CFA for the PSMLS are presented in Table 2. The four-factor structure of the scale, derived from the sample (n = 364), was validated with acceptable fit indices obtained through CFA. The HTMT analysis was performed to assess discriminant validity. The HTMT factor loading ratio was less than .85, supporting the hypothesis that discriminant validity was achieved (Henseler et al., 2015). Furthermore, the internal consistency of the overall PSMLS and its subdimensions was calculated and presented in Table 2. The findings indicate that both the overall scale and its subdimensions are reliable. Following the first- and second-order CFA analyses, criterion validity was evaluated (Borneman, 2010).

To this end, the correlations between the PSMLS subdimensions and the Digital Literacy Scale employed in this study were examined. The correlation values are presented in Table 3.

Table 3. Concurrent validity of the PSMLS

	Pearson correlation with an external criterion measure					
	Ethics and Responsibility	**General Knowledge and Functional Skills**	**Daily Usage**	**Advanced Production**	**Privacy and Security**	**Social Dimension**
PSMLS	.80**	.55**	.74**	.20**	.74**	.45**
Technical Competency	.66**	.46**	.68**	.13**	.68**	.38**
Social Relationships	.63**	.53**	.61**	.28**	.60**	.47**
Informational Awareness	.76**	.51**	.63**	.19**	.65**	.41**
Privacy and Algorithmic Awareness	.76**	.40**	.61**	.11*	.60**	.30**

Note. *p<.05; **p<.001

As shown in Table 3, a positive and significant correlation is evident between the overall PSMLS, its subdimensions, and the subdimensions of the Digital Literacy Scale. The findings suggest a significant and positive correlation between the overall PSMLS, its subdimensions, and the subdimensions of the Digital Literacy Scale. A notable observation is a low positive correlation between Advanced Production and Privacy and Algorithmic Awareness. The correlation coefficients range from .11 to .80, demonstrating significant relationships that vary from low to moderate to high levels ($p < .001$; $p < .05$).

Furthermore, the relationships between the PSML scale (including its subdimensions) and the gender and age ranges of the participants were also examined. The results of this investigation are presented in Table 4.

Table 4. Comparing the PSML between gender

	Mean (SD) in gender		t(p)
	Male (n =407)	**Female (n =457)**	
PSMLS	4.06 (.92)	4.16 (.89)	-1.56 (.12)
Technical Competency	4.26 (1.08)	4.37 (1.03)	-1.48 (.14)
Social Relationships	3.62 (1.10)	3.73 (1.12)	-1.51 (.13)
Informational Awareness	3.97 (1.09)	4.04 (1.04)	-0.85 (.39)
Privacy and Algorithmic Awareness	4.27 (.98)	4.37 (.95)	-1.45 (.15)

Table 4 presents a detailed examination of the disparities in the PSML and its subdimensions, focusing on the influence of gender among the study participants. The findings reveal that the mean scores for the overall scale and its subdimensions do not demonstrate statistically significant differences between genders ($p > .05$). This finding suggests that male and female participants have similar levels of perceived SML. However, the relationship between scale scores and age groups was analyzed using a one-way ANOVA test to assess differences in perceived SML. The findings of this analysis revealed that these differences were statistically significant, albeit with a small effect size ($F_{(3, 860)} = 13.40$, $p = .000$, $\eta^2 = .05$). After this significant finding, a Games-Howell post-hoc analysis (Juarros-Basterretxea et al., 2024) demonstrated that participants aged 21-30 years and 31-40 years exhibited significantly higher levels of perceived SML in comparison to participants aged 41 years and older. Specifically, participants under 40 years of age reported higher literacy levels ($M_{21\text{-}30} = 4.41$, $SD = .63$; $M_{31\text{-}40} = 4.13$, $SD = .92$) than those aged 41-50 years ($M_{41\text{-}50} = 4.03$, $SD = .94$) and 51+ years ($M_{51+} = 3.72$, $SD = 1.00$).

4. Discussion

The present study adapted the Perceived Social Media Literacy Scale (PSMLS) (Tandoc Jr. et al., 2021) to the Turkish cultural context and assessed its validity and reliability among educators. The first-order and second-order CFA results supported the scale's original 14-item, four-factor structure. These findings indicate a strong alignment between the dimensions of Technical Competency, Social Relationships, Informational Awareness, and Privacy and Algorithmic Awareness and the theoretical framework proposed in the original scale. The results of this study are consistent with those of previous studies on media literacy assessment, which emphasize the importance of cross-cultural validation in ensuring measurement accuracy (Toker et al., 2021; Ugurhan et al., 2020).

The first-order and second-order Confirmatory Factor Analysis (CFA) results demonstrated that the PSMLS maintains its structural validity in Turkish education. The initial CFA model yielded acceptable model fit indices; however, a refined model incorporating modification indices significantly improved model fit. The final model's fit indices (CFI = .96, TLI = .95, RMSEA = .07, SRMR = .04) indicate an acceptable-to-good model fit (Hu & Bentler, 1999). Despite the elevated chi-square/degrees of freedom ratio (χ^2/df = 6.17), this is a prevalent concern in large-sample studies, as chi-square values demonstrate sensitivity to sample size (Yurt, 2023). Consequently, greater emphasis was placed on CFI, TLI, RMSEA, and SRMR, which are less influenced by sample size and provide robust evidence of a well-fitting model. These findings are consistent with previous scale adaptation research, which used multiple fit indices to validate social media literacy constructs (MacCallum et al., 1996).

The reliability of the adapted scale was confirmed through the analysis of Cronbach's Alpha and McDonald's Omega coefficients, both of which exceeded the established threshold values. These results support the scale's internal consistency and confirm its robustness as a measurement tool. The high mean scores across subdimensions suggest that participants demonstrated strong SML competencies, particularly in technical proficiency, critical information evaluation, and privacy awareness. Participants with high scores in the Technical Competency subdimension demonstrated proficiency in managing digital platforms and controlling their online presence. Similarly, high scores in the Informational Awareness subdimension indicated that participants engage with digital content critically, actively verifying the accuracy of online information rather than passively consuming it. Furthermore, the significant Privacy and Algorithmic Awareness scores indicate that participants have a solid grasp on digital data processing, algorithmic content curation, and online security risks, which is in line with the results of previous digital literacy studies (Polanco-Levicán & Salvo-Garrido, 2022).

The present study examined the effects of age and gender on social media literacy. While no statistically significant gender differences were observed, age-related differences were evident, with younger educators (aged 40 and below) scoring higher in SML competencies. This finding aligns with previous studies suggesting that younger individuals are more digitally literate due to increased exposure to social media and digital tools (Livingstone & Helsper, 2007). However, research by Kahne and Bowyer (2017) suggests that social media literacy is not solely a function of age but also depends on professional training and experience. The absence of significant gender differences in this study aligns with Erstad (2015). However, it contrasts with research suggesting that male educators perceive themselves as more digitally competent than female educators (Greenhow & Lewin, 2016). These variations underscore the necessity for further research into gender-based perceptions of digital literacy and their implications for educational practices.

4.1. Study Limitations and Future Research Directions

A key limitation of this study is convenience sampling, which, while practical for large-scale data collection, may introduce selection bias. Since participants were recruited voluntarily from various urban centers, the sample may not fully represent the broader population, particularly individuals from rural areas or those with limited digital access. Additionally, the reliance on voluntary responses may have led to self-selection bias, with participants with higher digital engagement or stronger opinions on social media being more inclined to participate. In future studies, employing probability sampling techniques to enhance the generalizability of findings is recommended. Another limitation is that confirmatory factor analysis (CFA) was conducted on the entire sample, combining data from both teachers and school administrators. However, given that these groups have distinct professional roles and experiences, their perceptions of social media literacy may differ meaningfully. Conducting separate CFAs for each group or implementing multi-group confirmatory factor analysis (MG-CFA) would allow for a more nuanced understanding of whether the factor structure remains stable across different professional categories. Future research should explore these differences further to validate the PSMLS's applicability across diverse educational contexts. The participants were educators from the preschool, primary and secondary levels but not those at the tertiary level. Future studies may intentionally explore those at the tertiary level too.

5. Conclusion

The present study successfully adapted and validated the PSMLS for use among Turkish educators, confirming its structural validity and reliability. The scale is a comprehensive tool for assessing social media literacy among teachers and school administrators, offering insights into their technical competencies, critical engagement with digital content, and awareness of privacy and algorithmic influences. Given the increasing role of social media in education and professional communication, initiatives aimed at enhancing educators' digital literacy could prove highly beneficial. The findings of this study suggest that further integration of social media literacy training in teacher education programs could enhance educators' ability to navigate digital environments effectively and foster responsible digital citizenship among students. Future studies should continue investigating demographic and professional differences in SML, ensuring that educational policies and training programs align with the evolving digital landscape.

Statement of Researchers

Researchers' contribution rate statement:
MK: Conceptualization, methodology, investigation, data curation, writing- original draft preparation. MP: Data curation, writing-original draft preparation, software, investigation, validation, formal analysis. DO: Writing - review & editing, DKA: methodology, investigation, data curation, writing - review & editing,
Conflict statement:
The authors declare that they have no conflict of interest.
Data Availability Statement:
The data supporting this study's findings are available from the corresponding authors upon reasonable request.
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Ethical Considerations:
This research was approved by the Niğde Ömer Halisdemir University Ethics Committee's decision, No. 608039, dated 14/01/2025.
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6. References

Ak, N., & Arslantaş, T. (2024). Psychometric properties of the Turkish version of the Algorithmic Media Content Awareness (AMCA) scale. *Instructional Technology and Lifelong Learning, 5*(1), 171-191. https://doi.org/10.52911/itall.1447270

Arafat, S. Y., Chowdhury, H. R., Qusar, M. M. A. S., & Hafez, M. A. (2016). Cross cultural adaptation and psychometric validation of research instruments: a methodological review. *Journal of Behavioral Health, 5*(3), 129-136. http://dx.doi.org/10.5455/jbh.20160615121755

Battaglia, M. (2008). Convenience sampling. In *Encyclopedia of survey research methods* (pp. 149-149). Sage Publications, Inc.

Bayrakcı, S., & Narmanlıoğlu, H. (2021). Digital literacy as whole of digital competences: Scale development study. *Journal of Thought and Society*, (4), 1-30. Retrieved from https://dergipark.org.tr/en/download/article-file/1797036

Borneman, M. J. (2010). Criterion validity. In *Encyclopedia of research design* (pp. 292-296). Sage.

Brown, J. S., & Duguid, P. (2017). *The social life of information: Updated, with a new preface*. Harvard Business Review Press.

Buckingham, D. (2013). *Media education: Literacy, learning and contemporary culture*. John Wiley & Sons.

Byrne, B. M. (2011). *Structural equation modeling with Mplus: Basic concepts, applications, and programming* (1st ed.). Routledge. https://doi.org/10.4324/9780203807644

Byrne, B. M. (2016). Adaptation of assessment scales in cross-national research: Issues, guidelines, and caveats. *International Perspectives in Psychology, 5*(1), 51-65. https://doi.org/10.1037/ipp0000042

Carpenter, J. P., & Krutka, D. G. (2014). How and why educators use Twitter: A survey of the field. *Journal of research on technology in education*, *46*(4), 414-434. https://doi.org/10.1080/15391523.2014.925701

Cho, H., Cannon, J., Lopez, R., & Li, W. (2024). Social media literacy: A conceptual framework. *New Media & Society, 26*(2), 941-960. https://doi.org/10.1177/14614448211068530

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge. https://doi.org/10.4324/9780203771587

Deniz, K. Z. (2007). The adaptation of psychological scales*. Ankara University Journal of Faculty of Educational Sciences (JFES), 40*(2), 1-16. https://doi.org/10.1501/Egifak_0000000180

Du Preez, C., Van Greunen, D., & Foxcroft, C. (2024). An adaptation of digcomp for the South African context. In *2024 IST-Africa Conference (IST-Africa)* (pp. 1-9). IEEE. https://doi.org/10.23919/IST-Africa63983.2024.10569509

Erstad, O. (2015). Educating the digital generation-exploring media literacy for the 21st century. *Nordic Journal of Digital Literacy*, *10*(Jubileumsnummer), 85-102. https://doi.org/10.18261/ISSN1891-943X-2015-Jubileumsnummer-07

George, D., & Mallery, P. (2019). *IBM SPSS statistics 26 step by step: A simple guide and reference* (16th ed.). Routledge. https://doi.org/10.4324/9780429056765

Greenhow, C., & Lewin, C. (2019). Social media and education: Reconceptualizing the boundaries of formal and informal learning. In *social media and education* (pp. 6-30). Routledge.

Hall, J. (2008). Cross-sectional survey design. In *Encyclopedia of survey research methods* (pp. 173-173). Sage Publications.

Hambleton, R. K., Merenda, P. F., & Spielberger, C. D. (Eds.). (2004). Issues, designs, and technical guidelines for adapting tests into multiple languages and cultures. In *Adapting educational and psychological tests for cross-cultural assessment* (pp. 15-50). Psychology Press.

Hayes, A. F., & Coutts, J. J. (2020). Use omega rather than Cronbach's alpha for estimating reliability. But…. *Communication Methods and Measures, 14*(1), 1-24. https://doi.org/10.1080/19312458.2020.1718629

Heggestad, E. D., Scheaf, D. J., Banks, G. C., Monroe Hausfeld, M., Tonidandel, S., & Williams, E. B. (2019). Scale adaptation in organizational science research: A review and best-practice recommendations. *Journal of Management, 45*(6), 2596-2627. https://doi.org/10.1177/0149206319850280

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hobbs, R., & Tuzel, S. (2017). Teacher motivations for digital and media literacy: An examination of Turkish educators. *British Journal of Educational Technology, 48*, 7-22. https://doi.org/10.1111/BJET.12326

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

JASP Team (2024). JASP (Version 0.19.2) [Computer software].

Jenkins, H. (2007). Confronting the challenges of participatory culture: Media education for the 21st century (Part One). *Nordic Journal of Digital Literacy, 2*(1), 23-33. https://doi.org/10.18261/ISSN1891-943X-2007-01-03

Juarros-Basterretxea, J., Aonso-Diego, G., Postigo, Á., Montes-Álvarez, P., Menéndez-Aller, Á., & García-Cueto, E. (2024). Post-hoc tests in one-way ANOVA: The case for normal distribution. *Methodology, 20*(2), 84-99. https://doi.org/10.5964/meth.11721

Kahne, J., & Bowyer, B. (2017). Educating for democracy in a partisan age: Confronting the challenges of motivated reasoning and misinformation. *American Educational Research Journal*, *54*(1), 3-34. https://doi.org/10.3102/0002831216679817

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). The Guilford Press.

Koltay, T. (2011). The media and the literacies: Media literacy, information literacy, digital literacy. *Media, culture & society*, *33*(2), 211-221. https://doi.org/10.1177/0163443710393382

Lankshear, C., & Knobel, M. (Eds.). (2008). *Digital literacies: Concepts, policies and practices* (Vol. 30). Peter Lang.

Livingstone, S. (2008). Engaging with media—a matter of literacy?. Communication, Culture & Critique, 1(1), 51-62. https://doi.org/10.1111/j.1753-9137.2007.00006.x

Livingstone, S., & Helsper, E. (2007). Gradations in digital inclusion: Children, young people and the digital divide. *New media & society*, *9*(4), 671-696. https://doi.org/10.1177/1461444807080335

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological methods*, *1*(2), 130-149.

Manca, S., & Ranieri, M. (2017). Networked scholarship and motivations for social media use in scholarly communication. *International review of research in open and distributed learning*, *18*(2), 123-138. https://doi.org/10.19173/irrodl.v18i2.2859

Meyers, E. M., Erickson, I., & Small, R. V. (2013). Digital literacy and informal learning environments: an introduction. *Learning, Media and Technology, 38*(4), 355-367. https://doi.org/10.1080/17439884.2013.783597

Nagle, J. (2018). Twitter, cyber-violence, and the need for a critical social media literacy in teacher education: A review of the literature. *Teaching and Teacher Education, 76*, 86-94. https://doi.org/10.1016/j.tate.2018.08.014

Özel, A. (2023). Examining media literacy perceptions of preservice social studies teachers in Turkey. *Journal of Curriculum Studies Research, 5*(2), 86-117. https://doi.org/10.46303/jcsr.2023.21

Park, S. (2012). Dimensions of digital media literacy and the relationship with social exclusion. *Media International Australia, 142*(1), 87-100. https://doi.org/10.1177/1329878X1214200111

Polanco-Levicán, K., & Salvo-Garrido, S. (2022). Understanding social media literacy: A systematic review of the concept and its competences. *International Journal of Environmental Research and Public Health, 19*(14), 8807-8823. https://doi.org/10.3390/ijerph19148807

Rosseel, Y. (2012). Lavaan: An R package for structural equation modeling. *Journal of Statistical Software, 48*(2), 1-36. https://doi.org/10.18637/jss.v048.i02

Samala, A. D., Rawas, S., Criollo-C, S., Fortuna, A., Feng, X., Prasetya, F., ... & Hidayat, R. (2024). Social media in education: Trends, roles, challenges, and opportunities for digital-native generations–A systematic literature review. *Asian Journal of University Education, 20*(3), 524-539. https://doi.org/10.24191/ajue.v20i3.27869

Selwyn, N. (2012). *Education in a digital world: Global perspectives on technology and education*. Routledge.

Spector, P. E. (2019). Do not cross me: Optimizing the use of cross-sectional designs. *Journal of Business and Psychology, 34*, 125–137. https://doi.org/10.1007/s10869-018-09613-8

Solmaz, O., & Reinhardt, J. (2024). Engaging Turkish learners in digital participatory culture through social media? Enhanced language instruction. *CALICO Journal, 41*(1), 48-70. https://doi.org/10.1558/cj.25514

Soysal, S. (2023). Comparison of alpha, stratified alpha, and omega reliability coefficients in multidimensional test structures. *Journal of Ahmet Keleşoğlu Education Faculty, 5*(1), 213-236. https://doi.org/10.38151/akef.2023.51

Tandoc Jr., E., Yee, A., Ong, J., Lee, J., Xu, D., Han, Z., Matthew, C., Ng, J., Lim, C., Cheng, L., & Cayabyab, M. (2021). Developing a perceived social media literacy scale: Evidence from Singapore. *International Journal of Communication, 15*, 22. Retrieved from https://ijoc.org/index.php/ijoc/article/view/16118/3452

Tandoc Jr, E. C., Lim, Z. W., & Ling, R. (2018). Defining "fake news" A typology of scholarly definitions. *Digital journalism*, *6*(2), 137-153. https://doi.org/10.1080/21670811.2017.1360143

Toker, T., Akgün, E., Cömert, Z., & Edip, S., (2021). Digital competency scale for educators: Adaptation, validity, and reliability study. *Milli Egitim, 50*(230), 301-328. https://doi.org/10.37669/milliegitim.801607

Tommasi, F., Ceschi, A., Sartori, R., Gostimir, M., Passaia, G., Genero, S., & Belotto, S. (2023). Enhancing critical thinking and media literacy in the context of IVET: A systematic scoping review. *European Journal of Training and Development, 47*(1/2), 85-104. https://doi.org/10.1108/EJTD-06-2021-0074

Tüzel, S. (2012). Integration of media literacy education with Turkish courses. *Mustafa Kemal University Journal of Social Sciences Institute, 9*(18), 81-96. Retrieved from https://dergipark.org.tr/en/download/article-file/183003

Ugurhan, Y. Z. C., Kumtepe, E. G., Kumtepe, A. T., & Saykılı, A. (2020). From media literacy to new media literacy: A lens into open and distance learning context. *Turkish Online Journal of Distance Education, 21*(Special Issue-IODL), 135-151. https://doi.org/10.17718/tojde.770953

Ugurhan, Y. Z. C., Kumtepe, E. G., Kumtepe, A. T., & Saykılı, A. (2020). From media literacy to new media literacy: A lens into open and distance learning context. *Turkish Online Journal of Distance Education, 21*, 135-151. https://doi.org/10.17718/tojde.770953

Valle, N., Zhao, P., Freed, D., Gorton, K., Chapman, A. B., Shea, A. L., & Bazarova, N. N. (2024). Towards a critical framework of social media literacy: A systematic literature review. *Review of Educational Research, 20*(10), 1-46. https://doi.org/10.3102/00346543241247224

Williams, R.T. (2024). *The Relationship Between Social Meda and Pedagogy.* Cambridge Scholars Publishing. ISBN: 9781036400194

Yurt, E. (2023). *Sosyal bilimlerde çok değişkenli analizler için pratik bilgiler: SPSS ve AMOS uygulamaları* [Practical Insights for Multivariate Analyses in Social Sciences: SPSS and AMOS Applications]. Nobel.

Appendix

Perceived Social Media Literacy Scale Turkish Version
(Algılanan Sosyal Medya Okuryazarlığı Ölçeği Türkçe Versiyonu)

1- Kesinlikle Katılmıyorum; 2- Katılmıyorum; 3- Kararsızım; 4- Katılıyorum; 5- Kesinlikle Katılıyorum

Aşağıda sosyal medya okuryazarlığı (teknik yeterlilik, sosyal ilişkiler…) ile ilgili maddeler bulunmaktadır. Sizden aşağıda yer alan maddelere katılma düzeyinize göre yanıt vermeniz istenmektedir.		**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Teknik Yeterlilik	1) Sosyal medyada bir hesap açmayı biliyorum.					
	2) Sosyal medyada hesabımı silmeyi biliyorum.					
	3) Sosyal medyadaki hesabımı devre dışı bırakmayı biliyorum.					
	4) Sosyal medya hesabımda fotoğraf gibi içerikler paylaşmayı biliyorum.					
	5) Sosyal medya hesabımdaki istenmeyen içerikleri kaldırmayı biliyorum.					
Sosyal İlişkiler	6) Sosyal medya platformlarını yöneten telif hakkı yasalarını biliyorum.					
	7) Sosyal medya çatışmalarını (olumsuzlukları, tartışmaları vb.) uygun bir şekilde yönetmeyi biliyorum.					
	8) Görev yaptığım kurumun sosyal medya politikasının farkındayım.					
Bilgi Farkındalığı	9) Sosyal medyada paylaşılanların doğru olup olmadığını nasıl kontrol edeceğimi biliyorum.					
	10) Sosyal medyada gördüğüm farklı bilgileri doğrulamak için bilgi kaynaklarını nasıl kullanacağımı biliyorum.					
	11) Sosyal medyadaki bir bilginin doğru mu yanlış mı olduğunu ayırt edebiliyorum.					
Gizlilik ve Algoritmik Farkındalık	12) Facebook, X, Instagram gibi sosyal medya platformlarının bana sunulan içerikleri kontrol ettiğini biliyorum.					
	13) Sosyal medyada paylaştığım bilgilerin platformlar tarafından kalıcı olarak depolandığını biliyorum.					
	14) Sosyal medyada gördüğüm reklamların tercihlerim dikkate alınarak bana özel hazırlandığını biliyorum.					

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Us vs. them: moral, cognitive and affective language in group identity tweets

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Highlights:

- Nonviolent groups used more trust and positive emotion language in group identity tweets than violent groups.
- Violent groups used more discrepancy-related cognitive language in group identity tweets, signaling dissatisfaction and aspirations.
- In group identity tweets, left-leaning groups used more care-related moral language than right-leaning groups.
- Right-leaning groups used more sanctity-related moral language in group identity tweets than left-leaning groups.
- Patterns in affective, cognitive, and moral language in group identity tweets vary based on violence and ideology.

Abstract

Ideological groups leverage Twitter (now X) to cultivate strong group identities that sustain membership and foster intergroup hostility. Their positions may differ on the left-right political spectrum and their propensity for violence. Although all ideological groups develop strong group identities, research suggests that the language used to develop these identities may vary across different types of groups. This study investigates the use of affective, cognitive, and moral language in group identity tweets – those tweets that include first- and third-person plural pronouns (e.g., "us", "them") – from diverse ideological groups. This study found that nonviolent groups use trust and positive emotions more than violent groups in group identity tweets, whereas violent groups use discrepancy to a greater extent. Left-leaning groups use care (virtue and vice) to a greater extent than right-leaning groups, and the latter use sanctity (virtue) more. Implications of these findings are discussed.

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1. Introduction

Extremism on social media platforms like Twitter (now X) has captured national and global attention, as ideological groups use the platform for purposes ranging from community-building to disseminating hate, radical beliefs, and calls for violence (Holbrook, 2015; The New York Times, 2022). Understanding how violent and nonviolent ideological groups differ in their online presence and influence is crucial, particularly as such groups target vulnerable populations with messages that perpetuate division and hatred (Connelly et al., 2016). The reach of these groups extends beyond their immediate followers, influencing the broader public and young people in particular, who are more susceptible to radicalization through exposure to extreme online content (Bene, 2017; Sugihartati et al., 2020). By exploiting individuals' psychological and social needs, such content can foster group membership tied to extreme ideologies and even incite offline violence (Gallacher et al., 2021; Ward, 2020).

While shared beliefs may initially attract individuals to these groups, they can cultivate strong group identities that sustain membership and foster intergroup hostility (Long, 2023). Group identity can deepen division, as members adopt an "us versus them" mindset, leading to prejudice and aggression toward out-groups (Mason, 2018; Rousseau, 1998; Merrilees et al., 2013; Rains et al., 2017). Ideological groups, regardless of their ideological orientation or propensity for violence are adept at leveraging this dynamic by emphasizing social identities through first- and third-person plural pronouns (e.g., "we," "us," "they," "them"), which intensify group affiliation and delineate out-groups (Eastman, 2016; Iyengar et al., 2012).

The linguistic cues employed with these pronouns also play a pivotal role in fostering group identity and perpetuating polarization (Long & Crabtree, 2024; Martinez-Ebers et al., 2021). Ideological groups strategically use emotional language to generate affective commitment, cognitive language to shape cause-and-effect narratives, and moral language to frame issues as matters of right and wrong (Ness et al., 2017; Sterling & Jost, 2018). However, violent and nonviolent groups on both sides of the ideological spectrum emphasize these language types differently, reflecting their distinct core values and strategies (Angie et al., 2011; Graham et al., 2009). In fact, experts have cautioned against treating "extremism" as a homogenous phenomenon, noting that different groups leverage social media in nuanced ways (Freelon et al., 2022; Jamte & Ellesen, 2020). It remains unclear whether differences in these linguistic patterns extend to group identity tweets that explicitly focus on identity formation through group-oriented pronouns and related language. Given the prevalent use of social identity language in these groups' messaging to promote social categorization (Tajfel, 1978; Eastman, 2016; Rousseau, 1998) and influence social media platform users (Jensen, et al., 2023), it is important to understand how the nuanced use of affective, cognitive, and moral language extends to these messages.

To address this gap, we explore how ideological groups use language to construct and communicate group identity on Twitter, examining differences in affective, cognitive, and moral language across two key dimensions: violence and political orientation. Specifically, we investigate how violent and nonviolent groups differ in using emotional appeals, reasoning strategies, and moral framing. We also assess how left-leaning and right-leaning groups vary in these same linguistic patterns. By analyzing these distinctions within group identity tweets, we aim to understand better the rhetorical mechanisms ideological groups use to engage audiences, foster cohesion, and reinforce ideological boundaries. This study offers practical insights into the nuanced linguistic strategies used by ideological groups to construct and communicate group identity online. By identifying how violent and nonviolent groups across both sides of the ideological spectrum differ in their use of affective, cognitive, and moral language, the findings can inform the development of tailored counter-narratives and interventions to mitigate polarization and prevent radicalization. Furthermore, focusing specifically on group identity tweets, this research highlights how ideological groups foster in-group cohesion and out-group hostility, providing a foundation for more targeted social media content moderation policies. These findings can also guide platform algorithms to detect and address harmful content better while supporting policymakers and educators in designing programs addressing the psychological and social needs these groups exploit to attract and radicalize members.

Ideological Groups and Social Identity

Ideological groups are individuals united by shared beliefs, values, and goals, which serve as frameworks for interpreting and responding to events (Angie et al., 2011; Van Dijk, 2013). These groups provide members with meaning, self-esteem, social identity, and certainty, fulfilling fundamental psychological needs (Aberson et al., 2000; Hogg, 2003). While some ideological groups promote prosocial goals, such as peace, social justice, and human rights, others advocate for exclusionary ideologies and, in some cases, support or justify the use of violence to achieve their objectives. These violent ideological groups often target individuals based on demographic characteristics, contributing to the rise of hate crimes in the United States (Connelly et al., 2016; FBI, 2019; SPLC, 2021). For the purposes of this study, ideological groups were categorized as violent or non-violent based on publicly available materials and organizational designations from watchdog groups (e.g., SPLC, FBI), academic literature, and evidence of promoting or engaging in violence in pursuit of their aims.

Political ideologies, while multifaceted, are often organized along a left–right continuum, particularly in Western political contexts such as the United States, where this framework is commonly used to classify values and policy preferences (Jost, 2006). Left-leaning ideologies in the U.S. context generally emphasize equality, social justice, and progressive reform, including anti-capitalism, environmental advocacy, and anti-imperialism (Coopsey & Merrill, 2020). In contrast, right-leaning ideologies prioritize tradition, authority, and free-market principles, often highlighting nationalism, ethnocentrism, and the preservation of traditional social hierarchies (Graham et al., 2015; Jost et al., 2009). We acknowledge that these political terms are culturally dependent and context-specific, and our usage reflects their predominant meanings in U.S. sociopolitical discourse. Ideological groups on both ends of the spectrum use their ideological tenets to attract and engage members. Social media platforms like Twitter play a critical role in this process, providing a medium for disseminating narratives, fostering group identity, mobilizing demonstrations, recruiting members, and coordinating violent actions (Conway, 2017).

Social identity is central to ideological groups' communication, recruitment, and retention strategies. These groups aim to develop a collective sense of belonging among members and create distinct boundaries between themselves and out-groups. Online communications, such as tweets referencing "we/us" to indicate in-group cohesion or "they/them" to delineate outsiders, are particularly effective in promoting group identity. We refer to these as *group identity tweets*. By priming individuals to think in terms of "we" and "they," ideological groups foster a dichotomy that strengthens in-group solidarity while reinforcing intergroup distinctions (Eastman, 2016; Fiol, 2002). Inclusive pronouns ("we/us") signal shared values and unity. In contrast, exclusive pronouns ("they/them") highlight division and potential antagonism, fostering positive attitudes toward the in-group and negative perceptions of out-groups (Brewer & Gardner, 1996; LeVine & Campbell, 1973).

Research shows that group identity formation is vital for attracting members who share aligned identities or experience identity uncertainty, characterized by confusion about who they are and how to behave. This process provides clarity and structure, particularly appealing to individuals in uncertain or transitional life phases (Hogg, 2003). While identification with a group does not inherently lead to violence, strongly identifying with a group under perceived threats can increase the likelihood of hostile behaviors toward out-groups (Fischer et al., 2010; Merrilees et al., 2013). Social identity thus shapes situational appraisals, emotions, and behaviors, becoming a powerful tool for intragroup cohesion and out-group antagonism, especially in conditions of perceived threat to the group (De Cremer & van Vugt, 1999; Iyengar et al., 2012).

Ideological groups across the political spectrum rely on group identity communication (i.e., via tweets) to engage their audiences, construct a collective identity, and mobilize support. This process is not confined to one end of the ideological spectrum or a particular level of violence; instead, it reflects a shared strategy to unify members, reinforce group boundaries, and amplify their ideological messages. By examining group identity tweets, this study explores how these groups employ language to foster social identity and maintain influence in online spaces.

Affective, Cognitive, and Moral Language in Group Identity Tweets

Affective, cognitive, and moral language are powerful tools to strengthen social identity and foster group cohesion. According to social identity theory, individuals derive a significant portion of their self-concept from their membership in social groups (Tajfel & Turner, 1979). This social identity can be strengthened through language that emphasizes shared values, goals, and group membership, as well as distinctions between "us" and "them" (Brewer & Gardner, 1996). Identity uncertainty theory suggests that individuals who experience uncertainty about their social identity are particularly susceptible to the influence of groups that provide clarity and structure (Hogg, 2007). By using affective, cognitive, and moral language, ideological groups create a sense of belonging, reinforce ideological boundaries, and reduce identity uncertainty for their followers. These strategies help shape individuals' perceptions of themselves as part of a larger collective, while simultaneously demarcating the in-group from out-groups.

The specific use of affective, cognitive, and moral language in ideological group messaging is expected to vary significantly based on the group's ideological orientation and propensity for violence. Violent groups are often motivated by a sense of existential threat and a desire to protect or advance their worldview through forceful means, which may lead them to employ more emotionally charged, morally justified, and ideologically certain language (Matsumoto et al., 2012; Knight et al., 2022). For example, violent groups may use affective language to evoke anger or fear, cognitive language to justify their violent actions as a means of self-defense or cultural preservation, and moral language to justify violence as a moral imperative to protect the in-group (Byrne et al., 2013; Brownlow et al., 2020). Nonviolent groups, on the other hand, may focus more on positive emotional appeals, ideological clarity, and moral language that promotes justice and equality without resorting to violence (Scrivens et al., 2022). Similarly, left- and right-leaning groups emphasize different moral and cognitive frameworks to justify their actions and beliefs, with left-leaning groups typically stressing fairness and inclusivity, while right-leaning groups focus on loyalty, authority, and tradition (Graham et al., 2009; Hahn et al., 2019). Understanding how these ideological and violent distinctions manifest in group identity tweets is crucial for identifying patterns in extremist rhetoric.

Affective Language and Group Identity

Affective language refers to words that express or elicit emotion, serving to evoke responses such as anger, fear, or trust. Ideological groups use affective language to amplify engagement, reinforce in-group cohesion and evoke emotional reactions toward perceived out-groups. For instance, words associated with "disgust" or "pride" can powerfully shape group sentiment and boundary-making. Many ideological groups on the Internet take advantage of this emotional influence, using positive and negative emotional language to draw individuals closer to their causes and away from competing ideologies (Dunbar et al., 2014).

More extreme ideological groups, especially those sanctioning violence and hate, frequently use negative emotions such as fear, anger, and disgust in their online communication (Byrne et al., 2013; Ness et al., 2017). This emotional intensity serves to rally members and legitimize violent actions, framing them as righteous and necessary for group survival. Prior research suggests that violent extremists frequently use fear appeals and expressions of personal crisis or victimization to justify their violence, portraying their group as under siege (Knight et al., 2022; Byrne et al., 2013). These emotional appeals heighten group identification by creating a shared sense of urgency. Their expression increases immediately before acts of violence, suggesting that these emotions are instrumental in inciting groups to commit violence (Matsumoto et al., 2012).

In contrast, nonviolent ideological groups may use less aggressive forms of affective language, focusing more on feelings of injustice or exclusion rather than fear or disgust. These groups may evoke anger or resentment, but do so in a way that emphasizes ideological purity and the need for peaceful resistance (Scrivens et al., 2022). While they may still engage in emotionally evocative language, nonviolent groups typically avoid the more direct calls for violent action seen in their violent counterparts.

Research Question 1: How does affective language in group identity tweets differ between violent and nonviolent ideological groups?

Further distinctions in affective language may emerge across political orientations. Left-leaning ideological groups often use emotionally intense language to rally disadvantaged populations against perceived oppression and inequality, frequently expressing solidarity and collective resistance (Choi et al., 2023). These groups might emphasize themes of justice, equality, and collective action, using emotionally evocative language to inspire hope and mobilize for social change. Given their greater openness to experience and higher self-esteem, more positive themes may emerge in their communications (Jost et al., 2003).

Conversely, right-leaning ideological groups will likely frame their emotional appeals to defend traditional values, national identity, and social order. Their affective language may center more on fear of societal collapse or moral decay, evoking anger and anxiety over the perceived threats posed by out-groups (Schlenker et al., 2012). Fear may be particularly present in their online messaging given their higher death anxiety and greater fear of threat and loss (Jost et al., 2003).

Research Question 2: How does affective language in group identity tweets differ between left-leaning and right-leaning ideological groups?

Cognitive Language and Group Identity

Cognitive language involves terms that indicate through processes, including reasoning, explanation, uncertainty, and causal attribution. This type of language helps ideological groups structure narratives that interpret events in line with their worldview – often by attributing blame, highlighting certainty, or contrasting alternative viewpoints. Violent ideological groups often use cognitive language to rationalize their violent actions, framing them as necessary for the protection or advancement of the group's ideology. These groups are likely to employ language that emphasizes certainty, moral superiority, and the justification of violence, often framing their actions as a response to perceived existential threats (Brownlow et al., 2020; Kruglanski, 1989). Cognitive appeals may include claims of historical inevitability or the need for violent resistance to preserve the group's values, reinforcing a sense of certainty and resolve.

Nonviolent ideological groups, while still using cognitive language to promote their worldview, are less likely to frame their ideology in terms of violent resistance. Instead, they may focus more on ideological clarity and the need for peaceful action to address perceived injustices. However, cognitive language in nonviolent groups may still reflect strong ideological commitment, as they attempt to present a unified narrative about societal problems and solutions (Kruglanski, 2004). These groups may emphasize cognitive dissonance reduction, framing their cause as morally justified despite the lack of violent action.

Research Question 3: How does cognitive language in group identity tweets differ between violent and nonviolent ideological groups?

Left-leaning ideological groups are likely to use cognitive language that emphasizes causality and insight to explain societal issues, particularly systemic inequalities and injustices. Their cognitive framing often highlights the root causes of societal problems, such as capitalism, discrimination, or environmental degradation, and uses language that stresses the need for structural change and collective action to address these issues (Choi et al., 2023; Pliskin et al., 2014). These groups are more likely to use tentative language when discussing potential solutions, emphasizing uncertainty and the need for continued dialogue and reform to achieve social justice. Cognitive language in left-leaning ideological groups may also highlight discrepancies in the current social system, identifying the gap between societal ideals and the realities faced by marginalized populations.

In contrast, right-leaning ideological groups often use cognitive language to emphasize the causes and consequences of perceived societal threats, such as the erosion of traditional values, national identity, or cultural heritage. Their cognitive framing tends to focus on certainty and the inevitability of conflict or societal collapse unless strong measures are taken to preserve the in-group and its values (Jost et al., 2003; Webber et al., 2018). Right-wing extremists are likely to employ more decisive and confident language, framing issues as clear-cut and stressing the need for strong action to protect the in-group from external and internal threats. They may also highlight discrepancies between the idealized traditional values and the perceived moral decay in contemporary society. This use of cognitive language reinforces a sense of urgency and in-group cohesion, as right-leaning ideological groups often portray themselves as the defenders of societal order and cultural purity (Graham et al., 2009).

Research Question 4: How does cognitive language in group identity tweets differ between left-leaning and right-leaning ideological groups?

Moral Language and Group Identity

Moral language frames actions, events, or groups in terms of right and wrong, justice and injustice. It draws on shared moral values (e.g., fairness, loyalty or purity) to legitimize the group's actions and condemn those of opposing groups. Unlike affective language, which targets emotion, or cognitive language, which targets understanding, moral language targets judgment and obligation, portraying behaviors or beliefs as virtuous or corrupt. Violent ideological groups often invoke moral language to justify violence, particularly by appealing to binding moral foundations like loyalty, authority, and sanctity (Coady, 2004; Graham & Haidt, 2012). These groups may downplay individualizing moral foundations such as care and fairness, instead emphasizing the moral imperative to defend the group and its values, even at the cost of violating ethical principles (Hahn et al., 2019). Moral language in violent ideological groups frequently portrays violence as a necessary evil to uphold cultural purity or societal order, often justifying harm to out-group members as a means of protecting the in-group (Hahn et al., 2024).

Nonviolent ideological groups, on the other hand, may still use moral language but are more likely to emphasize individualizing moral foundations, such as care, fairness, and justice (Paruzel-Czachura et al., 2023). These groups focus on framing their ideology as a morally superior alternative to mainstream societal norms, appealing to empathy and fairness to promote social change without violence. While they may still highlight out-group moral failings, the moral language in nonviolent groups typically focuses more on ideological purity and peaceful resistance than justifying harm.

Research Question 5: How does moral language in group identity tweets differ between violent and nonviolent ideological groups?

Across political orientations, left-leaning ideological groups are more likely to emphasize individualizing moral foundations, such as care and fairness, to justify their activism and critique of existing power structures.

These groups frame their cause regarding human rights, equality, and justice, often using moral language to highlight the importance of fairness and the rights of marginalized groups. In contrast, right-leaning ideological groups emphasize binding moral foundations, particularly loyalty and sanctity, which support their focus on preserving traditional values and resisting perceived threats to societal stability (Graham et al., 2009). Their moral language often stresses the importance of protecting the in-group from the moral decay and existential threats posed by out-groups.

Research Question 6: How does moral language in group identity tweets differ between left-leaning and right-leaning ideological groups?

By examining the use of affective, cognitive, and moral language in group identity tweets, this study provides insight into how different ideological groups—violent and nonviolent, left-leaning and right-leaning—employ language to construct social identities, mobilize support, and legitimize their causes. The differences in language use are critical for understanding the dynamics of online extremism and the role of social media in fostering group cohesion and ideological polarization.

2. Method

Sample

The sample consisted of 172 Twitter users representing 62 ideological groups. Among these, 124 were linked to nonviolent groups and 48 to violent groups; 45 were associated with left-leaning groups and 127 with right-leaning groups; and 53 group accounts, 39 leader accounts, and 80 prominent member accounts. The identification of the groups was based on information from the Southern Poverty Law Center's (SPLC) Hatewatch blog, a report on left-wing extremism prepared for the U.S. Department of Energy (Seger, 2001), the Counter Extremism Project, and the Armed Conflict Location & Event Data (ACLED) Project. From the SPLC and ACLED sites and searching news media, we identified these groups' leaders and prominent members. We searched for the Twitter accounts of the groups, their leaders, and prominent members, and each user downloaded the most recent 3,200 tweets, the maximum retrievable via the Twitter API, in January 2023 using Node XL (Smith et al., 2010). As a result, the tweet dataset spans from 2009 to late 2022, depending on each user's posting frequency. This period encompassed major sociopolitical events, including national elections, racial justice protests, and the COVID-19 pandemic, which likely influenced tweet themes and engagement.

Since our focus is group identity tweets, we retained only tweets that contained a score greater than zero for either "we" pronouns (e.g., we, us, our) or "they" pronouns (e.g., they, their, them) features of the Linguistic Inquiry and Word Count program (LIWC; Tausczik & Pennebaker, 2010). LIWC provides a proportion of words relevant to the "we" and "they" categories relative to the number of words in each tweet. This process reduced the dataset to tweets referencing collective identity and out-group distinctions. We calculated the aggregate LIWC score for "we" and "they" features at the user level across all qualifying tweets. Each user received a unique identification number, group affiliation code, and classifications for violence, ideological stance, and role (group, leader, or member), as described below.

Group Classification

Violence distinction was determined through a Factiva article search from 2016 to 2022 containing group names and a search string of 37 words indicative of violence (e.g., attack, kill, violence, armed). A set of 3 trained content coders read the articles and recorded the group's name, the article's date, the source of information, the violent event date, and the event description. Any group involved in at least one crime was classified as violent. Additionally, to determine the political position of these groups (right- or left-leaning), information from the SPLC and the Twitter accounts affiliated with the ideological groups was used.

Measuring Affective, Cognitive, and Moral Language

Affective language was assessed using the NRC Emotion Lexicon via the Syuzhet package in R, which classifies words according to Plutchik's (2001) eight core emotions: anticipation, joy, trust, fear, surprise, sadness, disgust, and anger. Each tweet was scored on the presence and intensity of these emotion categories. Tweets containing one or more emotion-related terms received non-zero values, indicating affective content.

Cognitive language was assessed using six cognitive process categories from LIWC: insight, causality, discrepancy, tentativeness, certainty, and differentiation (Tausczik & Pennebaker, 2010). These categories reflect the extent to which tweets contain language associated with reflection, reasoning, or contrasting perspectives.

Moral language was assessed using the Moral Foundations Dictionary (MFD; Graham et al., 2009), implemented in LIWC. This dictionary includes terms tied to five foundational moral domains—care, fairness, loyalty, authority, and sanctity—classified as either virtue (morally approved) or vice (morally condemned). Tweets containing one or more terms from these categories were scored based on their proportion relative to tweet length.

While these linguistic categories are not mutually exclusive and may co-occur within a tweet (e.g., a moral condemnation that also evokes anger), they serve distinct psychological and rhetorical purposes. Our analytic approach treats them as independent but not exclusive dimensions, enabling us to detect the primary emphasis of each tweet. To mitigate interpretive ambiguity, we apply lexicons validated in prior research and focus on patterns at the user/group level rather than isolated lexical choices. We also contextualized interpretation of scores by reviewing representative tweet samples to ensure that terms were used in ideologically consistent ways (e.g., "loyalty" invoked as a moral virtue vs. sarcastic critique).

Covariate – User Role

Prior research indicates that different roles within ideological groups behave differently, including in their online communication (Jasko & LaFree, 2020; Phadke & Mitra, 2021). Therefore, user roles, including official group accounts, leaders, and prominent members were categorized. Prominent members included any members with key roles other than group leader (e.g., legal counsel, VP of operations, speaker). The reason behind the exclusion of group followers is that we are interested in the linguistic strategies employed by organizations and/or their representatives.

3. Results

Table 1 provides a summary of research questions and key findings. Table 2 displays descriptive statistics for the study variables for the overall sample, as well as for violent and nonviolent affiliation, and right- and left-leaning groups, separately (see supplemental materials for correlations between study variables).

Table 1. Summary of research questions and results

Research Questions	Results
RQ1: How does affective language in group identity tweets differ between violent and nonviolent extremist groups?	Nonviolent: higher trust and positive affect scores
RQ2: How does affective language in group identity tweets differ between left-leaning and right-leaning extremist groups?	No significant differences
RQ3: How does cognitive language in group identity tweets differ between violent and nonviolent extremist groups?	Violent: higher discrepancy scores
RQ4: How does cognitive language in group identity tweets differ between left- and right-leaning extremist groups?	No significant differences
RQ5: How does moral language in group identity tweets differ between violent and nonviolent extremist groups?	No significant differences
RQ6: How does moral language in group identity tweets differ between left-leaning and right-leaning extremist groups?	Left-leaning: higher care scores Right-leaning: higher sanctity scores

Hierarchical linear modeling (HLM) was used to study the effects of role, violence classification, and political ideology while accounting for the clustered data structure (Raudenbush & Bryk, 2002). The dataset for this analysis had two levels: 172 users (level 1) nested within 62 groups (level 2). Each user had an average score for each language variable across all tweets scraped from their account, serving as the level 1 data. User role served as a level 1 covariate. At level 2, violence classification and political ideology served as group features. Statistical analysis was carried out using R 2024.04.0 (R Core Team, 2024), the *lme4* (*v*1.1-35.3; Bates, et al., 2015), the *GLMMadaptive* (*v*0.9-1; Rizopoulos, 2023) packages and the *r2mlm* package (Shaw, et al., 2023). Interclass correlations (ICC) were calculated for each social identity variable to assess the proportion of variance in the use of those languages accounted for by group membership. ICC ranges from 0 to 1, where a coefficient close to 1 means that a large proportion of the variation in the outcome can be explained by which group a person belongs to, rather than individual differences within the group.

Table 2. *Means* and standard deviations for study variables for the overall sample, users affiliated with nonviolent, violent, right- and left-leaning ideological groups

	Overall		Nonviolent		Violent		Right-leaning		Left-leaning	
Variable	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
We/us	3.57	1.45	3.51	1.34	3.74	1.71	3.45	1.40	3.93	1.55
They/them	2.09	1.11	2.00	1.05	2.30	1.23	2.23	1.19	1.69	0.72
Insight	1.39	0.76	1.36	0.80	1.46	0.64	1.40	0.84	1.38	0.48
Cause	1.32	0.66	1.32	0.58	1.32	0.84	1.37	0.71	1.17	0.43
Discrepancy	1.33	0.70	1.26	0.55	1.52	0.98	1.38	0.75	1.21	0.55
Tentativeness	1.55	0.75	1.54	0.76	1.55	0.71	1.49	0.74	1.71	0.74
Certainty	1.20	0.59	1.18	0.55	1.24	0.70	1.21	0.62	1.17	0.51
Differentiation	2.08	1.46	2.05	1.59	2.17	1.04	2.06	1.61	2.14	0.92
Perception	1.66	0.89	1.54	0.67	1.96	1.26	1.61	0.96	1.80	0.65
Anticipation	0.68	0.25	0.69	0.27	0.65	0.22	0.68	0.27	0.68	0.21
Disgust	0.32	0.20	0.32	0.19	0.33	0.21	0.33	0.21	0.31	0.14
Fear	0.76	0.34	0.77	0.34	0.74	0.34	0.74	0.37	0.83	0.22
Joy	0.53	0.26	0.54	0.26	0.51	0.24	0.54	0.28	0.51	0.17
Sadness	0.46	0.22	0.47	0.23	0.46	0.20	0.46	0.24	0.48	0.15
Surprise	0.31	0.14	0.32	0.14	0.28	0.14	0.31	0.15	0.30	0.12
Trust	1.04	0.46	1.09	0.48	0.92	0.40	1.05	0.51	1.00	0.28
Negative	1.02	0.43	1.03	0.44	1.00	0.40	1.00	0.48	1.08	0.27
Positive	1.49	0.59	1.56	0.62	1.33	0.46	1.47	0.62	1.55	0.50
Anger	0.58	0.28	0.58	0.28	0.58	0.31	0.56	0.31	0.64	0.18
Care virtue	0.51	0.44	0.50	0.36	0.55	0.60	0.46	0.33	0.65	0.65
Care vice	0.55	0.40	0.52	0.38	0.62	0.46	0.48	0.36	0.74	0.45
Fairness virtue	0.28	0.38	0.30	0.40	0.21	0.30	0.31	0.42	0.17	0.14
Fairness vice	0.15	0.18	0.14	0.17	0.19	0.20	0.16	0.20	0.13	0.09
Loyalty virtue	0.78	0.92	0.71	0.52	0.96	1.52	0.74	1.04	0.87	0.41
Loyalty vice	0.03	0.06	0.03	0.07	0.03	0.05	0.04	0.07	0.02	0.04
Authority virtue	0.66	0.43	0.69	0.45	0.57	0.37	0.68	0.47	0.61	0.30
Authority vice	0.17	0.26	0.18	0.25	0.15	0.30	0.19	0.30	0.12	0.08
Sanctity virtue	0.50	0.67	0.54	0.69	0.39	0.60	0.61	0.74	0.19	0.21
Sanctity vice	0.23	0.23	0.22	0.24	0.23	0.21	0.21	0.22	0.28	0.26

Note. Overall n = 172; Nonviolent n = 124; Violent n = 48; Right-leaning n = 127; Left-leaning n = 45.

For affective language, anticipation (ICC=0.184), disgust (ICC=0.404), fear (ICC=0.198), joy (ICC=0.233), sadness (ICC=0.191), surprise (ICC=0.218), trust (ICC=0.069), anger (ICC=0.303), general negative affect (ICC=0.385), and general positive affect (ICC=0.224) were evaluated. Providing insight on research questions one and two, violence classification significantly predicted the use of trust appeals (β = -0.219, p < .05, R^2_{fvm}=0.147) and general positive affect appeals (β = -0.323, p < .05, R^2_{fvm}=0.237), while the effect of role was controlled at level 1. The results suggest that nonviolent groups leverage trust (Figure 1) and positive affect (Figure 2) more than violent groups in their group identity tweets. Political ideology did not significantly predict affective language in group identity tweets. See Table 3 for full results.

For cognitive language, insight (ICC=0.319), cause (ICC=0.123), discrepancy (ICC=0.283), tentativeness (ICC=0.463), certainty (ICC=0.196), and differentiation (ICC=0.187) were evaluated. Addressing research questions three and four, violence classification significantly predicted discrepancy use (β = 0.374, p < .05, R^2_{fvm}=0.322) while the effect of role was controlled at level 1. This suggests that violent groups employ discrepant language (i.e., hedging language such as “would” or “could”) more than nonviolent groups in group identity tweets (Figure 1). Political ideology did not significantly predict cognitive language in group identity tweets.

Finally, for moral language, care virtue (ICC=0.243), care vice (ICC=0.604), fairness virtue (ICC=0.280), fairness vice (ICC=0.114), loyalty virtue (ICC=0.154), loyalty vice (ICC=0.310), authority virtue (ICC=0.131), authority vice (ICC=0.222), sanctity virtue (ICC=0.391), and sanctity vice (ICC=0.312) were evaluated. For some moral language features, the distribution was positively skewed, thus a gamma distribution was imposed where appropriate. Addressing research questions five and six, violence classification did not significantly predict moral language in group identity tweets. On the other hand, political ideology significantly predicted care virtue (β = 0.229, p < .05, R^2_{fvm}=0.248), care vice (β = 0.256, p < .05, R^2_{fvm}=0.601), and sanctity virtue (β = -1.18, p < .01, R^2_{fvm}=0.163) language. The results suggest that left-leaning groups use caring virtues (i.e., compassion; Figure

2) and vices (i.e., neglect) more than right-leaning groups in group identity tweets. Right-leaning groups use sanctity virtues (i.e. purity) more than left-leaning groups in group identity tweets. See Table 5 for full results.

Table 3. HLM results for emotion language

Variables	Anticipation			Trust			Joy			Surprise		
	Model 1 (β)	Model 2 (β)	Model 3 (β)	Model 4 (β)	Model 5 (β)	Model 6 (β)	Model 7 (β)	Model 8 (β)	Model 9 (β)	Model 10 (β)	Model 11 (β)	Model 12 (β)
Intercept	0.71**	0.71**	0.70**	1.10**	1.19**	1.20**	0.58**	0.59**	0.60**	0.28**	0.28**	0.26**
Level 1												
Role	-0.02	-0.01	-0.01	-0.04	-0.05	-0.07	-0.03	-0.02	-0.03	0.01	0.02	0.02
Level 2												
Violence		-0.07			-0.22*			-0.07			-0.04	
Ideology			-0.02			-0.12			-0.05			0.00
AIC	31.44	36.49	37.87	239.36	237.00	240.99	36.27	38.19	38.82	-172.96	-163.01	-161.95
BIC	50.25	32.14	53.52	258.18	252.65	256.64	55.08	53.84	54.46	-154.14	-147.36	-146.30
R^2_{fvm}	0.393	0.214	0.192	0.112	0.147	0.065	0.342	0.265	0.236	0.280	0.255	0.247

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left- leaning. ** $p < 0.01$; * $p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

Variables	Disgust			Sadness			Fear			Anger		
	Model 13 (β)	Model 14 (β)	Model 15 (β)	Model 16 (β)	Model 17 (β)	Model 18 (β)	Model 19 (β)	Model 20 (β)	Model 21 (β)	Model 22 (β)	Model 23 (β)	Model 24 (β)
Intercept	0.31**	0.28**	0.30**	0.48**	0.48**	0.48**	0.74**	0.76**	0.68**	0.59**	0.58**	0.56**
Level 1												
Role	0.01	0.02	0.02	-0.01	-0.01	-0.01	-0.00	-0.01	0.02	-0.01	-0.01	-0.00
Level 2												
Violence		0.01			-0.01			-0.03			-0.03	
Ideology			-0.02			0.00			0.10			0.02
AIC	-67.69	-64.93	-65.34	-17.42	-14.46	-14.76	130.31	132.04	130.54	64.25	68.37	68.24
BIC	-48.88	-49.28	-49.69	1.39	1.19	0.89	149.12	147.69	146.19	83.07	84.02	83.89
R^2_{fvm}	0.484	0.409	0.412	0.188	0.208	0.207	0.228	0.212	0.201	0.421	0.321	0.312

Variables	Positive Affect			Negative Affect		
	Model 25 (β)	Model 26 (β)	Model 27 (β)	Model 28 (β)	Model 29 (β)	Model 30 (β)
Intercept	1.67**	1.75**	1.62**	1.02**	1.04**	1.00**
Level 1						
Role	-0.11	-0.10	-0.07	-0.02	-0.02	-0.02
Level 2						
Violence		-0.32*			-0.05	
Ideology			0.02			0.05
AIC	314.75	312.28	318.72	204.09	204.54	204.26
BIC	333.57	328.28	334.37	222.90	220.19	219.91
R^2_{fvm}	0.317	0.237	0.218	0.389	0.399	0.397

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left-leaning. ** $p < 0.01$; * $p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

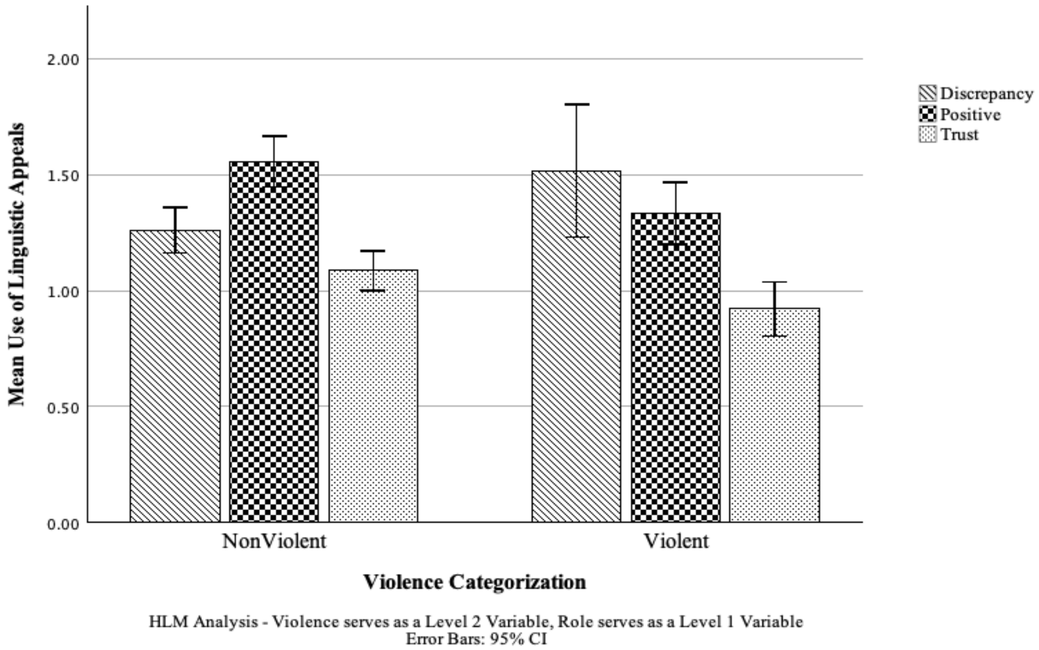

Figure 1. Use of Discrepancy, Positive Affect, and Trust Language in the Group Identity Tweets of Violent and Non-Violent Groups

Table 4. HLM results for cognitive language

Variables	Insight			Cause			Discrepancy			Tentativeness		
	Model 1 (β)	Model 2 (β)	Model 3 (β)	Model 4 (β)	Model 5 (β)	Model 6 (β)	Model 7 (β)	Model 8 (β)	Model 9 (β)	Model 10 (β)	Model 11 (β)	Model 12 (β)
Intercept	**1.27****	**1.33****	**1.37****	**1.14****	**1.09****	**1.24****	**1.53****	**1.41****	**1.73****	**1.91****	**1.90****	**1.91****
Level 1												
Role	0.04	0.02	0.01	0.09	0.10	0.06	-0.09	-0.08	-0.16	**-0.21***	**-0.19***	**-0.19***
Level 2												
Violence		0.08			0.10			**0.37***			0.00	
Ideology			-0.02			-0.15			-0.33			-0.02
AIC	356.43	406.56	406.46	351.90	359.82	359.06	371.54	371.30	373.25	366.74	371.79	371.52
BIC	375.24	422.21	422.11	370.71	375.47	374.71	390.35	386.95	388.89	385.55	387.44	387.17
R^2_{fvm}	0.753	0.330	0.333	0.269	0.190	0.119	0.363	0.322	0.300	0.588	0.466	0.465

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left-leaning. **$p < 0.01$; *$p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

Variables	Certainty			Differentiation		
	Model 13 (β)	Model 14 (β)	Model 15 (β)	Model 16 (β)	Model 17 (β)	Model 18 (β)
Intercept	**1.18****	**1.16****	**1.20****	**1.65****	**1.70****	**1.75****
Level 1						
Role	0.01	0.02	0.01	0.20	0.16	0.16
Level 2						
Violence		0.04			0.31	
Ideology			-0.03			0.12
AIC	316.59	323.83	323.60	543.26	628.40	628.86
BIC	335.40	339.48	339.25	562.08	644.05	644.51
R^2_{fvm}	0.242	0.208	0.212	0.806	0.237	0.214

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left-leaning. **$p < 0.01$; *$p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

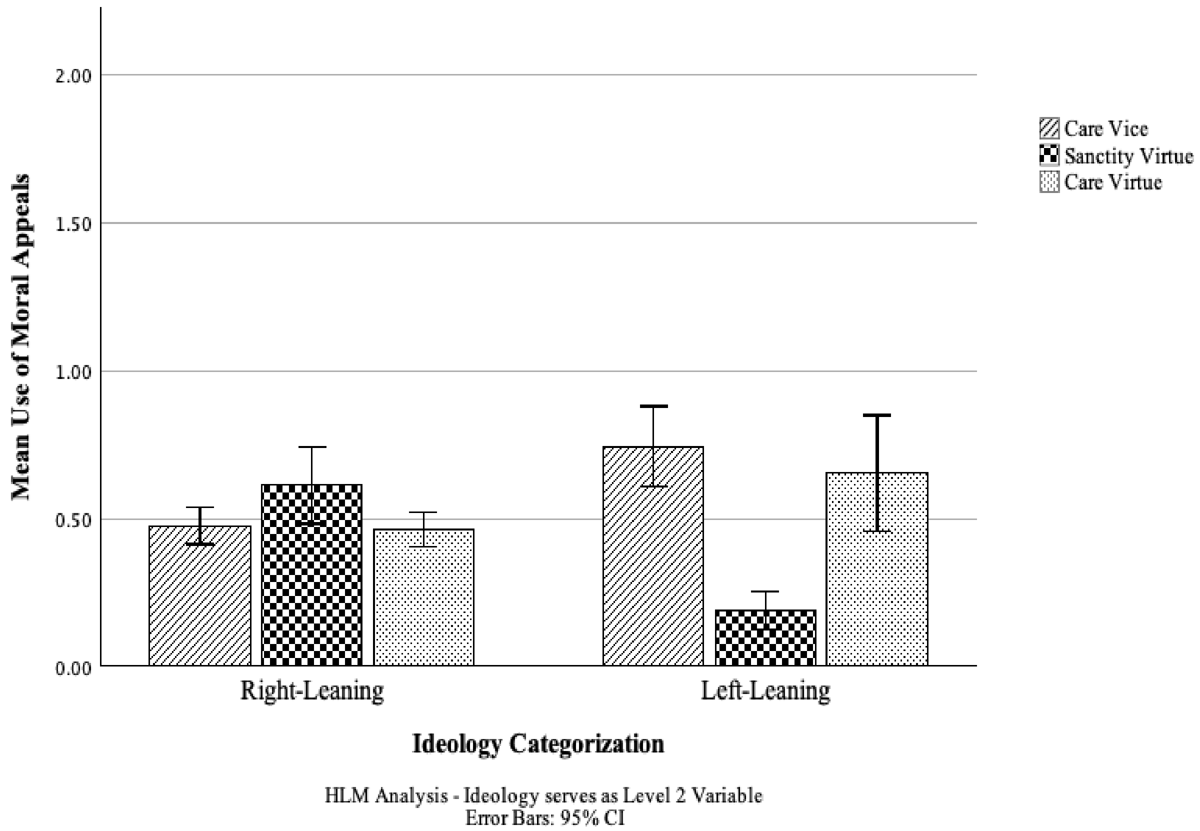

Figure 2. Use of Care and Sanctity Language in the Group Identity Tweets of Left and Right-Leaning Groups

Table 5. HLM results for moral language

Variables	Care Virtue (Care)			Care Vice (Harm)			Fairness Virtue (Fairness)[a]			Fairness Vice (Cheating)[a]		
	Model 1 (*β*)	Model 2 (*β*)	Model 3 (*β*)	Model 4 (*β*)	Model 5 (*β*)	Model 6 (*β*)	Model 7 (*β*)	Model 8 (*β*)	Model 9 (*β*)	Model 10 (*β*)	Model 11 (*β*)	Model 12 (*β*)
Intercept	**0.66****	**0.66****	**0.45****	--	**0.61****	**0.48****	**-1.97****	**-1.84****	**-1.16****	**-1.95****	**-2.10****	**-1.82****
Level 1												
Role	-0.09	-0.08		--	-0.06		0.34	0.32		0.04	0.07	
Level 2												
Violence		0.03			0.16			-0.30			0.31	
Ideology			**0.23***			**0.25***			-0.61			-0.21
AIC	183.66	219.66	211.28	--	160.57	153.54	-780.10	-778.70	-780.40	-1002.30	-1000.90	-1002.50
BIC	202.48	235.31	223.83	--	176.22	166.08	-767.50	-763.00	-767.80	-989.70	-985.20	-990.00
R^2_{fvm}	0.618	0.226	0.248	--	0.620	0.601	0.042	0.053	0.056	0.001	0.015	0.010

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left-leaning. a=Gamma Distribution imposed on positively skewed dataset. Model 4 failed to converge. **$p < 0.01$; *$p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

Variables	Loyalty Virtue (Loyalty)[a]			Loyalty Vice (Betrayal)[a]			Authority Virtue (Authority)			Authority Vice (Subversion)[a]		
	Model 13 (*β*)	Model 14 (*β*)	Model 15 (*β*)	Model 16 (*β*)	Model 17 (*β*)	Model 18 (*β*)	Model 19 (*β*)	Model 20 (*β*)	Model 21 (*β*)	Model 22 (*β*)	Model 23 (*β*)	Model 24 (*β*)
Intercept	-0.01	-0.17	-0.30	**-3.88****	**-3.80****	**-3.33****	--	**0.67****	**0.65****	**-1.66****	**-1.56****	**-1.64****
Level 1												
Role	-0.13	-0.09		0.21	0.19		--	0.00		-0.05	-0.07	
Level 2												
Violence		0.28			-0.18			-0.14			-0.20	
Ideology			0.16			**-0.65**			-0.05			-0.51
AIC	-21.90	-20.70	-21.70	-2374.50	-2372.70	-2375.50	--	216.10	212.19	-1245.10	-1243.30	-1246.30
BIC	-9.30	-5.00	-9.10	-2361.90	-2356.90	-2362.00	--	231.75	224.74	-1232.50	-1227.50	-1233.70
R^2_{fvm}	0.006	0.020	0.006	0.006	0.007	0.021	--	0.155	0.152	0.000	0.004	0.054

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left-leaning. a=Gamma Distribution imposed on positively skewed dataset. Models 19 failed to converge. **$p < 0.01$; *$p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

Variables	Sanctity Virtue (Sanctity)[a]			Sanctity Vice (Degradation)[a]		
	Model 25 (*β*)	Model 26 (*β*)	Model 27 (*β*)	Model 28 (*β*)	Model 29 (*β*)	Model 30 (*β*)
Intercept	**-1.36****	**-1.25****	**-0.49****	**-1.36****	**-1.36****	**-1.58****
Level 1						
Role	0.34	0.32		-0.07	-0.07	
Level 2						
Violence		-0.30			-0.00	
Ideology			**-1.18****			0.32
AIC	-486.60	-485.20	-493.00	-863.10	-861.10	-863.70
BIC	-474.00	-469.50	-480.40	-850.50	-845.30	-850.10
R^2_{fvm}	0.030	0.040	0.163	0.002	0.002	0.018

Note. N = 172. Role is coded 1 = group account, 2 = prominent member, 3 = leader; Violence is coded 0 = nonviolent, 1 = violent; Ideology is coded 0 = right-leaning, 1 = left-leaning. a=Gamma Distribution imposed on positively skewed dataset. **$p < 0.01$; *$p < 0.05$. R^2_{fvm} indicates the total proportion of the variance in the DV explained by the model.

4. Discussion

Before delving into the discussion, it is important to acknowledge several limitations of this study. First, our sample included only group identity tweets that employed first- and third-person plural pronouns. While these pronouns are a key marker of social identity, groups may use explicit labels to refer to themselves (e.g., "Americans") and members of the out-group (e.g., "radicals"). Prioritizing ideological diversity in our sample made compiling a comprehensive, generalized list of in-group and out-group labels across all groups challenging. We encourage future research to expand upon our work by including group identity tweets that explicitly reference such labels in addition to pronouns.

Second, categorizing groups as violent or nonviolent posed methodological challenges, and we decided to rely on media reports documenting violent actions. Future studies could explore whether our findings hold when employing alternative classification methods, given that some instances of violence may not be covered in the media.. Additionally, our approach treated all recorded violent acts—from verbal intimidation to homicide—as equivalent. While this approach offered a pragmatic starting point, future research could differentiate crime severity to examine whether the intensity of violence correlates with variations in messaging patterns. Finally, regarding scope, this study focused exclusively on Twitter, and future research should investigate whether similar patterns emerge across platforms with different user bases, content norms, and communication styles. Addressing these limitations will enhance our understanding of the interplay between group identity messaging, ideological tendencies, and social media contexts.

Despite these limitations, we have noteworthy findings to discuss. This study found no significant differences in the use of negative affective language (e.g., anger, fear, disgust) in group identity tweets between violent and nonviolent ideological groups. This contrasts with earlier research indicating that violent groups generally employ more negatively charged emotional language than their nonviolent counterparts in online communications, such as websites and social media posts, which are not limited to group identity messaging (Byrne et al., 2013; Dunbar et al., 2014; Ness et al., 2017). Additionally, our findings differ from those of Scrivens and colleagues (2022), who reported that nonviolent groups tend to express more negative sentiment toward out-groups than violent groups. Instead, we observed that both violent and nonviolent groups exhibit similar levels of negative affective language when discussing themselves or out-groups, with these scores notably lower than their use of positive affective language. Taken all together, our results suggest that ideological groups across the political spectrum, whether violent or nonviolent, tend to convey a predominantly positive sentiment in group identity tweets. This trend is particularly pronounced among nonviolent groups, which used the highest levels of positive affective and trust-related language finding consistent with their broader emphasis on hope and positive emotions in general online communications (Jensen et al., 2024).

The reason for these contrasting findings is likely related to the corpus of social media posts used in this research design. Using group identity tweets as the basis of analysis allowed for a nuanced exploration of ideological group linguistic patterns within tweets that leverage a specific communication tactic: appeals to social identity and the engagement in social categorization. Given that social categorization is a foundational component of ideological group development, it is equally as important to understand these messaging tactics within a more nuanced set of data, as it is to understand how violent and nonviolent groups differ in general communications as past research has discussed (e.g., Byrne et al., 2013; Dunbar et al., 2014; Ness et al., 2017; Scrivens et al., 2022). Since social identity language has significant implications for group development and cohesion, member attitude development, and viewer dissemination intentions (Connelly et al., 2016; Jensen et al., 2023), it is critical to understand better the patterns of language used when social identity is salient and used as an influence mechanism. Therefore, it is theoretically and practically interesting to note that, while violent and nonviolent groups use different levels of negative affect in their general social media communication, they leverage similar levels when attempting to appeal to social identities. As such, positively affective language may be viewed as a more effective influence tactic when social identity and categorization are being discussed, highlighting the benefits of the in-group over the shortcomings of the out-group.

Second, similar to affective language, ideological groups across the political spectrum—whether violent or nonviolent—showed minimal differences in their use of cognitive language (e.g., cause, certainty, differentiation) in group identity tweets. Unlike affective and moral language, cognitive language lacks an established body of research exploring expected differences among ideological groups. This may be because such language cues are universally employed across ideological groups to construct narratives that interpret world events through their ideological lens. These cues often emphasize distinctions between in-groups and out-groups, contrast their narratives with alternative accounts, and strategically balance uncertainty with certainty, occasionally employing tentative language to challenge the status quo. Our study did, however, identify a significant difference in the use of discrepancy language, where violent groups employed it more frequently than nonviolent groups. Discrepancy cues, such as "would," "can," "want," and "could," often signal aspiration, dissatisfaction, or a call to action (Higgins, 1987; Pezzuti, 2023). These cues align with the rhetoric of violent groups, which frequently highlight perceived injustices or deficiencies in the current state of affairs to mobilize support. In group identity tweets, such language may focus on envisioning a transformed future or addressing grievances, reinforcing their calls for radical change. Moreover, discrepancy language can serve as a psychological mechanism to justify violent actions, framing them as necessary to bridge the gap between the present reality and their envisioned ideal. By employing this framing, violent groups may strengthen their narratives, galvanize followers, and create a heightened sense of urgency, distinguishing their rhetorical strategies from nonviolent groups.

Third, our findings reveal that the propensity for violence was not a predictor of moral language use in group identity tweets; instead, political ideology emerged as the primary driver. This suggests that the emphasis on moral issues in identity formation is shaped more by ideological beliefs than by offline violent tendencies. Specifically, we found that left-leaning groups emphasized care language more than right-leaning groups, while the latter used sanctity language more frequently in their group identity tweets. These findings align with previous research on moral language in broader online communications, which indicates that left-leaning groups prioritize individualizing moral foundations (e.g., care, fairness), whereas right-leaning groups highlight binding foundations (e.g., loyalty, sanctity; Graham et al., 2009). For left-leaning groups, the use of care language likely reflects their emphasis on compassion, inclusivity, and addressing inequalities. By centering their identity on these moral values, they foster solidarity among their followers while advancing a transformative agenda aimed at systemic change and protecting marginalized groups. This focus on care resonates strongly with their ideological base, reinforcing their collective commitment to progressive ideals.

In contrast, the use of sanctity language by right-leaning groups in group identity tweets likely reflects their concerns about purity, tradition, and moral order. This language aligns with their focus on preserving cultural, religious, and societal norms, often evoking themes of protection—whether of cultural heritage, moral values, or national identity. By framing issues as a defense of sacred ideals against perceived threats, sanctity language reinforces in-group cohesion and appeals to a shared sense of moral duty and reverence for tradition. This rhetorical strategy allows right-leaning groups to tap into deeply held emotional and moral convictions, fostering unity and a collective sense of purpose among their followers. These findings offer important theoretical and practical implications. Theoretically, this research advances our understanding of social identity development in online messaging, particularly within ideological groups. The distinctions observed between violent and nonviolent groups and groups with differing political ideologies provide valuable insights into the psychological and social needs these groups leverage in shaping their online identities. These findings help refine existing theories by illustrating how groups strategically employ language to cultivate membership and mobilize support.

Practically, these results offer actionable insights for counter-messaging and deradicalization efforts. By recognizing the distinct patterns in messaging used by violent and nonviolent groups and left-leaning and right-leaning ideologies, practitioners can develop more targeted interventions to disrupt the narratives these groups promote. For example, counter-messaging strategies may be better tailored to address the moral foundations (e.g., care vs. sanctity) that resonate with different groups, ultimately aiming to reduce the appeal of extremist ideologies. Additionally, the patterns observed in group identity language may serve as diagnostic tools for identifying groups with a higher proclivity toward violence. However, further research is needed to confirm the predictive value of these indicators.

Statement of Researchers

Researchers' contribution rate statements

Conceptualization – all authors. **Data curation** – all authors. **Formal analysis** – JS, HS, ABL. Funding acquisition – MJ, SC. **Investigation**– MM, DP, BS, ABL. **Methodology** – HS, JS, ABL. **Project administration** – MJ, SC, ABL. **Software** – JS, HS. **Supervision** – ABL, SC, MJ. **Writing – original draft** – MM, DP, ABL. **Writing – review & editing** – ABL, JS, CG.

Conflict statement:

The authors declare that they have no conflict of interest

Data Availability Statement:

The data that support the findings of this study are openly available in Open Science Framework at https://osf.io/9re56/files/osfstorage/67917d0b00d1c3f372b5395d

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Ethical Considerations:

All data used for analysis was publicly available, no additional participant data requiring additional consent forms was collected.

The Authors' Biographies

Ares Boira Lopez earned her Ph.D. in Industrial-Organizational Psychology from the University of Oklahoma, with a minor in Quantitative Psychology. For over three years, she served as Research Grant Team Lead on a federally funded project examining ideological rhetoric and influence online, where she led the design of experimental studies, managed qualitative and quantitative data analysis, and translated findings into actionable insights for counter-messaging strategies. This work, funded by National Counterterrorism Innovation, Technology, and Education Center (NCITE), has contributed to multiple government reports, national conference presentations, and peer-reviewed publications. She now works as a Research Specialist at NCITE, where she leads the development and validation of psychological assessments to evaluate behavioral threat recognition and response in counterterrorism and targeted violence prevention programs. Dr. Boira Lopez's broader research interests include extremist organizations, AI-assisted creativity, collective leadership, and affect variability.

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Dr. Marina Mery is driven to leverage her extensive education in I/O psychology and experience in research methodology to assist in the talent assessment process for employees and organizations. After earning her PhD in Industrial/Organizational (I/O) Psychology from the University of Oklahoma, she joined SKS Consulting Group. In her role as a talent assessment consultant, she has been able to apply I/O principles to strengthen personnel decision-making for organizations.

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6. References

Aberson, C. L., Healy, M., & Romero, V. (2000). Ingroup bias and self-esteem: A meta-analysis. *Personality and Social Psychology Review*, *4*(2), 157-173. https://doi.org/10.31237/osf.io/92jah

Alava, S., Frau-Meigs, D., & Hassan, G. (2017). *Youth and violent extremism on social media: Mapping the research*. UNESCO Publishing. https://doi.org/10.54675/sttn2091

Angie, A. D., Davis, J. L., Allen, M. T., Byrne, C. L., Ruark, G. A., Cunningham, C. B., ... & Mumford, M. D. (2011). Studying ideological groups online: Identification and assessment of risk factors for violence. *Journal of Applied Social Psychology*, *41*(3), 627-657. https://doi.org/10.1111/j.1559-1816.2011.00730.x

Auxier, B. & Anderson, M. (2021, April 7). Social Media Use in 2021. *Pew Research Center.* https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021/

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models using lme4. *Journal of Statistical Software, 67*(1), 1-48. https://doi.org/10.18637/jss.v067.i01

Blazak, R. (2001). White boys to terrorist men: Target recruitment of Nazi skinheads. *American Behavioral Scientist*, *44*(6), 982-1000. https://doi.org/10.4324/9780203446188-36

Braddock, K. (2023). *Cognition, emotion, communication, and violent radicalization*. The Routledge Handbook on Radicalization and Countering Radicalization. https://doi.org/10.4324/9781003035848-12

Brady, W. J., & Van Bavel, J. J. (2021). Social identity shapes antecedents and functional outcomes of moral emotion expression in online networks. https://doi.org/10.31219/osf.io/dgt6u

Brewer, M. B., & Gardner, W. (1996). Who is this" We"? Levels of collective identity and self-representation. *Journal of Personality and Social Psychology*, *71*(1), 83. https://doi.org/10.1093/oso/9780199269464.003.0006

Brownlow, S., Fogelman, E.L., Hirsch, S. (2020). How self-reflection influences the use of cognitive and analytical language. *Psychology and Cognitive Sciences Open Journal, 6*(1), 11-14. https://doi.org/10.17140/pcsoj-6-154

Chen, A., Chen, K., Zhang, J., Meng, J., & Shen, C. (2023). When national identity meets conspiracies: the contagion of national identity language in public engagement and discourse about COVID-19 conspiracy theories. *Journal of Computer-Mediated Communication*, 28(1), zmac034. https://doi.org/10.1093/jcmc/zmac034

Cheney, G. (1983). The rhetoric of identification and the study of organizational communication. *Quarterly Journal of Speech*, *69*(2), 143-158. https://doi.org/10.1080/00335638309383643

Chermak, S., Freilich, J., & Suttmoeller, M. (2013). The organizational dynamics of far-right hate groups in the United States: Comparing violent to nonviolent organizations. *Studies in Conflict & Terrorism*, *36*(3), 193-218. https://doi.org/10.1080/1057610x.2013.755912

Connelly, S., Dunbar, N. E., Jensen, M. L., Griffith, J., Taylor, W. D., Johnson, G., Hughes, M., & Mumford, M. D. (2015). Social categorization, moral disengagement, and credibility of ideological group websites. *Journal of Media Psychology,* 28(1). https://doi.org/10.1027/1864-1105/a000138

Conway, M. (2017). Determining the role of the internet in violent extremism and terrorism: Six suggestions for progressing research. *Studies in Conflict & Terrorism, 40*(1), 77-98. https://doi.org/10.1080/1057610x.2016.1157408

De Cremer, D., & Van Vugt, M. (1999). Social identification effects on social dilemmas: A transformation of motives. *European Journal of Social Psychology*, *29*(7), 871-893. https://psycnet.apa.org/doi/10.1002/(SICI)1099-0992(199911)29:7%3C871::AID-EJSP962%3E3.0.CO;2-I

Devine, C. J. (2015). Ideological social identity: Psychological attachment to ideological in-groups as a political phenomenon and a behavioral influence. *Political Behavior*, *37*(3), 509-535. https://doi.org/10.1007/s11109-014-9280-6

Dunbar, N. E., Connelly, S., Jensen, M. L., Adame, B. J., Rozzell, B., Griffith, J. A., & Dan O'Hair, H. (2014). Fear appeals, message processing cues, and credibility in the websites of violent, ideological, and nonideological groups. *Journal of Computer-Mediated Communication*, *19*(4), 871-889. https://doi.org/10.1111/jcc4.12083

Eastman, A. S. (2016). Breaches in the Public Sphere. Racialized Terms of Inclusion in a Text of Transition: Francisco Calcagno's Aponte. *Bulletin of Spanish Studies*, *93*(9), 1591-1608. https://doi.org/10.1080/14753820.2016.1149333

Ellis, C., & Stimson, J. A. (2012). *Ideology in America*. Cambridge University Press.

Fiol, C. M. (2002). Capitalizing on paradox: The role of language in transforming organizational identities. *Organization Science*, *13*(6), 653-666. https://doi.org/10.1287/orsc.13.6.653.502

Fischer, P., Kastenmüller, A., & Greitemeyer, T. (2010). Media violence and the self: The impact of personalized gaming characters in aggressive video games on aggressive behavior. *Journal of Experimental Social Psychology*, *46*(1), 192-195. https://doi.org/10.1016/j.jesp.2009.06.010

Freelon, D., Bossetta, M., Wells, C., Lukito, J., Xia, Y., & Adams, K. (2022). Black trolls matter: Racial and ideological asymmetries in social media disinformation. *Social Science Computer Review,* *38*(5), 608-623. https://doi.org/10.1177/0894439320914853

Frenkel S., & Conger, K. (2022, December 2nd). Hate Speech's Rise on Twitter Is Unprecedented, Researchers Find. *The New York Times.* https://www.nytimes.com/2022/12/02/technology/twitter-hate-speech.html

Frimer, J. A., Gaucher, D., & Schaefer, N. K. (2014). Political conservatives' affinity for obedience to authority is loyal, not blind. *Personality and Social Psychology Bulletin*, *40*, 1205- 1214. https://doi.org/10.1177/0146167214538672

Gallacher, J. D., Heerdink, M. W., & Hewstone, M. (2021). Online engagement between opposing political protest groups via social media is linked to physical violence of offline encounters. *Social Media + Society*, *7*(1). https://doi.org/10.1177/2056305120984445

Giner-Sorolla, R., Bosson, J. K., Caswell, T. A., & Hettinger, V. E. (2012). Emotions in sexual morality: Testing the separate elicitors of anger and disgust. *Cognition and Emotion*, 26(7), 1208–1222. https://doi.org/10.1080/02699931.2011.645278

Graham, J., Haidt, J., & Nosek, B. A. (2009). Liberals and conservatives rely on different sets of moral foundations. *Journal of Personality and Social Psychology*, *96*, 1029-1046. https://doi.org/10.1037/a0015141

Graham, T., Jackson, D., & Broersma, M. (2015). New platform, old habits? Candidates' use of Twitter during the 2010 British and Dutch general election campaigns. *New Media & Society,* *18*(5), 765-783. https://doi.org/10.1177/1461444814546728

Hahn, L., Tamborini, R., Novotny, E., Grall, C., & Klebig, B. (2019). Applying moral foundations theory to identify terrorist group motivations. *Political Psychology*, *40*(3), 507-522. https://doi.org/10.1111/pops.12525

Haidt, J., & Graham, J. (2007). When morality opposes justice: Conservatives have moral intuitions that liberals may not recognize. *Social justice research*, *20*(1), 98-116. https://doi.org/10.1007/s11211-007-0034-z

Haidt, J., Graham, J., & Joseph, C. (2009). Above and below left–right: Ideological narratives and moral foundations. *Psychological Inquiry*, *20*(2-3), 110-119. https://doi.org/10.1080/10478400903028573

Hogg, M. A. (2003). Social identity. In M. R. Leary & J. P. Tangney (Eds.), *Handbook of self and identity* (pp. 462–479). Guilford.

Hogg, M. A. (2014). From uncertainty to extremism: Social categorization and identity processes. *Current Directions in Psychological Science*, *23*(5), 338-342. https://doi.org/10.1177/0963721414540168

Holbrook, D. (2015). A critical analysis of the role of the internet in the preparation and planning of acts of terrorism. *Dynamics of Asymmetric Conflict*, *8*(2), 121-133. https://doi.org/10.1080/17467586.2015.1065102

Horgan, J. (2024). *Terrorist minds: the psychology of violent extremism from Al-Qaeda to the far right.* Columbia University Press.

Iyengar, S., Sood, G., & Lelkes, Y. (2012). Affect, not ideology, a social identity perspective on polarization. *Public opinion quarterly*, *76*(3), 405-431. https://doi.org/10.1093/poq/nfs059

Jensen, M., Connelly, S., Miranda, S., Song, H., Boira Lopez, A., Gordon, C., Stewart, J.W., & National Counterterrorism Innovation, Technology, and Education Center (2023). *Messaging Matters: Ideological Influence Online Year 3 Final Report,* (Publication No. 51). https://digitalcommons.unomaha.edu/ncitereportsresearch/51/

Jost, J. T., Federico, C. M., & Napier, J. L. (2009). Political ideology: Its structure, functions, and elective affinities. *Annual Review of Psychology, 60*, 307-337. https://doi.org/10.1146/annurev.psych.60.110707.163600

Kahan, D. M. (2013). Ideology, motivated reasoning, and cognitive reflection. *Judgment and Decision Making, 8*(4), 407-424. https://doi.org/10.2139/ssrn.2182588

Kelley, H. H. (1973). The processes of causal attribution. *American Psychologist*, *28*(2), 107. https://doi.org/10.1037/h0034225

Lea, M., Spears, R., & De Groot, D. (2001). Knowing me, knowing you: Anonymity effects on social identity processes within groups. *Personality and Social Psychology Bulletin*, *27*(5), 526-537. https://doi.org/10.1177/0146167201275002

Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & Emotion*, *14*(4), 473-493. https://doi.org/10.1080/026999300402763

LeVine, R. A., & Campbell, D. T. (1973). Ethnocentrism: Theories of conflict, ethnic attitudes, and group behavior. https://doi.org/10.2307/2149001

Malka, A., & Lelkes, Y. (2010). More than ideology: Conservative–liberal identity and receptivity to political cues. *Social Justice Research*, *23*(2), 156-188. https://doi.org/10.1007/s11211-010-0114-3

Mason, L. (2018). Ideologues without issues: The polarizing consequences of ideological identities. *Public Opinion Quarterly*, *82*(S1), 866-887. https://doi.org/10.1093/poq/nfy005

Meleagrou-Hitchens, A., & Kaderbhai, N. (2017). Research perspectives on online radicalization: A literature review 2006-2016. *VOX-Pol Network of Excellence*.

Merrilees, C. E., Cairns, E., Taylor, L. K., Goeke-Morey, M. C., Shirlow, P., & Cummings, E. M. (2013). Social identity and youth aggressive and delinquent behaviors in a context of political violence. *Political Psychology*, *34*(5), 695-711. https://doi.org/10.1111/pops.12030

Mumford, M. D., Bedell-Avers, K. E., Hunter, S. T., Espejo, J., Eubanks, D., & Connelly, M. S. (2008). Violence in ideological and non-ideological groups: A quantitative analysis of qualitative data. *Journal of Applied Social Psychology*, *38*(6), 1521-1561. https://doi.org/10.1111/j.1559-1816.2008.00358.x

Ness, A. M., Johnson, G., Ault, M. K., Taylor, W. D., Griffith, J. A., Connelly, S., & Jensen, M. L. (2017). Reactions to ideological websites: The impact of emotional appeals, credibility, and pre-existing attitudes. *Computers in Human Behavior*, *72*, 496-511. https://doi.org/10.1016/j.chb.2017.02.061

Noel, H. (2014). *Political ideologies and political parties in America*. New York: Cambridge University Press. https://doi.org/10.1017/cbo9781139814775

Pliskin, R., Bar-Tal, D., Sheppes, G., & Halperin, E. (2014). Emotions and emotion regulation in political conflicts. *Current Directions in Psychological Science, 23*(6), 430-435. https://doi.org/10.1177/0146167214554

Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist*, *89*(4), 344-350. http://www.jstor.org/stable/27857503

Postmes, T., Spears, R., & Lea, M. (1999). Social identity, group norms, and "deindividuation": Lessons from computer-mediated communication for social influence in the group. In N. Ellemers, R. Spears, & B. Doosje (Eds.), *Social identity: Context, commitment, content*. Oxford: Blackwell.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical Linear Models. Applications and Data Analysis Methods* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Rains, S. A., Kenski, K., Coe, K., & Harwood, J. (2017). Incivility and political identity on the Internet: Intergroup factors as predictors of incivility in discussions of news online. *Journal of Computer-Mediated Communication*, 22(4), 163-178. https://doi.org/10.1111/jcc4.12191

Rip, B., Vallerand, R. J., & Lafrenière, M. A. K. (2012). Passion for a cause, passion for a creed: On ideological passion, identity threat, and extremism. *Journal of personality*, *80*(3), 573-602. https://doi.org/10.1111/j.1467-6494.2011.00743.x

Rizopoulos, D. (2023). *Generalized linear mixed models using adaptive gaussian quadrature*. R package version 0.9-1. https://doi.org/10.32614/cran.package.glmmadaptive

Rousseau, D. M. (1998). Why workers still identify with organizations. *Journal of Organizational Behavior*, 217-233. https://doi.org/10.1002/(sici)1099-1379(199805)19:3<217::aid-job931>3.0.co;2-n

Schwarz, N., Bless, H., & Bohner, G. (1991). Mood and persuasion: Affective status influences the processing of persuasive communications. In M. Zanna (Ed.), *Advances in experimental social psychology* (Vol. 24, pp. 161–197). Academia Press. https://doi.org/10.1016/s0065-2601(08)60329-9

Sharma, E., Saha, K., Ernala, S. K., Ghoshal, S., & De Choudhury, M. (2017). Analyzing ideological discourse on social media: A case study of the abortion debate. In *Proceedings of the 2017 International Conference of The Computational Social Science Society of the Americas* (pp. 1-8). https://doi.org/10.1145/3145574.3145577

Shaw, M., Rights, J. D., Sterba, S. S., & Flake, J. K. (2023). r2mlm: An R package calculating R-squared measures for multilevel models. Behavior Research Methods, *55*(4), 1942-1964. https://doi.org/10.3758/s13428-022-01841-4

Smith, M., Milic-Frayling, N., Shneiderman, B., Mendes Rodrigues, E., Leskovec, J., & Dunne, C. (2010). NodeXL: A free and open network overview, discovery and exploration add-in for excel 2007/2010. College Park, MD: Morgan Kaufmann.

Swann, W. B., Gómez, Á., Dovidio, J. F., Hart, S., & Jetten, J. (2010). Dying and killing for one's group: Identity fusion moderates responses to intergroup versions of the trolley problem. *Psychological Science*, *21*, 1176-1183. https://doi.org/10.1177/0956797610376656

Tajfel, H. E. (1978). *Differentiation between social groups: Studies in the social psychology of intergroup relations*. Academic Press.

Tajfel, H., Turner, J., C., Austin, W., C., & Worchel, S. (1979). An integrative theory of intergroup conflict. *Organizational identity: A reader*, 56, no. 65 https://doi.org/10.1093/oso/9780199269464.003.0005

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*(1), 24-54. https://doi.org/10.1177/0261927x09351676

Thagard, P. (2015). The cognitive–affective structure of political ideologies. *Emotion in group decision and negotiation*, 51-71. https://doi.org/10.1007/978-94-017-9963-8_3

Turner, J. C., & Reynolds, K. J. (2011). Self-categorization theory. *Handbook of Theories in Social Psychology*, *2*(1), 399-417. https://doi.org/10.4135/9781446249222.n46

Van Dijk, T. A. (2013). Ideology and discourse analysis. *The Meaning of Ideology* (pp. 110-135). Routledge.

Van Dijk, T. A. (1998). Opinions and ideologies in the press. In Bell, A., & Garrett, P. D. (Ed) *Approaches to media discourse*. (pp. 21-63). Oxford: Blackwell.

Voelkel, J. G., & Brandt, M. J. (2019). The effect of ideological identification on the endorsement of moral values depends on the target group. *Personality and Social Psychology Bulletin*, *45*(6), 851-863. https://doi.org/10.31234/osf.io/c4dx8

Ward, M. (2020). Walls and cows: social media, vigilante vantage, and political discourse. *Social Media+ Society*, *6*(2). https://doi.org/10.1177/2056305120928513

Wojcieszak, M. (2010). "Don't talk to me": Effects of ideologically homogeneous online groups and politically dissimilar offline ties on extremism. *New Media & Society, 12*(4), 637-655. https://doi.org/10.1177/1461444809342775

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REVIEW ARTICLE OPEN ACCESS

Multilingual X/Twitter sentiment analysis of geopolitical risk using granger causality focusing on the Ukraine war and financial markets

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Highlights:

- Possible to build a geopolitical risk index from X / Twitter historical data.
- Can use this index to identify large events such as the Ukraine war
- This index also provides predictive information on changes in financial markets.
- These changes occur on the daily level and the hourly level.

Abstract

This paper investigates the changes in financial assets and markets from December 1st, 2021, to April 30th, 2022, during the start of the Ukraine War. These dates roughly correspond to the prelude to the War in December 2021 to a few weeks after Russian troops withdrew from the Kyiv area on April 7th, 2022. We used the Goldstein 1992 Results Table to create Positive and Negative Geopolitical Risk bigrams (Goldstein, 1992). With these bigrams, we collected over 3.6 million tweets during our research period in seven different languages (English, Spanish, French, Portuguese, Arabic, Japanese, and Korean) to capture worldwide reaction to the Ukraine War. Using various sentiment analysis methods, we constructed a time series of changes in the daily Geopolitical Risk sentiment. We explored its relationship to 39 financial assets and markets at various time lags. We found through Granger causality that the geopolitical risk time series contained predictive information on several assets and market changes.

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1. Introduction

On February 24th, 2022, Russia launched an invasion of Ukraine, formally starting the Ukraine War. This invasion was telegraphed months ahead of time, and contrary to the Russian expectation of a short conflict, the Ukraine War has continued up to the time of writing our study, more than three years later. This war represents one of the most important increases in geopolitical risk in our world today. Caldara and Iacoviello define "geopolitical risk as the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations. Geopolitical risk captures both the risk that these events materialize, and the new risks associated with escalating existing events" (Caldara & Iacoviello, 2022, p. 2). This definition effectively describes the Ukraine War, and as Caldara and Iacoviello show, geopolitical risks impact various financial markets and assets (Caldara & Iacoviello, 2022). However, getting up-to-date information on geopolitical events on a large scale can potentially be time-consuming (Caldara & Iacoviello, 2022). Thus, we wanted to test whether there was a low-cost, quicker way to evaluate geopolitical risk. Thus, we turned to social media, specifically X / Twitter.

Founded in 2006, the microblogging platform X / Twitter has become one of the most popular social networking platforms globally, boasting 611 million active monthly users and ranking seventh in worldwide daily engagement (Zote, 2025). For research purposes, Pak and Paroubek put best why X / Twitter is an effective resource:

> Microblogging platforms are used by different people to express their opinion about different topics, thus it is a valuable source of people's opinions. Twitter contains an enormous number of text posts and it grows every day…Twitter's audience varies…Therefore, it is possible to collect text posts of users from different social and interests groups. Twitter's audience is represented by users from many countries….it is possible to collect data in different languages (Pak & Paroubek, 2010, p. 1).

Their last point is especially important for our study, as we aim to track worldwide sentiment; therefore, we need text written in multiple languages. Vicinitas states that English language tweets comprise only 30% of tweets posted. This means that a significant portion of all tweets will be excluded if we only collect English-language tweets. However, by including Japanese, Spanish, French, Portuguese, Arabic, and Korean, we can obtain approximately 85% to 90% of all tweets posted to X / Twitter. Therefore, using these languages will give us a larger corpus of tweets and better understand the overall sentiment surrounding the Ukraine War and associated geopolitical risks. To collect and analyze tweets related to the Ukraine War, we employed a combination of the X / Twitter API, sentiment analysis techniques, Granger causality, and finally the "Goldstein Index," which we define later in this paper. The rest of our paper is outlined as follows: Section 2 describes the key concepts employed for our analyses, Section 3 provides a literature review of previous work on geopolitical risk, media, and social media, and how they can affect financial markets. Section 4 details our methodology, while Section 5 displays our results. Section 6 discusses our findings, and Section 7 concludes.

2. Key Concepts

Three key concepts—the "Goldstein Index," sentiment Analysis, and Granger Causality—are the backbone of our research.

2.1. Goldstein Index

The "Goldstein Index" is a concept that comes from the 1992 paper A Conflict–Cooperation Scale for WEIS Events Data by Goldstein, who made use of the World Events Interaction Survey ("WEIS") data set. The WEIS data was developed by McClelland, which is "a record of the flow of action and response between countries (as well as non-governmental actors, e.g., NATO) reflected in public events reported daily in the New York Times from January 1966 through December 1978" (McClelland, 2006). The individual WEIS events can be grouped into "61 event types" (Goldstein, 1992, p. 2). Goldstein constructed a panel of eight International Relations faculty at USC to analyze and score the WEIS events (Goldstein, 1992, p. 6). This panel was individually given 61 cards with each WEIS event type and asked to "sort the cards into cooperative (friendly) actions and conflictual (hostile) ones" (Goldstein, 1992, p. 7) and rank them on a scale with -10 as the most conflictual and +10 as the most cooperative. The resulting rankings from each panel member were then averaged, creating what we refer to as the "Goldstein Index," a table of all 61 WEIS event types ordered from most conflictual to most cooperative. This table is the basis for our data gathering procedure, further described in our Methodology section. One potential bias of the "Goldstein Index" to note is mentioned by Goldstein as at the time of his writing: the table "seems to reflect the continuing emphasis placed on military affairs by international relations scholars" (Goldstein, 1992). However, this bias does not concern us greatly as our study revolves around the Ukraine War, a military affair.

2.2. Sentiment Analysis

Sentiment Analysis, as defined by Sim et al., is a field of document classification that classifies subjective impressions, sensibilities, attitudes of textual documents, individual opinions, on a topic, unlike text mining, which extracts information from text (Sim, 2021). Sentiment analysis programs, thus, try to define a given text as positive or negative, or potentially some other emotion such as anxiety (Gilbert & Karahalios, 2010). There are two main ways to accomplish sentiment analysis: Rules-based methods and Machine Learning based methods (Pota, 2021). Rules-based methods are typically lexicon dictionaries that assign specific values to certain words. The lexicon is then compared to the given text, and any matching words between the lexicon and the text are counted, and a sentiment score is given. As Cambria states, this is a popular sentiment analysis method "because of its accessibility and economy" (Cambria, 2013). As for the second method, machine learning based models, while more computationally heavy, have "the best results … obtained by deep learning approaches, using neural networks with various architectures, based on convolutional layers, …, recurrent layers, or the most recent transformers, constituting the layers of prominent systems employing BERT (Bidirectional Encoder Representation from Transformers)" (Pota, 2021, p. 1). For our study, we employed a combination of different methods including Rules-based methods, recurrent layers becoming recurrent neural networks ("RNNs") and transformer BERT models (Hutto & Gilbert, 2014; Devlin, et al, 2017; Géron, 2019; Inoue, et al, 2021). This combination proved necessary as different languages responded better to different sentiment analysis models.

2.3. Granger Causality

First detailed by Granger in his 1969 paper, Granger causality aims to find "the direction of causality between two related variables and also whether or not feedback is occurring" (Granger, 1969, p. 1). Since then, Granger causality tests have been used in various studies, including the Thurman and Fisher study, which aim to predict whether eggs Granger cause chickens or chickens Granger cause eggs (Thurman & Fisher, 1988). However, it should be noted that causality in this case does not mean the typical definition of causality, i.e., a change in one variable causes the change in another, but rather as Gilbert and Karahalios put it: "Although the technique has the word "causal" in it, we are not testing true causation. We can only say whether one time series has information about another." (Gilbert & Karahalios, 2010, p. 4). Moreover, as Granger himself states, his definition of causality mentions that "1. The cause occurs before the effect, and 2. The cause contains information about the effect that is unique and is not found in any other variable. A consequence of these statements is that the causal variable can help forecast the effect variable after other data has first been used." (Granger, 2003, p. 6). Thus, the null hypothesis for the Granger Causality Test is that the two time series are unrelated or provide any predictive information about each other. While the alternative hypothesis, which is accepted at a p-value less than 0.05, is that one tested time series does provide predictive information about the other time series. For this case study, we followed the lead of Bollen et al., who used Granger causality to test "whether one time series has predictive information about the other or not" (Bollen et al., 2011, p. 4). We chose to use Granger causality over traditional correlation to examine the relationship between the change in the sum of sentiment trend and the financial asset, as traditional correlation tests for a linear relationship between the variables, in other words, it checks to see if the variables change together at a constant rate. Granger causality works better for this paper as it tests if one series contains predictive information about the other, i.e., if one trend moves, does the other also move in the future. Since social media news reacts faster than the financial markets change their prices, the two time series will have a lag between them and not vary at the same time, thus Granger causality is a better statistical test for this paper.

3. Literature Review

Multitudes of studies use sentiment analysis, especially with X / Twitter. For example, Pak and Paroubek showed in their study how to effectively use X /Twitter to construct a corpus of tweets and use sentiment analysis on those tweets to derive insights (Pak & Paroubek, 2010). Additionally, Rajput et al used X / Twitter to analyze sentiment analysis around the Coronavirus pandemic (Rajput et al., 2020). Baker et al. (2021) used X / Twitter to "construct a database of more than 14 million tweets that contain a keyword related to 'uncertainty'…from June 1st, 2011, and March 1st, 2021". They transformed the count of these tweets into a time series and used that time series to measure economic uncertainty in the US during their research period. The Baker study was important for us as their use of keywords also provided a basis for us to use keywords to gather data for our analysis with the “Goldstein Index”.

Many papers have also explored the relationship between news media and the effect on various financial markets through sentiment analysis. Using sentiment analysis to key in on anxiety-related terms in a large online blog, LiveJournal, Gilbert and Karahalios found through using Granger causality analysis that “increases in expressions of anxiety…predict downward pressure on the S&P 500 index” (Gilbert & Karahalios, 2010, p. 1). Uhl also showed that using a corpus of Reuters news articles, the sentiment analysis of those articles over time could “predict changes in stock returns better than macroeconomic factors” (Uhl, 2014, p. 1). Tetlock, et al., 2008, takes a more expansive approach to the returns of specific firms in the S&P 500 index by using sentiment analysis on articles from the Wall Street Journal and the Dow Jones News Service from 1980 to 2004 (Tetlock, et al., 2008, p. 2) to show that the number of negative words used in the articles about the firms can forecast lower earnings for the firms.

Three papers influenced our research: Bollen et al. (2011), Amen (2020), and Caldara and Iacoviello (2022). While Bollen et al. provided a framework about how to work with Granger causality and X/Twitter, Caldara and Iacoviello, and Amen provided the theoretical basis for working with trends in geopolitical risk data and the assets we should investigate that might be affected by geopolitical events, such as the Ukraine War. Bollen et al. researched whether the change in moods and the change in the Dow Jones index were linked. To do so, they complied a X / Twitter corpus of tweets containing “author’s mood states” (Bollen et al., 2011, p. 2) and analyzed them through sentiment analysis programs to identify six moods: “Calm, Alert, Sure, Vital, Kind, and Happy” (Bollen et al., 2011). Creating a time series from the tweets’ sentiment, Bollen et al. then used Granger causality to find if the change in mood sentiment that predates a change in the Dow Jones index. They found that out of the six moods, only Calm passed the Granger causality test and had information that predicted the change in the Dow Jones from 2 – 6 lags (Bollen et al., 2011).

On the other hand, Caldara and Iacoviello, and Amen focused specifically on geopolitical risk. Caldara and Iacoviello built the Geopolitical Risk (GPR) index, which used the count of news articles that mentioned their keyword indicators for geopolitical risks across 11 different English language newspapers starting from 1985 (Caldara & Iacoviello, 2022, p. 7). This GPR index captured the changes in geopolitical risks, and Caldara and Iacoviello were able to show how the increases in the GPR index predicted lower stock returns (Caldara & Iacoviello, 2022). Lastly, Amen built the Thorfinn Sensitivity Index (TSI), which uses “over 30,000 daily feeds” (Amen, 2020) to construct a daily index of the weight average of 12 geopolitical risk groups which experts have scored based on the news feeds that have come in for that day (Amen, 2020, p. 2). Amen then compares the changes in the TSI to changes in various “safe havens” and “risky assets” (Amen, 2020, p. 6) to develop trading strategies. Caldara and Iacoviello, and Amen had a wide range of assets and markets that provided a starting point for our analyses. Appendix A contains Table A.1, which shows the different financial assets we considered and their sources, while Table A.2 regroups them into the asset class categories we used.

Finally, we explored more recent research to compare our methods to. Niu et al. (2023) followed a similar data-gathering procedure as Caldara and Iacoviello, collecting news stories from ten English-language papers looking for key geopolitical words to build a time series showing the change in geopolitical risk (Niu et al., 2023, p. 4). Building on Caldara and Iacoviello, they used various machine learning methods to predict changes to the S&P 500 based on the geopolitical risk time series data. They found that Support Vector Regressions provided the highest predictive ability of their methods tested (Niu et al., 2023). Yilmazkuday (2024), constructed a study showing how geopolitical risk affected the stock prices worldwide to different degrees. For example, a one-unit increase in geopolitical risk caused a 0.8 decrease in stock prices in Latvia (Yilmazkuday, 2024). They also studied the Ukraine War and found that most affected countries’ stocks were near the source of the geopolitical risk, i.e., Ukraine (Yilmazkuday, 2024). They also used the geopolitical risk keywords from Caldara and Iacoviello to build the geopolitical risk timeline and compare the stock values of the markets in different countries worldwide (Yilmazkuday, 2024). These two studies helped solidify our data collection methodology, as we also used a variation of the Caldara and Iacoviello method.

We aim to extend the literature by combining the “Goldstein Index” with X / Twitter to see if we can capture large geopolitical events, such as the Ukraine War and see how the sentiment around a geopolitical event can affect different financial assets on an equivalate or smaller time scale than both Caldara and Iacoviello, whose index captures both daily and monthly data, and Amen, whose index is only for daily. Additionally, we aim to capture the global impact of a geopolitical event by using multiple languages. While many studies only look at English tweets [Pak and Paroubek, 2010; Baker et al., 2021], or perhaps one additional language like Italian for Pota et al. (2011), or Dutch for Kleinnijenhuis. (2013), we aim to capture a more expansive, worldwide sentiment using the seven languages we study.

4. Method

Our methodology for this paper consists of three parts. The first was data gathering, the second was sentiment analysis, and the last was financial market analysis with Granger causality.

4.1. Data Gathering

As described earlier, we used the "Goldstein Index" as the basis for our data gathering. Many studies that worked with X / X/Twitter (Abouzahra & Tan, 2021; Baker et al., 2021; Beykikhoshk et al., 2015) have made use of keywords to collect tweets through the X / X/Twitter API, and so we decided to follow these methodologies. However, the "Goldstein Index" does not fit neatly into the X / Twitter API framework, as shown below in Table 1.

Table 1. A recreation of the portion from the Goldstein Paper showing the table Goldstein created. As can be seen, many of the phrases Goldstein uses would not work with the Twitter / X API as they are too long or awkward.

New Weights for WEIS Events		
Event Type	**Weight**	**SD**
223-Military attack; clash; assault	-10.0	0.0
211-Seize position or possessions	-9.2	0.7
222-Nonmilitary destruction / injury	-8.7	0.5
221-Noninjury destructive action	-8.3	0.6
182-Armed force mobilization, exercise, display; military buildup	-7.6	1.2
195-Break diplomatic relations	-7.0	1.3
173-Threat with force specified	-7.0	1.1
174-Ultimatum; threat with negative sanction and time limit	-6.9	1.4

To address this issue, we split the phrases in the index into single terms (such as "attack," "clash," "assault") and bigrams (two-term phrases like "military attack," "military clash," "military assault"). These smaller phrases are more manageable for the X/Twitter API, which allowed us to collect more data. Through experimentation, we found that while the single terms gathered more data, these tweets addressed various topics rather than the geopolitical tweets we searched for. The bigrams, on the other hand, provided a better corpus of tweets for geopolitics, even though there were fewer of them. Thus, we chose to use bigrams for our study, as their increased precision over the data collected was more valuable for our research.

As described earlier, we investigated not only English tweets but also incorporated additional languages to understand worldwide sentiment regarding the Ukraine War better. To do this, we had our "Goldstein Index" bigrams for French, Portuguese, Arabic, Japanese, and Korean translated by Gengo, a professional translation company. For Spanish, we used an independent translator. We deemed it important to use a human translator over machine translation because, as described by Pearse: "while [machine] fluency improves, mistranslation still occurs, so it is still vital to have a human translator check and edit the machine translation" (Pearse, 2020). Appendix B shows a world map highlighting the coverage we gained using multiple languages.

Next, we gathered the tweets from December 1st, 2021, to April 30th, 2022, the timeframe around the start of the Ukraine War. To do so, we implemented "Twarc" (2022), which collects and stores tweets from the X/Twitter API[1] from specific periods that use keywords such as our "Goldstein Index" bigrams. For our research, we used the top ten negatively and positively weighted bigrams that returned a non-zero number of tweets, where the majority of tweets focused on geopolitics. For example, while "call truce" ranked below "policy support" (2.9 and 4.5, respectively), many of the tweets we obtained for "policy support" focused more on internal politics than geopolitics than the "call truce" tweets, thus "call truce" was used. We also removed tweet duplicates removed by the "text" variable and the "created_at" variable generated from the X/Twitter API from our tweet data, as we viewed anything retweeted within the exact second after the original posting as most likely a bot. However, this removal did not cause significant data loss. This method collected over 3.6 million tweets for our research period. After collecting the tweets, we moved on to the sentiment analysis of the tweets' text.

[1] https://developer.twitter.com/en/docs/twitter-api/tweets/filtered-stream/introduction

4.2 Sentiment Analysis

Three different methods were applied for the sentiment analysis process. For English, we implemented the VADER Lexicon developed by Hutto and Gilbert. VADER is a rules-based sentiment analysis lexicon that is highly accurate, especially on short English texts (96%), such as tweets (Hutto & Gilbert, 2014, p. 9). For Arabic, we turned to CamelBERT, developed by Inoue et al. Based on the BERT model, a multi-layer Transformer-based model used for various natural language processing tasks, CamelBERT achieves the same functionality as BERT, including accurate sentiment analysis results for Arabic. However, for Spanish, French, Portuguese, Japanese, and Korean, we created our own RNN models to obtain the sentiment for tweets (Géron, 2019). While there were Transformer models trained for these languages (such as BETO by Cañete et al for Spanish, BERTimbau by Souza et al for Portuguese, CamemBERT by Martin et al for French, KR-BERT by Lee et al for Korean, and Bert-Base-Japanese by Tohoku-nlp), we found through testing that our X/Twitter data received either poor sentiment accuracy or had an extended processing time when evaluated by these BERT models. While these models are generally accurate overall, there were a few reasons why they did not work for our data. First, there was a mismatch between our X / Twitter data and the pre-training data that the various BERT models use. X/Twitter data is short text only, while the pre-trained data did not use this short text data exclusively, which could cause lower sentiment accuracy. Second, our computational limitations prevented the BERT models from executing in a reasonable time, as they are generally large models, and we had a vast amount of data. Thus, we turned to creating RNNs. RNNs are effective in this task because they can remember short sequences, such as tweets, and return a sentiment analysis score. We found sentiment analysis short text datasets for each language (TASS 2020 for Spanish; Gamebusterz for French; Augustop for Portuguese; Darkmap for Japanese; Park for Korean) and thus could train effective RNNs off these datasets. These RNNs overcame the pretraining data problem of the BERT models and are significantly smaller, which improved runtime while maintaining a high sentiment accuracy.

4.3. Financial Markets and Granger Causality

With the sentiment obtained for each tweet in the different languages, we compiled the tweets into one data frame and grouped the tweets by day, attaining the sum of the sentiment for each day, thus creating a time series for the change in the sentiment by day. We compared this time series to the various financial assets mentioned in Appendix A. We obtained the financial asset data for December 1st, 2021, to April 30th, 2022, through the Python package yfinance (Aroussi, 2023) and various other websites that contained the relevant financial asset data (CNBC, 2023; GoldHub, 2023; Investing.com, 2023a; Investing.com, 2023b; LiveCharts.co.uk, 2023; Monitor, 2023). However, these financial assets all trade at different times, and certain regions observe different holidays that close the markets. Thus, we needed to alter our sum of sentiment time series so that each date would line up correctly. Additionally, the financial data time series is needed to check for stationarity. Stationarity for a time series is defined as "a flat-looking series, without trend, constant variance over time, a constant autocorrelation structure over time, and no periodic fluctuations (seasonality)" (National Institute of Standards, 2023). Stationary checks are important as Granger causality only works under the assumption of stationary time series (Granger, 1969). Thus, differencing (where the current observation is subtracted from the previous observation) makes a time series stationary. If differencing is not done, the Granger causality results would be useless; they are applied to the financial and sentiment time series. Afterwards, Granger causality was tested to see if the sentiment analysis of the tweets obtained with the "Goldstein Index" bigrams can provide information about forecasting the change in the various financial assets. It should be noted that we did not create a Vector Autoregression (VAR) model as Caldara and Iacoviello did, as they focused more on trying to forecast the change of the model variables. In contrast, we were more interested in investigating the relationship between the sentiment on social media and various financial assets. So, Granger causality applied better in our case.

For the Granger causality model specifications, we were testing to see if the financial asset is exogenous to the sum of sentiment, i.e. if the sum of "Goldstein Index" sentiment trend Granger causes the change in the price of the financial asset, which makes the financial asset price the endogenous variable and the change in the sum of sentiment the exogenous variable. Once we made our time series stationary through differencing, we could apply Granger causality to see if the sentiment analysis of the tweets obtained with the "Goldstein Index" bigrams can provide information about forecasting the change in the various financial assets.

For the hourly time frame, the whole methodology is repeated. The only change is that for the time series, we sum the sentiment at the hourly level instead of the daily level and obtain the financial data at the hourly level as well.

5. Results

Table 2 below shows each bigram's tweet count with a negative weight ("Goldstein Negative") for each language.

Table 2. The number of tweets that contained each Bigram from December 1st, 2021, to April 30th, 2022, for the "Goldstein Negative" Category.

Bigrams	English	Spanish	French	Portuguese	Arabic	Japanese	Korean	Total
Military Invasion	931,256	180,118	23,357	20,398	3,234	4,514	662	1,163,539
Military Attack	722,575	116,651	19,825	14,585	7,029	40,735	545	921,945
Military Clash	44,495	18,172	742	13,332	1,567	5,390	2,475	86,173
Military Assault	180,108	8,650	2,986	426	396	395	0	192,961
Seize Position	3,774	5	691	14,934	2,614	4	68	22,090
Seize Possession	1,460	27	4	782	478	0	1	2,752
Non-Military Destruction	7	5,813	38	1,641	66	0	0	7,565
Non-Military Injury	1	23	0	96	29	0	0	149
Force Mobilization	3,795	8,953	3,421	1,274	2,210	63	714	20,430
Force Exercise	50,138	50,117	1,650	1,263	3,959	4,339	366	111,832
Total	1,937,609	388,529	52,714	68,731	21,582	55,440	4,831	2,529,436

For our research period, we collected 2,529,436 tweets that used one of these bigrams across all 7 languages, of which 591,547 were non-English. We included "Military Invasion" as a bigram for this specific study that was not included in the original Goldstein Index. While the original Goldstein Index would work in all other contexts for different events, since the Ukraine War was an invasion, leaving out the bigram synonym of "Military Invasion" would have missed over a million tweets from this study, which would have been severely detrimental. Table 3 shows the tweets count for each bigram with a positive weight ("Goldstein Positive") for each language.

Table 3. The number of tweets that contained each Bigram from December 1st, 2021, to April 30th, 2022, for the "Goldstein Positive" Category.

Bigrams	English	Spanish	French	Portuguese	Arabic	Japanese	Korean	Total
Military Assistance	443,872	37,954	33,368	3,369	3,327	4,914	8,248	535,052
Economic Aid	111,168	137,250	9,997	6,552	390	55,645	2,388	323,390
Substantive Agreement	1,219	1,553	17,996	65	309	69	234	21,445
Suspend Sanctions	34,326	7,222	1,518	689	1	0	158	43,914
Diplomatic Recognition	16,062	4,500	493	199	183	11	202	21,650
Grant Privilege	9,608	1,572	204	519	1,055	3,421	4,420	20,799
Call Truce	55,011	1,477	233	1,347	716	7	1,899	60,717
Material Assistance	9,127	2,357	323	377	6,944	0	198	19,326
Endorse Position	7,278	6,907	1,457	81	503	3,243	15,881	35,350
Verbal Support	10,330	2,446	10,337	304	57	3	553	24,030
Total	698,001	203,238	75,926	13,529	13,485	67,313	34,181	1,105,673

For the "Goldstein Positive" category, we collected 1,105,673 tweets, of which 407,672 were non-English. This brings the total number of tweets during our study period to 3,635,109, with nearly 70% of tweets coming in the "Goldstein Negative" Category and 27% being non-English.

Figure 1 is the daily count of tweets captured by the "Goldstein Index" bigrams from December 1st, 2021, to April 30th, 2022. This represents a total of 151 days. Each day is the total count of tweets captured by each topic with the Goldstein Negative and Goldstein Positive bigrams. The count of Goldstein's bigram tweets starts rising around two weeks before the start of the Invasion. He remains, on average, three times higher than before the War started, indicating increased discussion of geopolitical events on X / Twitter.

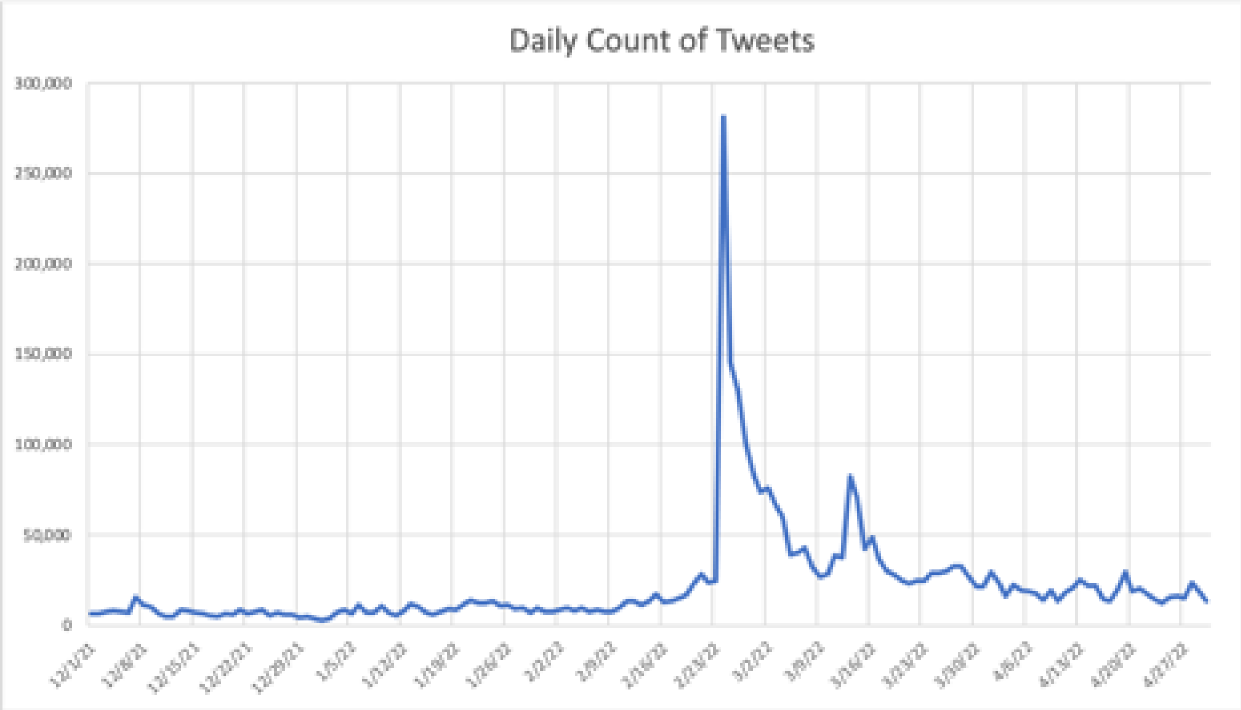

Figure 1. Daily Count of Tweets in both “Goldstein Positive” and “Goldstein Negative” Bigram Categories

Figure 2 displays the change in the Daily Sum of Sentiment, the start of the Ukraine War is on February 24th, 2022, which is evident by the large decrease in sentiment. The average sum of sentiment after the start of the War, like the count, was around three times more negative than before the start of the War. This indicates that, while more people were talking about geopolitics, that they were talking about it in a more negative way than usual, which is unsurprising given the scale and the devastation the Ukraine War caused during this time.

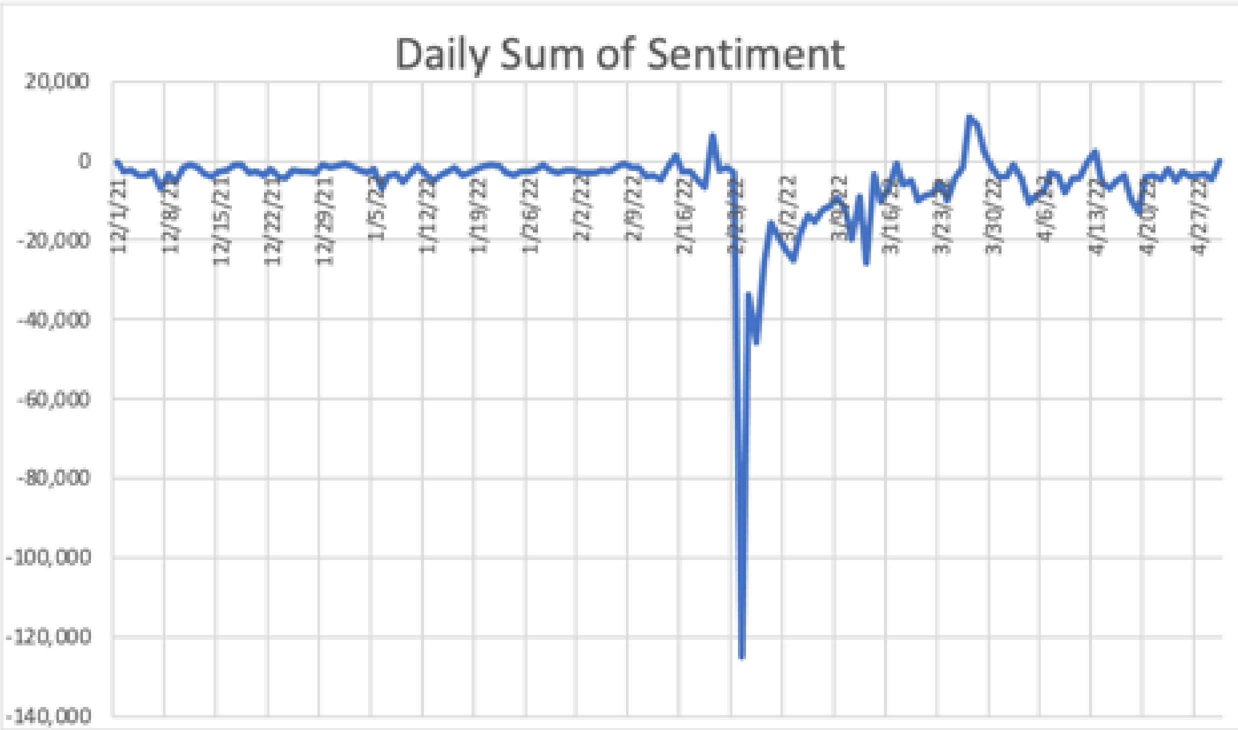

Figure 2. Daily Sum of Sentiment for all Tweets in both “Goldstein Positive” and “Goldstein Negative” Bigram Categories

Following a similar procedure to C. Pop et al., we chose to examine the Granger causality relationship between the daily sum of sentiment and each financial asset at different lagged values. In C. Pop et al., they used "the Granger causality was considered for one lag, five lags (a typical trading week), and 20 lags (the average number of trading days within a month)" (C. Pop et al., 2016, p. 132). Tables 4 – 6 show the results from the Granger Causality tests, where Table 4 shows the results of one lag (which represents one day), Table 5 shows the results of five lags, and Table 6 shows the results of 10 lags. Note that these tables only display the financial assets for which the sum of the sentiment time series provides predictive information of the change in the financial asset at the lagged value. Any asset that doesn't appear in the table, but does in Appendix A, either did not have any Granger causality with the sum of the sentiment, or it did, but the "feedback" (Granger, 1969, p. 5), denoted by "reverse okay" in our tables also passed. To check this "feedback", we see if the financial asset could provide information about the change in the sum of sentiment and pass the Granger causality test. Any test with a p-value less than 0.05 means that one can reject the Null Hypothesis of the Granger causality test and say that the daily sum of the sentiment time series does have forecasting, predictive information for the financial asset at the indicated lag. However, if the feedback test (which is when the variables of the original Granger causality test are reversed and tested) also passes, this would make the original Granger causality test meaningless as this would mean that the asset price trend and the change in the sum of sentiment trend would Granger cause each other, thus neither variable would contain predictive information about the other. Important to note here on the structure of the following tables, for organization, we included all the passing results for each lag, all in one table. Each entry in the tables below is the individual result for the Granger causality test between the change in the sum of sentiment and the financial asset.

Table 4. Granger Causality Results for Lag 1 Against the Different Financial Assets Separated by Asset Class.

Granger Causality	Sent_Sum	P-Value	Reverse Okay	Reverse P-Value
Gold Price	Yes	0.004988	Yes	0.438339
Gold Futures	Yes	0.040277	Yes	0.53574
Wheat Futures	Yes	0.002161	Yes	0.599003
German 10y Bond	Yes	0.043168	Yes	0.618356
FTSE 100	Yes	0.003308	Yes	0.880743
10 Year US Treasury	Yes	0.035314	Yes	0.82779
10 Year US Futures	Yes	0.022427	Yes	0.909091
EUR	Yes	0.035038	Yes	0.08545
GBP	Yes	0.006035	Yes	0.080256
AUD	Yes	0.044733	Yes	0.154349
MXN	Yes	0.021253	Yes	0.149475

Table 5. Granger Causality Results for Lag 5 Against the Different Financial Assets Separated by Asset Class.

Granger Causality	Sent_Sum	P-Value	Reverse Okay	Reverse P-Value
Oil Price	Yes	0.042714	Yes	0.904926
Oil Futures	Yes	0.03906709	Yes	0.928638
Wheat Futures	Yes	6.46596E-08	Yes	0.944131
German 10y Bond	Yes	0.005677	Yes	0.845183
FTSE 100	Yes	0.001391	Yes	0.860171
10 Year US Treasury	Yes	0.003009	Yes	0.714947
IG-ETF	Yes	0.044506	Yes	0.518171
10 Year US Futures	Yes	0.001307	Yes	0.708251
Bitcoin-Futures	Yes	0.013295	Yes	0.384176
2Y-Treasury Yield	Yes	0.030406	Yes	0.593837
GBP	Yes	0.005202	Yes	0.702139
MXN	Yes	0.04897	Yes	0.793235
RUB	Yes	0.000424	Yes	0.903236
Bitcoin	Yes	0.016982	Yes	0.333437

Many studies have looked at the Monthly (Caldara & Iacoviello, 2022; Niu et al., 2023; Yilmazkuday, 2024) or Daily levels (Pop, C. et al., 2016; Amen, 2020). However, we wanted to see if we could find forecasting information on an even smaller time scale. Thus, we redivided our tweet data into individual hours and reran the Granger Causality tests on a smaller subset of financial assets exhibited in Table 7 below.

Table 6. Granger Causality Results for Lag 10 Against the Different Financial Assets Separated by Asset Class.

Granger Causality	Sent_Sum	P-Value	Reverse Okay	Reverse P-Value
Gold Price	Yes	0.003813	Yes	0.489212
Oil Price	Yes	3.09826E-07	Yes	0.936389
Gold Futures	Yes	0.000121234	Yes	0.969781
Oil Futures	Yes	8.57092E-08	Yes	0.927111
Wheat Futures	Yes	1.3972E-14	Yes	0.608716
Nikkei 225	Yes	0.032658	Yes	0.680651
German 10y Bond	Yes	0.000445	Yes	0.826079
FTSE 100	Yes	0.001059	Yes	0.806077
10 Year US Treasury	Yes	0.000575	Yes	0.23006
Defense-ETF	Yes	0.005718	Yes	0.803637
Metals-ETF	Yes	0.039279	Yes	0.977376
10 Year US Futures	Yes	0.000117	Yes	0.212961
Bitcoin-Futures	Yes	0.010613	Yes	0.727189
EUR	Yes	0.000284	Yes	0.984743
GBP	Yes	0.000997	Yes	0.943754
MXN	Yes	0.000004	Yes	0.857881
RUB	Yes	0.000002	Yes	0.98621
Bitcoin	Yes	0.004504	Yes	0.214014

Table 7. Granger Causality Results for the Hourly Sum of Sentiment Time Series Against the Different Financial Assets Separated by Asset Class.

Granger Causality	Sent_Sum	Number of Lags (up to 24)	P-Value	Reverse Okay	Reverse P-Value
EUR	Yes	10	0.0196	Yes	0.0578
JPY	Yes	12	0.0262	Yes	0.7542
RUB	Yes	1	0.0019	Yes	0.3641
GBP	Yes	8	0.0362	Yes	0.1647
MXN	Yes	12	0.006	Yes	0.2507
EURGBP	Yes	5	0.0431	Yes	0.1953
AUD	Yes	10	0.018	Yes	0.35
ZAR	Yes	12	0.022	Yes	0.3978
BNB	Yes	1	0.0111	Yes	0.082
Metals-ETF	Yes	12	0.0443	Yes	0.5334
CSI-300	Yes	8	0.0386	Yes	0.5287
Sensex	Yes	5	0.0019	Yes	0.6829
FTSE 100	Yes	4	0.0013	Yes	0.2928
Gold Futures	Yes	6	0.0005	Yes	0.2823
Oil Futures	Yes	21	0.0179	Yes	0.2311

It should be noted that while the sum of sentiment was shown not to provide any predictive information for HY_ETF, the IG_ETF, and the Nikkei 225 within the 24 lags (representing at least one full day of data), it did show outside this limit, at 48 lags, 60 lags, and 30 lags respectively.

6. Discussion

With our initial tweet gathering, we found it unsurprising that more than twice the number of tweets were in the "Goldstein Negative" category, given the nature of the Ukraine war. However, this shows that not only does the "Goldstein Index" find significant geopolitical events, but when our sentiment analyses are run on the captured tweets, they return an accurate sentiment result as shown by the significant decrease in sentiment at the onset of the Ukraine War, followed by a sustained increase in negative sentiment relative to the before the War.

While we investigated 39 different financial assets time series, we found that only 11 assets were Granger causal with the sum of the sentiment from the "Goldstein Index" tweets at Lag 1, with the most immediate lag representing one day of trading. However, as we increased the number of lags, we found that more assets were Granger causal, i.e., the change in sum of sentiment provided predictive information for the change in the asset value (14 for Lag 5, a week of trading, and 19 for Lag 10, roughly two weeks of trading). One explanation for this is that news can take time to disperse and affect the market, especially with " sticky " assets, meaning their prices do not move quickly (Hayes, 2021). As Kleinnijenhuis et al. describe, “news impact may not be limited to short-term effects, however. Long-term graphs showed that hope versus fear sentiments in financial news preceded actual economic developments.” (Kleinnijenhuis et al, 2013). This means it may take time for certain financial asset prices to change in response to big geopolitical events such as the Ukraine War. Thus, as we increase the number of lags, which represent the number of days after the change in the sum of “Goldstein Index” sentiment, it might have provided time for the changes in the finance assets’ price to be realized and thus increasing the number of financial assets that the “Goldstein Index” sentiment change is predictive of. For example, the change in sentiment was Granger causal to Steel Futures at 20 lags, nearly a month of trading after the change in sentiment. That said, there were some assets even when the maximum number of lags were used, the “Goldstein Index” sentiment never showed any predictive information, such as USD vs CNY Foreign Exchange Rate, which means that the “Goldstein Index” sentiment time series would not have any use in predicting the change in value of the asset.

As for the successful analyses, our findings match Caldara and Iacoviello, who “document that stock returns experience a short-lived but significant drop in response to higher geopolitical risk. The stock market response varies substantially across industries, with the defense sector experiencing positive excess returns, and with sectors exposed to the broader economy, for instance, steelworks and mining, experiencing negative returns” (Caldara & Iacoviello, 2022, p. 3). This was shown by both the Defense ETF and the “Metals and Mining” ETF time series, which relate to the “Goldstein Index” sentiment, which was our proxy for geopolitical risk. Also, we discovered that both Oil Price and 2 Year US Treasury Bond Yield time series had a relationship with the “Goldstein Index” which Caldara and Iacoviello stated that their Geopolitical Risk Index had as well (Caldara & Iacoviello, 2022, p. 19). In addition, there was a mix of both the “risky” and the “haven” assets describe by Amen appeared (Amen, 2020, p. 6). However, the FTSE 100 was only the “risky asset” (Amen, 2020, p. 6), to appear in all three different lag tests. While the US Treasury 10 Year Yield, was the only “haven asset” (Amen, 2020, p. 6) to appear in all three lag tests. A few of our assets that we wanted to investigate appeared as well. Out of our assets, we found that both GBP/USD and USD/MXN appeared in all three lag tests.

One surprise in our Granger causality analyses was that only Bitcoin and BNB emerged among the cryptocurrencies. As Baur et al. find, “Bitcoin is mainly used as a speculative investment” (Baur et al, 2018, p. 2). Thus, we assumed that Bitcoin and the other cryptocurrencies would experience a price change due to their status as a “risky asset” (Amen, 2020, p.6) and the massive change in sentiment generated by the start of the Ukraine War. While this was not the case, these results are consistent with the findings of Rognone et al., which “suggest investor enthusiasm for Bitcoin irrespective of the sentiment of the news” (Rognone et al., 2020, p. 1). This also aligns with the results from Abraham et al. (2018, who found that tweet volume was a better indicator of Bitcoin and Ethereum price changes than tweet sentiment (Abraham et al., 2018, p. 2). However, their methodology specifically collected tweets with keywords for Bitcoin and Ethereum and only in English (Abraham et al., 2018, pp. 8 - 9). This difference in methodologies might explain the slight variation we observe with the sum of sentiment for the “Goldstein Index” tweets time series, having predictive information for the Bitcoin time series.

After completing the Daily Level analyses, we wanted to see if we could capture predictive information about financial assets at a smaller time interval when the sum of sentiment from “Goldstein Index” tweets was broken down to the hourly level. Amen’s Thorfinn Sensitivity Index analyses were conducted only on the daily level, as were those of Bollen et al., and Caldara and Iacoviello’s GPR Index (Caldara & Iacoviello, 2022, p. 1). Unlike the Daily Granger causality analyses, we found that many Forex assets, which trade 24 hours a day, responded to changes in sentiment within less than half a day. This result aligns with Rognone et al., who found that “Forex comoves and reacts homogeneously to news” (Rognone et al., 2020, p. 1). It reinforces Nofsinger's findings, which state that “financial markets adjust to changes in mood faster than real markets” (Nofsinger, 2005, p. 3). This discovery is important as it suggests that changes in sentiment can provide predictive information about shifts in the Forex time series over shorter time intervals than other geopolitical risk indices, potentially informing different trading options in Forex markets.

The USD vs RUB exchange rate was crucial, as the Ruble is the Russian currency. We found that at the Daily Level, a change in Goldstein Index sentiment had predictive power regarding changes in the USD vs RUB after five lags (approximately a week of trading). However, at the Hourly Level, changes in the Goldstein Index sentiment contained predictive information for USD vs RUB changes within one hour. The nature of the conflict and the varying time scales could explain this difference between the daily and hourly lags. News about the Ukraine War updated frequently, especially at its onset, resulting in rapid changes in Goldstein Index information. As previously mentioned, Forex markets tend to respond to news, so the low lag value at the Hourly Level was unsurprising. However, at the Daily Level, the predictive information from the Goldstein Index could possibly be explained by the amalgamation of data at that level. At the Daily Level, smaller hourly changes would be averaged out. While the Goldstein Index may have predictive information at a smaller time interval, at the Daily Level, aggregating all more minor changes might diminish the predictive information. Nevertheless, over time at the Daily Level, the overall trends between USD vs RUB and the Goldstein Index become clearer, explaining how the Goldstein Index demonstrates predictive power at five and ten lags, but not at the first lag (i.e., one day).

Two minor issues should be mentioned. The first is that we encountered the same issue as Bollen, et al., who detailed: "we have no knowledge of the 'ground truth' for public mood states, nor in fact for the particular subsample of the population represented by the community of Twitter.com users. This problem can only be addressed by increased research into direct assessments of public mood states vs. those derived from online communities such as Twitter" (Bollen et al., 2011). This is also related to a lack of a baseline econometric model for this data without any social media variables. Without the baseline model, the difference created by adding the change in the sum of sentiment time series as a variable to predict the change of the financial asset could not be found. However, this issue was outside of the purview of our study, as we were only investigating the relationship and not creating a prediction of how the financial asset would change. Additionally, by including a significant lead time (nearly three months) before the start of the Ukraine War, mitigates the effect described by Bollen, et al., as we were able to develop a baseline "ground truth" for X/Twitter sentiment regarding geopolitical risk. The second issue is with X/Twitter itself. While X/Twitter's demographics have slightly balanced out over time, X/Twitter users are more often younger and male. Thus, while capturing more sentiment worldwide, we could capture an uneven demographic, potentially skewing our results.

Lastly, we see several avenues for extending our research further. Adding Russian and Ukrainian, while not as popular on X / Twitter, to the languages we captured and analyzed could change our results. These additions may capture changes in financial markets and assets more specific to the Eastern European and Central Asian markets that were greatly affected by the Ukraine War, like Yilmazkuday's study. Another analysis examining the tweets captured by the "Goldstein Index" from May 2022 to the Present could prove interesting. Investigating how sentiment has changed since the initial outbreak of the war and seeing if the geopolitical risk sentiment still provides predictive information on the assets and markets in this study. There is the potential for more Arabic tweets in this period as Iran gets more involved in the Ukraine War. Also, focus on other big geopolitical risk events in the X / X/Twitter Age, such as Covid or the first Ukrainian invasion, to see if the "Goldstein Index" bigrams tweets produce similar results. Lastly, a study into sunflower seed futures could yield interesting results, as Ukraine was the largest producer of sunflower seeds before the War. Thus, sentiment around the Ukraine War might have predictive information about prices (Association, 2023).

7. Conclusion & Practical Implications

Using X/Twitter and sentiment analysis, we identified the start of the Ukraine War using the generic geopolitical bigrams from the "Goldstein Index." We also show that the increased negative sentiment lasted for months, relating to the heightened geopolitical risk caused by the invasion. This rise in negative sentiment was also reflected in various financial assets and markets through Granger causality. Some immediate effects, like with many Foreign Exchange Rates, showed differences after a change in X/Twitter sentiment in only a few hours, while other markets, such as the Nikkei 225, took almost two weeks of trading before the change in sentiment provided predictive information relevant to changes in the financial market.

Statement of Researchers

Researchers' contribution rate statement:

John Corcoran Burns: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Software; Validation; Visualization; Writing - original draft. **Tom Kelsey:** Funding acquisition; Project administration; Supervision; Writing - review – editing. **Carl Donovan:** Funding acquisition; Project administration; Supervision; Writing - review - editing

Conflict statement:

The authors declared no conflicts of interest.

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Data can be made available upon request. Please get in touch with the corresponding author.

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Approved by the School of Computer Science Ethics Committee for the University Teaching and Research Ethics Committee (UTREC) at the University of St Andrews.

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8. References

2018 Research on 100 Million Tweets: What It Means for Your Social Media Strategy for Twitter. (2018) Vicinitas https://www.vicinitas.io/blog/twitter-social-media-strategy-2018-research-100-million-tweets#language.

Twarc. (2023) Twarc https://twarc-project.readthedocs.io/en/latest/.

World Map: Simple. (2022) Map Chart https://www.mapchart.net/world.html.

Abouzahra, M., & Tan, J. (2021) Twitter Vs. Zika—the Role of Social Media in Epidemic Outbreaks Surveillance. *Health Policy and Technology*, vol. 10, no. 1, pp. 174-81, doi:https://doi.org/10.1016/j.hlpt.2020.10.014.

Abraham, J., Higdon, D., Nelson, J., & Ibarra, J. (2018) Cryptocurrency Price Prediction Using Tweet Volumes and Sentiment Analysis. *SMU Data Science Review*, vol. 1, no. 1, https://scholar.smu.edu/datasciencereview/vol1/iss3/1.

Altig, D., Baker, S. R., Barrero, J. M., Bloom, N., Bunn, P., Chen. S., Davis. S. J., Leather, J., Meyer. B.H., Mihaylov, E., Mizen, P., Parker, N. B., Renault .T., Smietanka, P., & Thwaites, G. (2020) Economic Uncertainty before and During the Covid-19 Pandemic. Working Paper Series, *National Bureau of Economic Research*, doi:10.3386/w27418.

Amen, S. (2020) Political Market Making: Trading Financial Markets Using Thorfinn Political Indices. Data, Foreign Exchange, General, vol. 2023, *Cuemacro*, https://www.cuemacro.com/2020/06/26/political-market-making/.

Aroussi, R. (2023) Reliably Download Historical Market Data from with Python. *Ran Aroussi* https://aroussi.com/post/python-yahoo-finance.

Association, National Sunflower (2023) *World Supply & Disappearance*. National Sunflower Association https://www.sunflowernsa.com/stats/world-supply/.

Augustop. (2019) *Portuguese Tweets for Sentiment Analysis*. Kaggle https://www.kaggle.com/datasets/augustop/portuguese-tweets-for-sentiment-analysis?select=TweetsWithTheme.csv.

Baker, S. R., Bloom, N., Davisc, S. J., & Renaultd, T. (2021) Twitter-Derived Measures of Economic Uncertainty. Twitter-based Uncertainty Indices, Economic Policy Uncertainty, May 13th, 2021, pp. 1-14. general editor, *Economic Policy Uncertainty*, https://www.policyuncertainty.com/media/Twitter_Uncertainty_5_13_2021.pdf.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of Exchange or Speculative Assets? Journal of International *Financial Markets, Institutions and Money*, vol. 54, pp. 177-89, doi:https://doi.org/10.1016/j.intfin.2017.12.004.

Beykikhoshk, A., Arandjelovic, O., Phung, D., & Venkatesh, S. (2015). Using Twitter to Learn About the Autism Community. *Social Network Analysis and Mining*, vol. 5, no. 1, doi:10.1007/s13278-015-0261-5.

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter Mood Predicts the Stock Market. *Journal of Computational Science*, vol. 2, no. 1, pp. 1-8, doi:10.1016/j.jocs.2010.12.007.

Brady, W. J., Will,s J. A., Jost, J. T., & Van Bavel, J. J. (2017). Emotion Shapes the Diffusion of Moralized Content in Social Networks. *Proceedings of the National Academy of Sciences*, vol. 114, no. 28, pp. 7313-18, doi:10.1073/pnas.1618923114.

Burns, J. C. (2024). *Automatic-GR* GitHub. https://github.com/jb370/Automatic-GR

Caldara, D., & Iacoviello, M., (2022). Measuring Geopolitical Risk. *American Economic Review*, 112(4) ,1194-225, doi:10.1257/aer.20191823.

Cambria, E. (2013). An Introduction to Concept-Level Sentiment Analysis. Advances in Soft Computing and Its Applications. *MICAI 2013*, Heidelberg, Berlin, doi:https://doi.org/10.1007/978-3-642-45111-9_41.

Cañete, J., Chaperon, G., Fuentes, R., Ho, J. H., Kang, H., & Pérez, J. (2020) BETO: Spanish BERT. *ICLR 2020*, https://github.com/dccuchile/beto?tab=readme-ov-file

CNBC. (2023). *U.S. 2 Year Treasury*. CNBC https://www.cnbc.com/quotes/US2Y.

Darkmap. (2016) *japanese_sentiment/data*, Github.com, https://github.com/Darkmap/japanese_sentiment/tree/master/data

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). Bert: Pre-Training of Deep Bidirectional Transformers for Language Understanding. *Google AI Language*. doi:10.48550/arxiv.1810.04805.

Engelberg, J., & Parsons, C. A. (2009). The Causal Impact of Media in Financial Markets. Workshop in Behavorial Finance, *Yale University*, pp. 1-44. http://www.econ.yale.edu/~shiller/behfin/2009_11/engelberg-parsons.pdf.

Gamebusterz. (2017) *xac*, French-Sentiment-Analysis-Dataset, Github.com, https://github.com/gamebusterz/French-Sentiment-Analysis-Dataset/bl ob/master/xac

Gamebusterz. (2017) *xaj,* French-Sentiment-Analysis-Dataset, Github.com, https://github.com/gamebusterz/French-Sentiment-Analysis- Dataset/blob/master/xaj

Géron, A. (2019). *Hands-on Machine Learning with Scikit-Learn and Tensorflow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly

Gilbert, E., & Karahalios, K. (2010). Widespread Worry and the Stock Market. *Proceedings of the International AAAI Conference on Web and Social Media,* vol. 4, no. 1, 2010, pp. 58-65, doi:10.1609/icwsm.v4i1.14023.

GoldHub. (2023). *Gold Spot Prices*. GoldHub https://www.gold.org/goldhub/data/gold-prices..

Goldstein, J. S. (1992). A Conflict-Cooperation Scale for Weis Events Data. *The Journal of Conflict Resolution*, vol. 36, no. 2, pp. 369-85, https://www.jstor.org/stable/174480.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica*, vol. 37, no. 3, p. 424, doi:10.2307/1912791.

Granger, C. W. J. (2003). Time Series Analysis, Cointegration, and Applications. *Nobel Prize*. https://www.nobelprize.org/uploads/2018/06/granger-lecture.pdf.

Hayes, A. (2023). *What Is Price Stickiness? Definition, Triggers, and Example*. ECONOMICS. Investopedia https://www.investopedia.com/terms/p/price_stickiness.asp#:~:text=%22Sticky%22%20is%20a%20general%20ec onomics,that%20is%20resistant%20to%20change.

Hutto, C. J. & Gilbert, E, (2014). Vader: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *International AAAI Conference on Weblogs and Social Media (ICWSM),* http://eegilbert.org/papers/icwsm14.vader.hutto.pdf.

Inoue, G., Alhafni, B., Baimukan, N., Bouamor, H., & Habash, N., (2021). The Interplay of Variant, Size, and Task Type in Arabic Pre-Trained Language Models. Proceedings of the Sixth Arabic Natural Language Processing Workshop, *Association for Computational Linguistics*, https://huggingface.co/CAMeL-Lab/bert-base-arabic-camelbert-mix-sentiment.

Investing.com. (2023a) *Germany 10-Year Bond Yield*. Investing.com https://www.investing.com/rates-bonds/germany -10-year-bond-yield-historical-data.

Investing.com. (2023b). *United States 2-Year Bond Yield*. Investing.com https://www.investing.com/rates-bonds/u.s.-2 -year-bond-yield-historical-data.

Kleinnijenhuis, J., Schultz, F., Oegema, D., & van Atteveldt, W. (2013) Financial News and Market Panics in the Age of High-Frequency Sentiment Trading Algorithms. *Journalism*, vol. 14, no. 2, pp. 271-91, doi:10.1177/1464884912468375.

Lee, S., Jang, H., Baik, Y., Park, S., & Shin, H. (2020). KR-BERT: a small-scale Korean-specific language model, *arXiv*, https://doi.org/10.48550/arXiv.2008.03979

Lhessani, S. (2023). *Python: How to Get Live Market Data (Less Than 0.1-Second Lag)* Medium https://towardsdatascience.com/python-how-to-get-live-market-data-less-than-0-1-second-lag-c85ee280ed93.

LiveCharts.co.uk. (2023) *Live Charts - Crude Oil Chart*. LiveCharts https://www.livecharts.co.uk/MarketCharts/crude.php.

Martin, L., Muller, B., Ortiz Suárez, P. J., Dupont, Y., Romary, L., de la Clergerie, É., Seddah, D., & Sagot, B. (2020). CamemBERT: a tasty french language model, *Proceedings of the 58th Annual Meeting of the Association of Computer Linguistics*, https://aclanthology.org/2020.acl-main.645/

McClelland, C. (2006). World Event/Interaction Survey (WEIS) Project, 1966-1978. *Inter-university Consortium for Political and Social Research* [distributor], doi: 10.3886/ICPSR05211.v3

Monitor, Markets. (2023) *Metals & Mining Overview.* ETF.com https://www.etf.com/topics/metals-mining.

Niu, Z., Wang, C., & Zhang, H. (2023). Forecasting stock market volatility with various geopolitical risks categories: New evidence from machine learning models. *International Review of Financial Analysis*, vol. 89, October 2023, https://doi.org/10.1016/j.irfa.2023.102738

Nofsinger, J. R, (2005). Social Mood and Financial Economics. *Journal of Behavioral Finance*, 6(3), 144-60, https://doi.org/10.1207/s15427579jpfm0603_4

Pak, A., & Paroubek, P. (2010) Twitter as a Corpus for Sentiment Analysis and Opinion Mining. Seventh International *Conference on Language Resources and Evaluation ({LREC}'10),* European Language Resources Association (ELRA), http://www.lrec-conf.org/proceedings/lrec2010/pdf/385_Paper.pdf.

Park, L. (2015) *Nsmc*. GitHub.com https://github.com/e9t/nsmc.

Pearse, B. (2021) *Human and Machine Translation: Both Alive and Kicking — and Here to Stay*. Translation & Localization Blog. Smart Cat https://www.smartcat.com/blog/human-and-machine-translation-both-alive-and-kicking-and-here-to-stay/

Pop, C., Bozdog, D., Calugaru, A., & Georgescu, M. A. (2016) *Chapter 7 - an Assessment of the Real Development Prospects of the Eu 28 Frontier Equity Markets.* Handbook of Frontier Markets, Academic Press, 2016, pp. 117-46, https://doi.org/10.1016/B978-0-12-803776-8.00007-0

Pota, M., Ventura, M., Fujita, H., & Esposito, M. (2021) Multilingual Evaluation of Pre-Processing for Bert-Based Sentiment Analysis of Tweets. *Expert Systems with Applications*, vol. 181, p. 115-119, https://doi.org/10.1016/j.eswa.2021.115119.

Prabhakaran, S. (2023) *Granger Causality Test in Python*. Machine Learning Plus https://www.machinelearningplus.com/time-series/granger-causality-test-in-python/.

Rajput, N. K., Grover, B. A., & Rathi, V. K. (2020) Word Frequency and Sentiment Analysis of Twitter Messages During Coronavirus Pandemic. *Computing Research Repository (CoRR)*, vol. abs/2004.03925, https://doi.org/10.48550/arxiv.2004.03925.

Rognone, L., Hyde, S., & Zhang, S. S. (2020) News Sentiment in the Cryptocurrency Market: An Empirical Comparison with Forex. *International Review of Financial Analysis*, vol. 69, https://doi.org/10.1016/j.irfa.2020.101462.

Smith, A. (2023) *23 Essential Twitter Statistics to Guide Your Strategy in 2023*. Sprout Blog. sproutsocial https://sproutsocial.com/insights/twitter-statistics/.

Souza, F., Nogueira, R., & Lotufo, R. (2020) BERTimbau: pretrained BERT models for Brazilian Portuguese, Intelligent Systems: *9th Brazilian Conference, BRACIS 2020*, https://dl.acm.org/doi/10.1007/978-3-030-61377-8_28

Standards, National Institute of. (2023) *Engineering Statistics Handbook: Stationarity. Process or Product Monitoring and Control*. National Institute of Standards https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc442.htm#:~:text=Stationarity%20can%20be%20defined%20in,no%20periodic%20fluctuations%20(seasonality).

Strycharz, J., Strauss, N., & Trilling, D. (2017) The Role of Media Coverage in Explaining Stock Market Fluctuations: Insights for Strategic Financial Communication. *International Journal of Strategic Communication*, vol. 12, pp. 1-19, https://doi.org/10.1080/1553118X.2017.1378220.

TASS 2020. (2020) Workshop on Semantic Analysis at Sepln 2020. *TASS 2020,* http://tass.sepln.org/2020/.

Tetlock, P. C. (2007). Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *The Journal of Finance*, vol. 62, no. 3, pp. 1139-1168, https://doi.org/10.1111/j.1540-6261.2007.01232.x

Tetlock. P. C., Saar-Tsechansky, M., & MacSkassy, S. (2008) More Than Words: Quantifying Language to Measure Firms' Fundamentals. *The Journal of Finance,* vol. 63, no. 3, pp. 1437-67, doi:10.1111/j.1540-6261.2008.01362.x.

Thurman, W., & Fisher, M. E. (1988). Chickens, Eggs, and Causality, or Which Came First? *American Journal of Agricultural Economics*, vol. 70, no. 2, pp. 237-38, https://webdoc.agsci.colostate.edu/koontz/arec-econ535/papers/thurman%20fisher%20(ajae%201988).pdf.

Tohoku-nlp (2020). *Bert-base-japanese,* Hugging Face, https://huggingface.co/tohoku-nlp/bert-base-japanese

Uhl, M. W. (2014). Reuters Sentiment and Stock Returns. *Journal of Behavioral Finance*, vol. 15, no. 4, pp. 287-98, https://doi.org/10.1080/15427560.2014.967852.

Wold, C. (2023). *Top 3 Defense Etfs (Ppa, Xar).* Investopedia https://www.investopedia.com/news/top-3-defense-etfs- ppa-xar/.

Yilmazkuday, H. (2024). Geopolitical Risk and Stock Prices. Department of Economics, *Florida International University,* Working Paper 2407, https://economics.fiu.edu/research/working-papers/2024/2407.pdf

YuJeong, S., Yun, D. Y., Hwang, C., & Moon, S. J. (2021). Korean Sentiment Analysis Using Natural Network: Based on Ikea Review Data. *International Journal of Internet, Broadcasting and Communication*, vol. 13, no. 2, pp. 173-78 https://doi.org/http://dx.doi.org/10.7236/IJIBC.2021.13.2.173.

Zach. (2023). *How to Perform a Granger-Causality Test in Python.* statology https://www.statology.org/granger-causality-test-in-python/.

Zote, J. (2025). *45+ Twitter (X) stats to know in marketing in 2025*. Sprout Blog. Sproutsocial https://sproutsocial.com/insights/twitter-statistics/

Appendix A

Table A1 below lists the financial assets and markets we analyzed for our study. The Caldara, Iacoviello, and Amen financial assets or markets come directly from their papers. Our Own assets or markets come from a few different sources. We were interested in expanding on the assets listed in the other papers (such as Gold Futures and Oil Futures), and we also wanted to look at smaller international markets or emerging markets (such as the Sensex or the USD-MXN FX Rate). In addition, we wanted to see if different cryptocurrencies outside of Bitcoin reacted differently to geopolitical events. Lastly, since our study involved the Ukraine War, we wanted to see how the Natural Gas markets and Wheat Market responded to the crisis, as both Russia and Ukraine are two of the world's largest producers of Wheat, and Russia is the primary source of Natural Gas for Europe. Table A2 is a reordering of the assets based on asset class.

Table A1. We analyzed the financial assets and markets and their sources.

Source	**Financial Asset or Market**
Caldara and Iacoviello (5)	Defense ETF, Metals and Mining ETF, Crude Oil Price, 2 Year US Treasury Yield, Steel Futures
Amen (19)	S&P 500 Index (US Stock Exchange), Morgan Stanley Capital International Index ("MSCI"), CSI 300 Index (Chinese Stock Exchange), FTSE 100 Index (UK Stock Exchange), Nikkei 225 (Japanese Stock Exchange), Bitcoin, USD vs. EUR, JPY, AUD, CNY, RUB, and ZAR FX Rates, VIX Index (Volatility Index), MSCI Futures, Bitcoin Futures, US High Yield (HY) ETF, US Investment Grade (IG) ETF, Gold Price, 10 Year US Treasury Yield
Our Own (15)	Gold Futures, Crude Oil Futures, 10 Year US Treasury Yield Futures, S&P BSE Sensex (Indian Stock Exchange), 10 Year German Bond Yields, USD vs. GBP, MXN FX Rates, EUR-GBP FX Rate, Ethereum (ETH), ChainLink (LINK), Ripple (XPR), Binance Coin (BNB), Algorand (ALGO), Wheat Futures, Natural Gas Futures

Table A2. The Financial Assets and Markets we analyzed grouped by Asset Class.

Asset Class	Asset or Market
Commodity (7)	Gold Price, Crude Oil Price, Gold Futures, Crude Oil Futures, Steel Futures, Wheat Futures, Natural Gas Futures
International Markets and Assets (5)	CSI 300, Nikkei 225, BSE Sensex, FTSE 100, 10 Year German Bond Yield
U.S. Based Markets and Assets (12)	S&P 500, MSCI, VIX, 2 Year US Treasury Yield, 10 Year US Treasury Yield, Defense ETF, Metals and Mining ETF, US HY ETF, US IG ETF, 10 Year US Treasury Yield Futures, Bitcoin Futures, MSCI Futures
Foreign Exchange Markets (9)	USD vs. EUR, JPY, GBP, AUD, MXN, ZAR, RUB, CNY, and EUR-GBP
Crypto Currencies (6)	Bitcoin, ETH, Link, XPR, BNB, ALGO

Appendix B

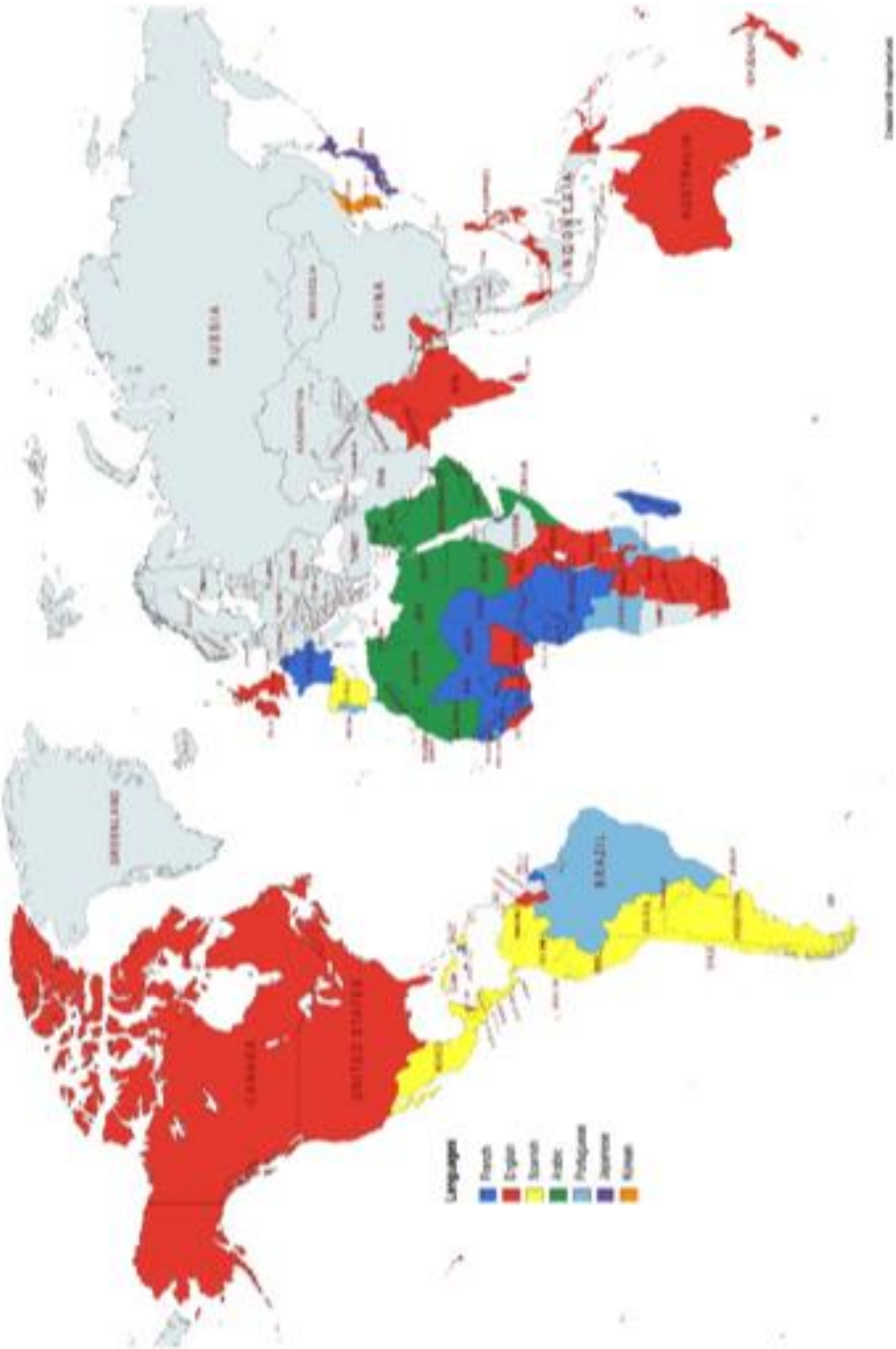

Figure B1. Map of countries that where one of the seven languages is one of the national languages used by that country. From World Map: Simple

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A digital ethnography of #BookTok content on TikTok

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Highlights:

- This research extends Schellewald's (2021) communicative forms to include unique categories within BookTok.
- This study adds theoretical insight regarding the Theory of Affordances and Uses and Gratifications Theory.
- The association between poster roles, book genres, and content categories in the subcommunity are documented.

Abstract

This research employed a mixed-methods digital ethnography to analyze BookTok, the subcommunity about books on TikTok. Grounded in the Theory of Affordances (Ronzhyn et al., 2022) and Uses and Gratifications Theory (Katz et al., 1973–1974), the study examined the frequencies of varying poster roles, book genres, and content categories in the subcommunity. More specifically, this data was first analyzed with qualitative notes. Following this, quantitative analysis was employed to determine if a connection existed between poster roles, book genres, and post type. This research added to theoretical understandings about social media while expanding TikTok research and knowledge about the wider book industry and marketplace. While making similar types of content overall, the findings demonstrated that the authors' behavior diverged from that of more general users, like readers, as readers are recommending on BookTok more than authors are promoting. This indicates that readers, outside the authors' control, are an important component of book marketing on BookTok. Posters' recommendations included memes, comedic content, accessories, etc.

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1. Introduction

TikTok is a social media app that has been popular since 2019, particularly after global Covid-19 lockdowns. Like other social media, the app allows book lovers to form a vibrant community. This community, called BookTok, is ripe for analysis in the same vein as BookTube on YouTube and Bookstagram on Instagram (Martens et al., 2022). The following research presents BookTok as a valuable online community for multiple stakeholders and social media. Similarly, a body of research still in its infancy continues to focus on TikTok in areas such as the Covid-19 pandemic and the political action of young people (Schellewald, 2021). Communication scholars and those from other fields see great potential for studying this platform (Zeng et al., 2021). There is no reason why the various industries and types of people involved with books would not also benefit from scholarly attention to TikTok.

This research uses digital ethnography to examine BookTok content. Such a methodology has been applied to TikTok, whether more generally or suited to a different niche (Schellewald, 2021; Southerton, 2021). Like other social media, TikTok also employs hashtags, which can facilitate research for ethnographic purposes (Jaramillo-Dent et al., 2022). While Martens et al. (2022) have already performed a digital ethnography on #BookTok, they examined different aspects such as a sample of book titles, English versus Danish language use, and certain BookToker profiles they pinpointed in their research. This research, however, is not concerned primarily with certain profiles, titles or language comparisons. Instead, it examines what types of content are made on BookTok, what book genres broadly are present, what roles users fulfill in this online community, and if there are connections between the aforementioned aspects. BookTok will also be a lens through which to scrutinize the broader content categories, or "communicative forms," proposed by Schellewald (2021). How do these forms apply or not to BookTok as a TikTok subcommunity?

In summation, the following research fulfills multiple purposes for both scholarly and industry audiences. On a scholarly level, it adds to a nascent body of research on TikTok. It dives into a specific community on the social media platform that is underutilized in research. Furthermore, it also aligns itself with theories of affordances and uses and gratifications. This focused look at a valuable community advances our understanding of theories surrounding digital media and TikTok in particular. Lastly, it compares the findings of other TikTok research by Schellewald (2021) and provides more material for future TikTok studies.

For industry audiences, there is even more value. By discovering and correlating the prevalence of different book genres, types of content, and roles of various users, anyone with a stake in books and/or publishing can gain a sense of what is prevalent on BookTok, which itself has commercial value as is discussed later. This usefulness may apply to writers, publishing agents, bookstore owners, book influencers, and more. Furthermore, as a snapshot of this community in time, this research preserves a piece of BookTok for anyone interested in book culture and/or social media in the early 2020s. Whether for commercial trends or personal interest analysis, this research also provides useful insight to many outside academic circles.

2. Literature Review

2.1. An Overview of TikTok Scholarship

TikTok is a huge success story in the social media ecosystem. Like other platforms such as Facebook and YouTube, its underlying corporate structure contributed to its rise. Spearheaded by the Chinese company ByteDance, TikTok emerged in 2017. By 2018, it had fully merged with Musical.ly, a platform that had garnered many teen users outside of China in the previous four years. This merger handed TikTok a premade base of users, which only exploded when Covid-19 spurred worldwide lockdowns in 2020. The pandemic helped TikTok's user base expand to all age groups as people sought ways to entertain themselves (Zeng et al., 2021). Over 100 million people regularly used TikTok by early 2021 (Peña-Fernández et al., 2022), establishing its value as a platform worthy of study.

Such a large number of users naturally piqued scholarly interest in TikTok in its early years. From 2019 to April 2021, the number of research articles about TikTok jumped from 13 to 122 (Zeng et al., 2021). Many of these articles involve health and Covid-19, as well as politics (Peña-Fernández et al., 2022; Zeng et al., 2021). Some studies focus on the creative and content-focused side, including influencers (Zeng et al., 2021) and social media challenges (Peña-Fernández et al., 2022). This research builds on Schellewald (2021), who spent six months analyzing the app and proposed many "communicative forms" (Schellewald, 2021). Interestingly, Schellewald (2021) also notes challenges on TikTok, such as doing popular dances, which fall under interactive content. The other categories include documentary, comedic, explanatory, communal, and meta content (Schellewald, 2021). These categories deserve further scrutiny in online subcultures, such as BookTok.

For the sake of brevity, interactivity typically involves challenges, duets of another's videos, or similarly interactive content. Documentary videos capture the user's mundane life experiences, such as in the workplace or shopping. Comedic content conversely presents a punchline, such as in a meme or a skit. Occasionally, these punchlines repurpose sound bites that are available on TikTok. Explanatory content, or how-to content, displays a process like a dance, baking, or some creative process. Communal content shows off friends and family in nearly any setting. This can also be blended with the aforementioned categories. Lastly, meta content references TikTok itself, such as with skits or other videos that address the algorithm (Schellewald, 2021). The results of this study will be compared to those of this framework for further validity.

TikTok research is limited but has grown rapidly in recent years (Zeng et al., 2021). Scholarly interest in it encompasses healthcare (Peña-Fernández et al., Southerton, 2021; 2022; Zeng et al., 2021), advertising (Peña-Fernández et al., 2022), influencers and online cultures (Zeng et al., 2021), and brand strategies for harnessing the platform's potential (Perreau, 2021). Crucially, Schellewald (2021) examines TikTok broadly and develops a typology of content that inspires this research. In summation, the current state of TikTok research is in its early stage, but certain trends are emerging and warrant deeper exploration.

2.2. Theoretical Foundations

The Theory of Affordances underpins the theoretical contributions of this research. Via a literature review, Ronzhyn et al. (2022) developed a working definition of affordances to apply to social media research. Before their synthesis, many researchers defined the same affordances under different terms and did not know how to structure them together. This theory also expanded into social media after it originated to conceptualize natural environments, so Ronzhyn et al. (2022) created their definition with application to social media in mind.

An affordance is some perceived quality of a platform, whether it exists or not (Ronzhyn et al., 2022). They stem from the relationship between the user and the digital environment, meaning that users can use affordances differently and that each social medium, such as TikTok, can provide unique affordances compared to other platforms. For instance, Schellewald (2021) compares Snapchat, which is used more for direct communication, to TikTok's 'For You' page. This technological difference connects users through the algorithm to the overarching TikTok ecosystem, giving the app a unique position to generate new trends. Because of this innate understanding of the differences between social media, users will act differently on each platform.

Previous research on affordances also proves the value of this research. Having covered over 200 articles in their literature review, Ronzhyn et al. (2022) do not list TikTok as a platform that has received significant study. Conversely, they identify it as one of the platforms gaining influence but still lacking research. Facebook is the most significant portion of their sample, followed by Twitter (now X). An ending recommendation is to explore those less-researched platforms. There is also speculation that platforms arise in the first place to fill a gap in affordances left empty by larger social media (Ronzhyn et al., 2022). This theory and its guidance for future social media research underpin the importance of analyzing a community like BookTok.

Users' contexts, such as their culture, affect affordances and how they are used. Primarily, these perceived qualities provide the potential of, and also hinder, action on the platform. In other words, what users perceive about a platform will affect how they choose to act or not act. Knowing this, creators will address that fact and then present how they are likely similar to the viewer. This type of content exemplifies visibility as a function of how platforms like TikTok are perceived.

Uses and Gratifications Theory also provides valuable theoretical insight. Developed by Katz et al. (1973–1974), this theory concerns the variety of roles the media fulfill for consumers, both active and passive. They also consider how much, if at all, the media generates consumer needs and how much the media satisfies consumers. People consume media for various reasons, and different people may take different gratifications away from the duplicate content. This theory attempts to balance the views of the media between a drug to pacify the general public into accepting reality as is and a force beholden to the audience to provide nothing more than escape. The media can fulfill many needs, which deserve categorization in various forms that media can take (Katz et al., 1973–1974). As summarized by Katz et al. (1973–1974), some of the original gratification typologies included entertainment, information, and connection to others and oneself. Regardless of differences in wording, these kinds of gratifications repeatedly show up.

Meservy et al. (2019) applied the theory to social media use to differentiate motives behind producing content from those behind consuming content. As Uses and Gratifications Theory explores using specific media over others, Meservy et al. (2019) wondered if people created or consumed content for different reasons. Some of the already established reasons for social media use include sharing opinions, entertaining oneself, educating oneself, and gaining social resources (Meservy et al., 2019).

Their findings provided a valuable understanding of people's behavior on social media. Younger users, for instance, more frequently want to pass time and gain social resources compared to their older counterparts (Meservy et al., 2019). Contrary to the researchers' hypothesis that entertainment, among other uses and gratifications, would align more with consumption behaviors, the entertainment motive did not differ significantly between producing and consuming content. In other words, it was a motivation for both actions (Meservy et al., 2019). Importantly for this research, sharing opinions and information most often served as motivation for producing content. Meservy et al. (2019) emphasize that creating content, unlike passive consumption, often requires users to be noticeable online in some way. A well-known creator will become recognizable in online communities. Therefore, Meservy et al. (2019) conclude that spreading information satisfies users' desires to be both visible and a contributing community member.

The two theories employed in this research complement each other by both describing the usage of media, and they both acknowledge the complexity surrounding the root causes of different uses. For example, Katz et al. (1973–1974) acknowledge that both passive and active viewers exist. They wonder how much viewers are satisfied with the media and how much it generates viewers' needs in the first place. They push back on the assumption that every piece of media can fulfill any need, instead identifying the need to "explore the social and individual conditions under which audiences find need" (Katz et al., 1973–1974, p. 521). Ultimately, they claim viewers challenge the media industry to fulfill their various needs better (Katz et al., 1973–1974). But they never solidify if the actual creation of media needs rests more in the hands of the media or the audience.

Similarly, in explaining the contextuality of affordances, Ronzhyn et al. (2022) acknowledge that the individual user with agency, the time and place they live, and the platforms themselves all contribute to how platforms are used. Sometimes, users and the platform have different visions of the medium, which can cause tension between the two groups. Affordances ultimately limit or encourage specific uses of platforms, whether a perception of them is legitimately real or imagined by users. Ronzhyn et al. (2022) have a much richer media landscape to examine than Katz et al. (1973–1974) did. For instance, TikTok and its users can disagree about the functions and perceptions of the platform in real time while on TikTok itself. Media allows much more two-way communication than in the past. Nevertheless, both theories admit or imply that usage rests on a relationship between the media and the audience. There is no clear answer yet regarding which is more powerful in generating different uses. There may never be a one-size-fits-all answer.

While social media research cannot assume a user's motivation from their content alone, patterns of the different roles of posters can be created just as patterns in the type of content can. Cross-referencing these patterns will determine if a specific type of poster typically creates a specific type of content. What role are they filling, and what content does that lead them to make? In BookTok, roles and content will be filtered through the lens of books. Many people, such as readers, authors, publishers, and more, have a stake in books. Therefore, it is worth analyzing what this community is, who is a part of it, and why they matter.

2.3. What is BookTok?

BookTok is a subcommunity on TikTok of users and influencers who make content about books and reading. The likeliest motivation behind this community is simply a passion for books, as opportunities to make money with TikTok are currently small. TikTok does not share the same economic model as YouTube for example. YouTube shares 45% of ad revenue with creators (Vallese, 2023). As of December 16, 2023, TikTok ended its Creator Fund, instead having paid creators enter the Creativity Fund. The catch is that this fund only monetizes videos over a minute long (Sternlicht, 2023). The prevailing consensus from large creators is apparent in all of these instances. The most significant sources of income are traditional, long YouTube videos and outside monetization, such as brand partnerships. Short online content is better suited to growing one's audience (Vallese, 2023). Therefore, influence and community seem to guide these creators (Martens et al., 2022). It is also noteworthy that the platform's functionality provides a different culture. Videos need not be long form, like some on YouTube, or as aesthetically curated as on Instagram (Martens et al., 2022).

BookTok also relies on the specific functionality of TikTok by including audio clips as meme types, for example. There are audios through which users might introduce themselves, such as an audio about one's unread book pile that is used in over 7,200 TikTok videos (Jerasa & Boffone, 2021). Other examples of what BookTok content entails are book reviews, recommendations, and overall trends geared towards bookish users (Jerasa & Boffone, 2021). This sense of community and sharing books ultimately helps both writers and readers. Simply discussing books in videos can lead to real consequences and tangible benefits.

2.4. Who is on BookTok?

Users are truly the heart and soul of BookTok, as is the case with many digital subcultures. One prime example of who is active on BookTok is teenagers. Many young people already use TikTok, so BookTok allows popular titles to connect with readers where they are (Jerasa & Boffone, 2021; Martens et al., 2022). Interestingly, young readers experience more choices on BookTok than in a traditional English class. It is no wonder that the Young Adult, or YA, category is so popular on the app. In the same vein of young people controlling their reading habits, it also creates opportunities for them to see themselves in books. BookTok can promote titles that feature LGBTQ+ and/or non-white stories and authors. This starkly contrasts some classrooms where certain texts are not allowed or considered academically viable (Jerasa & Boffone, 2021). In their thorough analysis of young people on BookTok, Jerasa and Boffone (2021) also conclude by encouraging teachers to embrace BookTok in whatever ways it might enhance the classroom reading experience. Martens et al. (2022) also acknowledge similar educational potential from this community. Laing (2017) provides valuable insight into the social media use of authors, the individuals who create the books. Many authors surveyed utilized Twitter and Facebook daily, listing platforms such as Goodreads and YouTube. Primarily, authors want to sell their books, connect with fans, and share their opinions. They also wish to discuss their writing and engage with fellow authors (Laing, 2017). Crucially, a sense of community among authors unintentionally developed due to efforts to reach readers (Laing, 2017). This research from 2017, however, was conducted before the already established rise of TikTok. Similar behavior from authors may be expected on BookTok.

2.5. The Commercial Value of BookTok

One of the greatest implications of this research is to demonstrate, examine, and better understand this medium to harness the commercial value of BookTok. BookTok and TikTok generally hold great commercial opportunities for the book industry, given this community's already established variety of people and content. The most pressing examples of this value come from the popular press. The *New York Times*, in an article by Harris (2022), includes Madeline Miller, author of *The Song of Achilles*, as a BookTok success story. Initially published in 2012, it sold 20,000 copies (Harris, 2022). A decade later, thanks to BookTok's marketing power, her novel reached two million sales. This extreme rise in popularity allows Miller to remain an author into the future (Harris, 2022).

Also mentioned is a deeply symbiotic relationship between BookTok and Barnes & Noble. The book retailer often showcases tables of books dedicated to popular BookTok titles. Via links and codes, BookTok also links to Barnes & Noble and vice versa (Harris, 2022). The Barnes & Noble website even has a BookTok page with titles grouped by genre and specific authors (Barnes & Noble, n.d.). Zarroli (2021) also reports for *NPR* on additional BookTok superstars. One example is Colleen Hoover, whose book, *It Ends With Us*, became a *New York Times* bestseller four years after publication (Zarroli, 2021). This was due to sudden, rapid virality on BookTok. Author Chloe Gong also debuted her bestseller, *These Violent Delights*. Despite her large audience on TikTok, however, Gong attributes success more to reader word of mouth than anything she posts (Zarroli, 2021). Needless to say, all of these occurrences in the popular press and industry chatter show anecdotal evidence of BookTok's power. It can make an author practically an overnight star regardless of how long a book's been out. Publishers currently have an early understanding of BookTok, particularly with how it can revitalize older titles.

2.6. Power of BookTok

Other scholarly evidence, such as the work of Lo (2020), also proves similar findings on the importance of platforms. This applies to multiple social media and multiple stages of publishing. For example, the Twitter hashtags #ownvoices and #DVpit make it easier for authors to showcase their diverse and/or marginalized identities, which lend real authenticity to their diverse stories. These hashtags help in the pitching process when authors want to find an agent for their books, as well as post-publication when a book deal is actually announced. The same article concedes the influence of BookTube and Bookstagram (Lo, 2020). It stands to reason that BookTok would be no different as a way for books to attain visibility in the social media landscape.

There are already tips for how brands can best engage with TikTok. These include maintaining an authentic brand presence and being adaptable when creating content. TikTok content is as much trial and error as it is deliberate. One must experiment with content while also being aware of what types of content are currently fashionable. TikTok allows brands to be flexible because it places the 'For You' page as more important than an account's followers. Brands can reach followers and unknown users. This is a key factor making TikTok unique (Perreau, 2021). Perreau (2021) lists paddlers as one type of user. Paddlers are new TikTok users of all generations who prefer to scroll endlessly and not go any deeper into the app beyond what their algorithm feeds them. These users should not be discounted because they provide such great algorithm honing for the app, doubling their time on TikTok compared to other social media and acting as a broad cohort for brands to assess the success of their content.

In terms of all social media, Nguyen et al. (2019) recommend strategies such as ensuring there are genuine reviews and content from actual users. People trust content from real readers when they buy. A social media presence should include events, promotions, and contests (Nguyen et al., 2019). These may include book signings or giveaways if you like a post and follow the author. All of this can be realistically worked into TikTok content. It has been shown, after all, that traditional and digital marketing methods work best when working with each other. This is true regardless of the size of the publisher (Beditz, 2018).

And of course, new stories should receive promotion (Nguyen et al., 2019). As BookTok has made clear it can promote older stories, that does not mean new stories should be avoided. This should be good news to authors and scholars. In this environment, research into BookTok proves valuable for authors old and new, as well as readers who will use BookTok to find information on the books and authors they like.

In summary, TikTok and the subcommunity of BookTok still have value to add to the existing literature. TikTok research has accelerated in recent years (Zeng et al., 2021), and it has more room to run. The content typology devised by Schellewald (2021) is a particular inspiration to this research. Furthermore, the Theory of Affordances (Ronzhyn et al., 2022) and Uses and Gratifications Theory (Katz et al., 1973–1974) provide ample theoretical foundations and work well in tandem to better understand how people use social media like TikTok. BookTok in particular is a fruitful environment for authors to succeed and readers to share their passions.

3. Method

3.1. Digital Ethnography

This study utilized a mixed methodology. Using a digital ethnography method, data was collected and content analyzed. Digital ethnography is the process of applying ethnographic principles to an interconnected, computerized environment (Grandinetti & Bruinsma, 2022). To do so is not new to TikTok, or even to algorithms in general, and builds on a scholarly tradition that has evolved over more than 20 years. This methodology requires authentic immersion, which oscillates between hard data such as hashtags and more subjective data such as how one's experience changes algorithmically over time (Grandinetti & Bruinsma, 2022).

Ethically, there has been debate over how private the information or content one posts online is, and different fields have different views (see Murthy, 2008). This research takes the position that social media content freely posted and freely available is fair game for researchers to analyze. Additionally, participants may be willing to share more or less depending on the media researchers use to communicate with them (Murthy, 2008). This is valuable for those who want to reach out digitally to human subjects, but this research is not concerned with that. Instead, the content made is what is most important, in addition to what that content communicates.

The method of data collection will be further explained later, but the basic approach mitigates ethical concerns. By accessing the top videos under #BookTok while not logged into TikTok, the researcher does not impose themselves onto any one creator. Rather, TikTok as a website is displaying the same BookTok for everyone to see, at least as far as the hashtag is concerned. The general public, including those with no TikTok account, could theoretically see the same pool of content. Furthermore, while digital ethnography stems from the qualitative approach (Murthy, 2008), presenting the data quantitatively and in aggregate further minimizes ethical concerns that any one creator or other individual may have. If they do not want their content to be public, the user has the freedom to alter the settings on and/or delete their content at any time, regardless of the researcher's actions.

Digital ethnography is an offshoot of ethnography, which Seaver (2017) explains in the application of ethnography to the study of algorithms. At its heart, ethnography analyzes different cultures. In a perfect world, ethnography entails immersive fieldwork that examines the norms and day-to-day operations of a particular culture (Seaver, 2017). In other worlds, one must immerse themselves in the culture in question and observe it. Seaver (2017) recommends a handful of tactics for the particular study of algorithms, but they appear to be useful tools for the overall field. Broadly speaking, they include scavenging or collecting data from a variety of types of sources, understanding what the researcher and even cultural insiders can or cannot access in the culture, and interviewing people to gain deeper insight. As Grandinetti and Bruinsma (2022) put it, ethnography requires immersion, and that may not always lend itself so easily to just objective or just subjective data.

Schellewald also recommends acknowledging the "complex and dynamic nature" of TikTok and other platforms (Schellewald, 2021, p. 1441). To avoid the personalized bias of one's algorithmic experience, focusing more on specific hashtags and less on automated content exposure, such as TikTok's 'For You' page is sometimes worthwhile. This is especially useful for exploring subcultures on an app like TikTok (Schellewald, 2021). Martens et al. (2022) began their BookTok research via #booktok, but then transitioned to specific popular users and titles, focusing on the English versus Danish languages.

This does not mean that digital research must be subjective. While Jaramillo-Dent et al. (2022) used hashtags and likes to collect a sample of TikTok content on immigration, they also used Python to perform a digital version of the snowball method. This automation gathered data, including related hashtags, audio, and more, from their predetermined sample of videos (Jaramillo-Dent et al., 2022). In this instance, subjective data and automated quantitative data combined to enrich the sample.

As authors like Schellewald (2021), Southerton (2021), and Grandinetti and Bruinsma (2022) showcase, exploring digital spaces is an experience that is never quite the same twice. The approaches to this methodology both share and differ on many aspects. BookTok as a community on TikTok is no less challenging to encompass, but such an endeavor is also incredibly worthwhile. Based on the design of previous studies examining TikTok in general, the following research questions guided the exploration of the BookTok community with the forethought that potential poster roles, book genres, and content categories would be evident in the data. The content categories were then analyzed to determine which roles, genres and types of content existed and whether there was a relationship between these variables. Pertinent research questions are as follows:

RQ1: What poster roles are most prevalent in BookTok content?

RQ2: Which genres of books are most prevalent in BookTok content?

RQ3: What overarching content categories arise from BookTok content?

RQ4: Which of the prevalent genres correspond to which of the poster roles in BookTok content?

RQ5: Which content categories correspond to which of the prevalent poster roles in BookTok content?

RQ6: Which content categories correspond to which of the prevalent genres in BookTok content?

Answers to these research questions will serve various purposes. The fundamental concerns are who posts, what kind of content they post, what kind of books they include in their content, and how these subcommunity aspects correlate.

Theoretically, BookTok is an example of consumers shaping the book industry with their content, similar to the assumption in Uses and Gratifications Theory that consumers push the media to address their needs better (Katz et al., 1973–1974). Furthermore, the Theory of Affordances (Ronzhyn et al., 2022) posits that the platform is a fundamental factor in the end product of what content is created. While this research does not compare BookTok to other online subcommunities about books (Lo, 2020), it provides a baseline of what BookTok is for future research to continue exploring it in the broader digital environment.

This research has also established BookTok's potential for impacting the book industry. By learning more about the people of this subcommunity, the genres towards which they gravitate, and the kinds of content they produce, various stakeholders in the book industry will have more information to guide business decisions and satisfy their customers.

3.2. Data Collection

Data collection and analysis was as follows. Two hundred videos were analyzed under the hashtag #BookTok. This was the same sample size as the TikTok study performed by Jaramillo-Dent et al. (2022), emulating their intentional sample of specific hashtags. Southerton (2021) used certain hashtags pertaining to her topic as well.

Kaye et al. (2021) focused on the hashtag #fyp, corresponding to the platform's 'For You' page. They additionally accessed TikTok from an internet browser rather than through the app. This does not require a login and reduces algorithm interference (Kaye et al., 2021). Schellewald (2021) also agrees that circumventing algorithms, such as researching via hashtags, is beneficial and even guides research themes. With these methods established, an analysis of the first 200 videos under #BookTok, which were not logged into TikTok, presented the best data sample for these research questions. This analysis concerned who makes the content, what type of content is made, and how it relates to book genres. When analyzing the first 200 videos under #BookTok, a spreadsheet was used to document relevant information about each video. Each video entry omitted the user's username; instead, the entries numbered 1–200. For each one, the role(s) of the user and genre(s) present were documented by the researcher. The date of posting for all videos was marked as well. Each video also had a section on the spreadsheet for research notes. Schellewald (2021) emphasized the importance of a spreadsheet and notes for each piece of content examined.

The first step was to content analyze the notes to identify repeating themes for category creation. This method reflects Schellewald's (2021) recommendation for determining whether there is enough information to create categories. In continuing this line of research, #BookTok illuminated new categories of content unique to that subculture. Categories developed from this sample were also compared and contrasted with the communicative forms created by Schellewald (2021).

The first video under # BookTok was always the starting point for every data collection session. Every video was reviewed, skipping those that had already been collected, until 200 videos were analyzed. Videos not in English were skipped and omitted from the sample, except for certain videos where the language did not impede the meaning of the content.

Data were collected over several weeks in May 2023, which was advantageous as it aligned with summer reading. Summer reading is a critical phenomenon for the industry, likely due to the excess free time many people enjoy (DeMarco, 2022). The book industry has capitalized on summer consumption since the 19th century. This trend persisted even through World War I, followed by an explosion of paperbacks in the 1930s and the introduction of the Kindle in the late 2000s. In 2020, the hit of the summer by Emily Henry was titled *Beach Read* (DeMarco, 2022). Both distant and recent historical trends indicate that summer reading is here to stay. Thus, May was an ideal month to examine this online book community on TikTok. Over several weeks, data were collected explicitly during sessions on Tuesdays and Fridays at 10:00 AM. This timing corresponded with some of the best posting times on TikTok, especially on Fridays, to capitalize on potential engagement changes (P.T., 2023). Each session included 25 posts to create a manageable workload and to analyze all 200 posts from May.

4. Results

The first element of the findings concerns the frequency of the different variables. These include the year the content was posted, the poster's role, the prominent book genre identified, and the content category. By measuring the frequency of these items, it becomes apparent what is most common in BookTok content. Calculating frequencies also allows for the crosstabulation of different variables, which can illustrate other important insights. To ensure the data's recency, the year of the posting was logged. Of the 200 videos in the sample, 47 (23.4%) were posted in 2023, 84 (41.8%) were posted in 2022, 65 (32.3%) were posted in 2021, and 4 (2.0%) were posted in 2020. Based on this, the bulk of the sample came from 2021 through May 2023, with most videos being from 2022. This information is important as it documents current practices.

RQ1 evaluated the occurrence and prevalence of poster roles. Poster roles concern the role, or the primary identifying purpose, of the user who posts the content. In other words, the role of a poster is what the user portrays themselves as. These may include authors, readers, libraries, and more in the world of books. In analyzing the 200 videos, five poster roles were established. Of these, 83 (41.3%) of the posters were creators. This poster role is a generic catch-all for someone who does not present themselves in a certain capacity, profession, skill, or persona. Another 71 (35.3%) of poster roles were readers, 21 (10.4%) were authors, and 17 (8.5%) were crafters or artists. This is every type of poster role with more than 10 occurrences. The other poster roles include bookstores, libraries, and other book platforms, one for teachers, and one for videos in which multiple people and/or roles were present. These roles encompassed 5 (2.5%), 1 (0.5%), and 2 (1.0%) videos, respectively. These results represent a broad representation of roles.

RQ 2 evaluated which genre of books was posted. The categories encompass recognizable genres such as romance, fantasy, and poetry, while also including less intuitive ones. One is a category for books in general, which does not deal with specific genres of books, but rather videos concerning books as a more abstract concept. There are also videos containing books with multiple genres and content, where one cannot correctly tell the genre from the video. This constitutes another category of genre. Lastly, there is a category for N/A, which is not applicable. Videos marked as this do not relate to books in any way. One example is a video in which a violinist takes a pop song and reimagines it to fit in a movie soundtrack. Of the 200 videos, 42 (20.9%) were about books in general, 39 (19.4%) were N/A, 36 (17.9%) were romance, and 24 (11.9%) were fantasy. These are the genres that comprised more than 10% of the sample.

The rest of the genres have 10 videos or less in the sample. Erotica/smut and videos with multiple and/or indistinguishable genres have 10 occurrences at 5.0%. Poetry has 7 (3.5%), and picture books and autobiography/memoir have 6 (3.0%). Self-help books comprise 4 videos (2.0%) and historical objects. Historical objects are books which, regardless of subject matter, are treated as artifacts or rare pieces from history. Science fiction appears 2 times (1.0%). Manga, thrillers, environmental fiction, non-fiction, and horror all have just 1 video each (0.5%). Environmental fiction is one case in which the most fitting genre was pulled from the Wikipedia page of the book itself ("The Overstory," 2023). Another case used the Amazon page of a book better to determine its genre (Amazon, 2022). Again, the results indicate a wide representation of interests by individuals posting in BookTok.

The frequency of different content categories was measured to answer RQ3. These include some categories that align well with those proposed by Schellewald (2021) and new categories that emerged seemingly uniquely on BookTok. Of the 200 videos in the sample, 39 (19.4%) were comedic, 38 (18.9%) were under recommendation, 32 (15.9%) were for promotion, and 31 (15.4%) comprised accessories, such as bookmarks, bookshelves, and other physical items meant to enhance one's experience with books. Another 21 videos (10.4%) were documentary, 13 (6.5%) were edits/aesthetics, and 10 (5.0%) were communal. The rest of the content categories had fewer than 10 occurrences each. These were educational with 8 (4.0%), challenge videos with 5 (2.5%), and meta videos with 3 (1.5%). As was demonstrated with poster roles and book genres, within the content roles, or types of content posted, there was not one overwhelming type of content. While many of the categories in Schellewald's (2021) typology appeared, this examination identified additional categories that may be specific to BookTok and include accessories and educational content. While educational may be related to explanatory, they are not how-to explanations. The role of the accessories category presents the ability of the poster to present the artistry and interpretation of the subject matter.

Based on the three categories posited in the research questions, crosstabulations were run to examine if potentially insightful relationships existed between variables. Three crosstabulations were performed. These are poster role and genre, poster role and content category, and genre and content category.

The crosstabulation of poster role and genre examines how many users of each type posted about various genres (see Table 1). This addresses RQ4. When a specific type of user frequently posts about a particular genre, an association emerges between these two variables. For example, readers as a group often post about romance and books in general, with 20 instances each. Creators, categorized as a general catch-all poster role, exhibited the highest crosstabulation with N/A at 38 instances in the sample. In other words, these are posters with no defined role who post videos on BookTok unrelated to books. Readers also contributed 9 posts in fantasy and 7 posts in erotica/smut. Creators had 7 posts in romance and 8 in fantasy, as well as 5 posts for picture books. In addition, the role of crafter/artist accounted for 7 posts, while creators had 12 related to books in general. The results of this crosstabulation were significant, χ^2 (96, N = 195) = 212, p = .001.

Table 1. Frequencies and percentages for book genres present for each poster role on BookTok

	Poster Role *n* (%)					
Genre	**Reader**	**Author**	**Crafter/ Artist**	**Creator**	**Others ***	**Total**
Romance	20 (55)	5 (14)	4 (11)	7 (19)	0	36
Fantasy	9 (37)	1	4 (16)	8 (32)	2	24
Multiple/unable to tell	6 (60)	1(10)	0	0	3 (30)	10
Nothing to do with books	0	0	1 (3)	38 (97)	0	39
Erotica/smut	7 (70)	2 (20)	0	1 (10)	0	10
Books in general	20 (48)	2	7 (16)	12 (29)	1	42
All others **	6 (18)	10 (29)	1	15 (44)	2	34
Total	68	21	17	81	8	195

* Poster role others: bookstore/library/platform, multiple people/roles, teacher

** Genre all others: Manga, thriller, historical object, not related to books, environmental fiction, picture book, nonfiction, autobiography/memoir, self-help science fiction

Table 2 presents the results for RQ5 about the relationship between poster roles and content categories. This refers to the types of content posted by each type of user. Readers, for instance, largely made posts that were recommendations (30 posts), comedic (19 posts), and in the accessories category (10 posts). Authors' posts were mainly promotional, comprising 17 of the 21 total posts attributed to them. As the name implies, the role of crafter/artist correlated strongly with the accessories category, which comprised 16 of the 17 posts under that poster role. Creators as a poster role had one of the larger spreads of content categories. For example, the poster role of creators had 18 comedic posts, 12 documentary posts, 11 posts under edits/aesthetics, and 10 promotional posts. The full results for the crosstabulation of poster role and content category are presented in Table 2. The results of this crosstabulation were significant, χ^2 (54, N = 200) = 253, p = .001.

Table 2. Frequencies and percentages for content categories present for each poster role on BookTok

	Poster Role *n* (%)					
Content Category	**Reader**	**Author**	**Crafter/ Artist**	**Creator**	**Others***	**Total**
Recommendation	30 (79)	0	0	7 (18)	1	38
Comedic	19 (48)	2	0	18 (46)	0	39
Promotion	1	17 (53)	1	10 (31)	3 (9)	32
Accessories	10 (32)	0	16 (52)	5 (16)	0	31
Documentary	7 (33)	1	0	12 (57)	1	21
Communal	1 (10)	1 (10)	0	8 (80)	0	10
Edits/aesthetics	2 (15)	0	0	11 (85)	0	13
Others**	1	0	0	12 (75)	3 (19)	16
Total	71	21	17	83	8	200

* Poster role others: bookstore/library/platform, multiple people/roles, teacher ** Content category others: challenge, educational

The final crosstabulation is for genre correlated to content category. In other words, what kinds of content on TikTok does each book genre inhabit? These results in full in Table 3, which answers RQ6 about the relationship between book genres and content categories. The largest book genre present was books in general, with 42 posts. Of these, the major content categories present included 14 posts for accessories, 12 comedic posts, and 10 documentary posts. The category of N/A had 39 total posts. That genre, or lack thereof, was mainly filled with comedic content (10 posts), communal content (7 posts), and edits/aesthetics (6 posts). The romance genre follows with 36 total posts, which are largely recommendations (13 posts), promotion (7 posts), and accessories (6 posts). The major content categories surrounding fantasy are accessories, with eight posts and four posts each that are recommendations and comedic. Five of the category's 10 posts were recommendations for posts with multiple genres or unidentifiable books. This was the same for erotica/smut with five being recommendations, three being comedic, and two being promotional. The results of this crosstabulation were significant, χ^2 (144, N = 195) = 283, p = .001.

Table 3. Frequencies and percentages for content categories present for each book genre on BookTok

Genre	**Rec**	**Com**	**Promo**	**Acces**	**Doc**	**CML**	**EA**	**Oth***	**Total**
Romance	13 (36)	5 (14)	7 (19)	6 (16)	3 (8)	0	2	0	36
Fantasy	4 (16)	4 (16)	2 (8)	8 (32)	2 (8)	1	3 (6)	0	24
Multiple/un-able to tell	5 (50)	1 (10)	2 (20)	0	1 (10)	0	0	1 (10)	10
Nothing to do with books	0	10 (26)	4 (19)	1	5 (20)	7 (18)	6 (15)	6 (15)	39
Erotica/smut	5 (50)	3 (30)	2 (20)	0	0	0	0	0	10
Books in general	0	12 (29)	1	14 (33)	10 (24)	1	1	3 (7)	42
Others**	11 (32)	2 (5)	12 (35)	1	0	1	1	6 (1)	34
Total	38	37	30	30	21	10	13	16	195

* Content Categories: Rec – Recommendation; Com - Comedic; Promo - Promotion; Acces - Accessories; Doc - Documentary; CML - Communal; EA = Edits/Aesthetics; Oth = Others that includes challenge or educational.
**Genre others - Manga; thriller, historical object, not applicable/not book related, environmental fiction, picture book, nonfiction, autobiography/memoir, self-help, science fiction, and horror.

5. Discussion

This research employed a mixed-methods digital ethnography to analyze BookTok, the subcommunity about books on TikTok. Grounded in the Theory of Affordances (Ronzhyn et al., 2022) and Uses and Gratifications Theory (Katz et al., 1973–1974), the study examined the frequencies of varying poster roles, book genres, and content categories in the subcommunity, as well as associations between all of those variables. In doing so, this research added to theoretical understandings about social media while also expanding TikTok research and knowledge about the wider book industry and marketplace. Methodologically, this research developed categories to describe BookTok content based on qualitative notes taken during data collection and quantified those categories in order to generate useful insights about the subcommunity.

Findings from this exploratory evaluation of BookTok content proved very interesting. While making similar types of content overall, authors' behavior diverged from that of more general users like readers. For example, there is a difference between content that recommends a book and content made by an author that promotes their book. Both of these exist, and both put certain books in a good light, albeit under different motives. Recommendations and promotional content were judged as separate categories for this reason.

The poster role and content category crosstabulation digs deeper into this. For instance, readers made recommendation content in 30 instances whereas promotional content made by authors only occurred 17 times in the sample. This means that readers are recommending on BookTok more than authors are promoting. How these findings should be interpreted depends on someone's BookTok goals, which ties into both theoretical approaches applied to this study. Recommendations by readers, making up 30 videos out of 200, comprise 15% of the sample alone. This speaks to the power of readers' digital word of mouth. Authors, on the other hand, may find this discovery disheartening. While authors' promotional content is prevalent, readers' recommendations are nearly double. This insinuates that much of the heavy lifting of book marketing on BookTok is done by readers who exist outside of the authors' control. However, this is likely a benefit to book consumers who can learn about potential reads directly from other readers. In other words, readers enjoy digital word of mouth amongst each other on this platform. Nevertheless, an author who wants to make an account to promote their books will find the impact of their content to be less fruitful than readers' organic opinions, which they cannot control.

Memes and comedic content provide an interesting counterexample. Both authors and readers make comedic content, commiserating and poking fun at different parts of the two lifestyles. For example, there is one video in which a reader uses an audio clip as a kind of meme punchline, lip syncing to it to make a joke about being unable to decide what to read. There is another video in which the user is driving a car and, via text on screen, implies that they cannot think of a good character name. This identifies them as likely a writer. The punchline of the joke is when the user is revealed to be driving through a cemetery. Both of these examples are comedic content, made by people with different roles in the BookTok community. However, whereas recommendations and promotional content should be separated categories because of different end goals, both memes by writers and readers can remain under the comedic category together. They both serve the same purpose. This finding aligns well with the comedic communicative form proposed by Schellewald (2021). Just as comedy is popular on TikTok in general (Schellewald, 2021), BookTok adopts this broad category for its own purposes and the interests of the subcommunity's members. That interest is, of course, books. There is also comedic content where the role of the user is just as a creator, not necessarily a reader or an author. One comedic video showed the user acting as different characters from *Twilight*. This could appeal to people whether they were familiar with the books, movies, or both. Regardless, all of these videos exist to be comedic. It should be noted, however, that readers and creators in general create the most comedic content with 19 and 18 posts, respectively.

Another prominent content category is accessories. These are videos not related to specific books or genres, but they showcase objects that all readers could use. Examples include special bookshelves, a thumb saver to help readers better hold pages, and one user making bookmarks. These are useful items that enhance the reading experience, whether they are bought or handmade. Accessories is a category also related to art, not entirely for the sake of usefulness. These videos had users assigned roles like artist or crafter. A prominent example of this is called a book nook. Book nooks are little dioramas about the size of a book. They can be made out of containers opened on one side and filled with painted and glued household objects, as well as small store bought objects. They create homemade scenes to fit in with books on a person's bookshelf, and can be made for the user themselves or as a gift for someone else. Accessories as a category can encompass both useful objects and arts and crafts. Not only does this category fill a unique niche in the subculture of BookTok, but it can also tie into the communal communicative form from Schellewald (2021). This applies when objects are given to or made for a loved one, as some in the sample are. In this case, it is both an offshoot of broader content on TikTok and a unique form of expression for BookTok. In this content category, most of the instances came from crafters/artists (16 posts) and readers (10 posts). Crafters and artists may show accessories they create whereas readers may show accessories they use.

Another new type of content is aesthetics. Aesthetics may be code for the general feel or tone of something. This correlates heavily to how genres are conceptualized. There are certain images and colors that come to mind with gothic horror as opposed to Victorian romance or science fiction, for example. These aesthetic videos invite the user in, much like the challenges category from Schellewald (2021) as a kind of game amongst the community. They often involve different images and color palettes in quick succession. Examples include which feminine archetype the viewer would be, which tragic plot each zodiac sign would have, or even other general aesthetic type settings attributed to certain zodiac signs. Another example that blends with art is a user who did elaborate makeup and cosplay to show which zodiac signs would be which districts from *The Hunger Games*. It is clear that zodiac signs are often connected to this based on the sample. Most edits/aesthetics were made by creators, and they most often appeared in the N/A genre. In other words, most of these kinds of posts did not correlate to any specific genre of books or even books in general.

There were also findings that defied expectations and even planned methods of data collection. Under #BookTok, many videos were about books, reading, or writing, but did not relate concretely to any single book or genre. Nevertheless, other videos in the sample were unrelated to books in any way, even tangentially. Many videos also challenged the presumed clear distinction between videos in English versus videos in other languages. In other words, it was assumed by the researcher that the language of a post always impeded the ability of an English speaker to understand it, but this was not the case. Language was not a barrier to understanding, especially for posts classified as N/A. These videos are not about books at all and may form an invasive category, and many of them blur the lines of language. For example, there were multiple videos in which a group of young men would go down a water ride, playing a song not in English and enjoying a summery, party atmosphere. In these videos, they were only lip-syncing, at most, to a song that was not in English. They were not saying anything. They remained in the sample because the overall essence of their video was not tied to knowledge of a different language.

Nevertheless, these videos had nothing to do with books at all. There were similar videos following the mishaps of an amusement park mascot, dressed as a giant frog, with a children's song in another language over the video. Again, language proved irrelevant to understanding the comedic scenarios of the video, but it still had nothing to do with books. Videos such as these are intriguing in the sample because there are enough to warrant their inclusion, but nothing about them relates to books. It could be speculated that the users posting them might use the BookTok hashtag simply to gain more views. While there is nothing intrinsically wrong with these videos, their presence in BookTok should alert users and researchers. These videos use hashtags that do not logically connect to them. After books in general, with 42 posts, N/A was the second largest genre in the sample with 39 posts. If nearly 20% of posts in the sample have no association with books at all, what does this say about BookTok, and why do people feel the need to attach unrelated content to BookTok? These are valid questions under this popular hashtag and potentially others. Nevertheless, there was plenty of relevant content as well. Romance and fantasy were prevalent book genres in the community, comprising 36 and 24 posts, respectively. Readers led the charge in both of these book genres. Creators also had many posts relating to them, while crafters/artists made an even number of posts for each. Most posts about romance books were recommendations, while most about fantasy were for accessories.

Holistically, the groups of content identified by Schellewald (2021) were documentary, comedic, explanatory, communal, meta, and interactive. Documentary and comedic content was prevalent on BookTok and aligned with those findings. Communal and educational content were also reasonably common and could be easily translated into explanatory content. Meta content was very uncommon. As for interactive content, there were not many challenges. However, edits/aesthetics emerged as a new phenomenon that did involve elements of interactivity. Recommendations, promotions, and accessories all appeared as new, prominent categories seemingly unique to BookTok. As a whole, the findings of Schellewald (2021) were supported only in part and expanded. What this means pragmatically for BookTok is that it is both a byproduct of TikTok more broadly and a unique subcommunity with its content styles. This supports the theoretical concept of affordances (Ronzhyn et al., 2022) because BookTok is using what is available on TikTok as a whole and repurposing how they communicate (see Schellewald, 2021) to help their own subcommunity flourish and develop a unique identity. In essence, BookTok is not simply a carbon copy of TikTok in general but rather an expansion upon it.

In addition to expanding on similar research, this study added theoretical insight with regards to affordances and Uses and Gratifications Theory. As aforementioned, affordances are the believed attributes of social media platforms, whether real or not, that encourage and restrict certain user behaviors (Ronzhyn et al., 2022). One conclusive affordance identified by Ronzhyn et al. (2022) is visibility. Research on BookTok supported the existence and use of this affordance. For example, almost 20% of the sample fell under the N/A genre, meaning that such content was not related to books at all. One example included videos of young men surfing a water ride and lip-syncing to music. Another example was funny content about a pair of amusement park frog mascots. These videos had nothing to do with books, but were present under the #BookTok hashtag. This seems to be a tool to achieve visibility. By using and essentially hijacking the popular hashtag, unrelated videos have a greater chance of gaining more views and engagement. The fact that they appeared in this sample speaks to the approach's success. Therefore, the visibility affordance could achieve disingenuous ends when users hijack popular hashtags with unrelated content. This is this study's most important addition to affordances research due to the high frequency of content deemed not applicable to the hashtag.

Content that strongly applies to BookTok fits the visibility and persistence affordances. Visibility, as mentioned before, means that someone will see the content, and persistence means that content can be saved and accessed again over time (Ronzhyn et al., 2022). BookTok content, as well as all TikTok content, applies to these affordances. Unless the user deletes content or specifies certain privacy settings, individual posts can be seen and found again. Many different posters would want to utilize these affordances. Readers post a lot of book recommendations (30 posts), authors post many promotions (17 posts), and crafters and artists create many posts under accessories (16 posts). These are all instances in which someone is showing off their work or expressing some kind of opinion. Whether having just read a book, written a book, or created something, posters will want users to interact with this content even after the hour or day it was posted. Certain content, especially if the poster is trying to push some product or opinion, is evergreen. Even when users make comedic content like memes, such as readers and creators often did in the sample, these jokes will not typically cease being funny the next day. Users will want other users to see their content and find it again if they so wish because the online community increasingly thrives with more engagement.

BookTok research also provided valuable insight for Uses and Gratifications Theory. Many of the different content categories fulfill uses and gratifications laid out by Meservy et al. (2019). Comedic content such as memes provides entertainment and relaxation. Most of the comedic content came from readers (19 posts) and creators (18 posts). Book recommendations lead to social interaction, sharing and seeking information, opinion expression, and overall utility of the platform. This was a huge portion of the sample of 200 posts because 30 posts were book recommendations by readers. Putting this into the broader findings, of the 71 readers in the sample, 49 of them either posted comedic content or book recommendations. Therefore, the uses and gratifications that can be associated with these two content categories are especially prominent.

Another example is authors who made up 10.4% of posters. Authors promoting their work fulfills the gratification of social capital, and there were 17 such posts in the sample. There are many other examples such as people who make art and crafts like book nooks. Of the 17 crafters/artists, 16 of their posts fell under accessories, which encompasses such art. Someone who wants to make their own would find a video about one useful. The creator making one for someone special also leads to social interaction. If someone makes an aesthetic video such as different aesthetics for different zodiac signs, that is entertainment as well as the creator expressing themselves. Most of these posts (11 out of the total 13) were made by creators, the most common poster role in the sample. In summation, many different types of content on BookTok meet all of these uses and gratifications as listed by Meservy et al. (2019). Due to the high frequency of certain poster roles and the clear relationship of certain roles with certain content categories, many uses and gratifications of certain kinds of content can be inferred with strong support.

Even failed hypotheses are supported by BookTok. Meservy et al. (2019) hypothesized that entertainment would be a gratification of consumption, but found that it did not differ from gratifications of producing content. The crafter role and accessories content category, which help answer RQ1 and RQ3 respectively, support this. While the exact motivations cannot be gleaned without surveying users and creators, basic assumptions can be made from the content itself. If a creator makes a piece of art, a book nook, or something like a custom bookmark, it is likely just as entertaining for the person to regularly make these crafts and share them online as it is for the person who watches their artistic content. This would be even more likely if a craft appeared in the content sample more than once as was the case with book nooks. In other words, observing BookTok supported not just established theoretical concepts, but also aligned with the finding of Meservy et al. (2019) that entertainment does not differ whether one is consuming or producing content. BookTok provides further support that the original hypothesis by Meservy et al. (2019) was incorrect.

This examination of BookTok also adds to the possibility of combining the Theory of Affordances (Ronzhyn et al., 2022) and Uses and Gratifications Theory (Katz et al., 1973–1974). It is worth restating that the two perspectives agree in two major ways. People use media in a variety of ways, and that usage rests on a relationship between the user and the medium. BookTok clearly encompasses a wide variety of uses. This research identified seven poster roles and ten content categories, and the relationship between them was significant according to the Chi Square results. The intersection of the two theories is clearest in the most prominent content categories for the reader, author, and crafter/artist poster roles. Readers make primarily recommendation content, authors make primarily promotional content, and crafters/artists make primarily accessories content. These are direct examples of different poster roles fulfilling uses that clearly fit their roles' functions. Readers should want to share their opinions on what they read, authors should want to promote their work, and crafters/artists should want to make things. The fact that none of these results are surprising proves that people are using BookTok to fulfill expected uses and gratifications.

This also ties into affordances, primarily the visibility affordance (Ronzhyn et al., 2022). As aforementioned in this study, readers, authors, and crafters/artists will want users to interact with their book recommendations, written work, or arts and crafts, respectively. These three poster roles in particular post on BookTok knowing that they will be visible. This also ties into the previously mentioned persistence affordance because posts will be able to be saved and seen multiple times (Ronzhyn et al., 2022). This is what a user such as an author would ideally want because someone can engage with their book even if they posted about it days or weeks ago. But crucially, they rely on users and the medium working interconnectedly.

Users could come across posts in a variety of ways, such as searching TikTok manually or surrendering to the algorithmic 'For You' page. These methods of discovery could work in tandem. For example, readers and authors posted 19 and two comedic posts, respectively. Perhaps a user comes across a meme by one of these creators and decides to visit their profile to watch more of their content. Maybe they like a number of posts, leading to greater visibility for a reader's book recommendation or an author's promotional content. As both theoretical perspectives indicate, success relies on the varying gratifications of the user and the relationship between the user and the medium. If both of these align, a user will find and interact with content they enjoy, creating a positive experience for both the person who watched the content and the poster of the content who received engagement. In this way, the two perspectives can work together not just in theory, but in concrete positive social media engagement. BookTok content supporting this with concrete, significant results is good for both social media theorists and users.

5.1. Limitations and Future Research

Despite the usefulness of this research, there are still limitations to take into account. Even though the sample covers multiple years, all of the data collection was done in May. The sample also only includes the first posts under the BookTok hashtag. This means only a snapshot of the BookTok community was utilized. To combat this limitation, future research should employ a longitudinal study of the community's content. Other research may also opt for a larger sample size of posts.

Another limitation of this study is the use of the BookTok hashtag itself. While the hashtag provides a great filter for a massive amount of content on TikTok, as well as limiting algorithmic bias in data collection, this tactic also excludes any posts about books on TikTok that do not use the BookTok hashtag. The hashtag also included a substantial number of posts unrelated to books or reading. Future research may use different methods to gather book content outside of certain hashtags, such as the incorporation of certain users by Martens et al. (2022).

Furthermore, these data were collected from the United States, and the bulk of the sample is in English, albeit with a few more ambiguous exceptions. Future research on BookTok should occur outside of the United States and be completed in other languages. Not only would this provide a greater understanding of the global use of BookTok, but it would also add insight into the global book community as a whole. For example, certain parts of the world may value or prioritize certain kinds of content or certain book genres more than others. A more global body of research can determine the extent of hegemony in digital book spaces.

In terms of overall value, this research has shed a light on an important community on TikTok, in addition to online book spaces. Further research should be done to better understand BookTok in other ways. One possibility is to examine BookTok through interviews with many users as Guiñez-Cabrera and Mansilla-Obando (2022) did. This could be expanded to other languages and regions of the world. Researchers may also analyze the subcommunity's prevalence of different races, genders, or economic classes. One could even analyze the average age and popularity of certain prominent books. Do older or newer books have an advantage or disadvantage towards gaining popularity? These are just some ways future research can add to the collective understanding of BookTok.

Other TikTok communities in different niches will also benefit from research directed at them. For example, do music creators on TikTok promote or recommend songs like BookTok does with books? The same question could be posed for television and film creators or other arts. There is virtually no limit to the amount of subcommunities and interests that can populate this social medium. A broader understanding of TikTok must be specified to the platform's varying niches.

This can be accomplished through digital ethnography or other research methods such as interviews. In some ways, are the arts presented differently on TikTok than posts about science, education, or other fields and industries? Do certain fields share content categories with some subcommunities, but not others? With enough research on TikTok subcommunities, could a family tree of content be generated, tying different niche content closely or distantly to each other? Specified analyses of certain profiles are a great way to examine this. BookTok creators, for example, may post content frequently about other art forms. Research must see in which communities' individuals post by examining single accounts holistically.

Statement of Researchers

Researchers' contribution rate statement:
Both authors conceptualized the study. The first author collected the data and wrote the preliminary draft. The second author analyzed the data and contributed to the final version of the manuscript.
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This study was exempt from human subjects.
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6. References

Amazon. (2022, February 28). Product details for A Million Kisses in Your Lifetime (Lancaster Prep) by Monica Murphy. https://www.amazon.com/Million-Kisses-Your-Lifetime/dp/B09TMT5W26

Barnes & Noble. (n.d.). BookTok. Barnes & Noble. https://www.barnesandnoble.com/b/booktok/_/N-2vdn

Beditz, M. (2018). The dynamic landscape of marketing children's books: Publishers find consistent success through a combination of online and traditional marketing to adults and children. Publishing Research Quarterly, 34(2), 157–169. https://doi.org/10.1007/s12109-018-9584-1

DeMarco, N. (2022, August 30). The state of the beach read. Book Riot. https://bookriot.com/history-of-the-beach-read/#:~:text=About%20half%20of%20us%20 read,time%20and%20brain%20space%20available.

Grandinetti, J., & Bruinsma, J. (2022). The affective algorithms of conspiracy TikTok. Journal of Broadcasting & Electronic Media, pp. 1–20. https://doi.org/10.1080/08838151.2022.2140806

Harris, E.A. (2022, July 6). How TikTok became a best-seller machine. The New York Times. https://www.nytimes.com/2022/07/01/books/tiktok-books-booktok.html

Jaramillo-Dent, D., Alencar, A., & Asadchy, Y. (2022). #Migrantes on TikTok: Exploring platformed belongings. International Journal of Communication, 16, 5578–5602. https://ijoc.org/index.php/ijoc/article/view/17435

Jerasa, S., & Boffone, T. (2021). BookTok 101: TikTok, digital literacies, and out-of-school reading practices. *Journal of Adolescent & Adult Literacy, 65*(3), 219–226. https://doi.org/10.1002/jaal.1199

Katz, E., Blumler, J. G., & Gurevitch, M. (1973–1974). Uses and gratifications research. *Public Opinion Quarterly, 37*(4), 509–523. https://doi.org/10.1086/268109

Kaye, D. B. V., Rodriguez, A., Langton, K., & Wikström, P. (2021). You made this? I made this: Practices of authorship and (mis)attribution on TikTok. International Journal of Communication, 15, 3195–3215. https://ijoc.org/index.php/ijoc/article/view/14544

Laing, A. (2017). Authors using social media: Layers of identity and the online author community. *Publishing Research Quarterly, 33*(3), 254–267. https://doi.org/10.1007/s12109-017-9524-5

Lo, E. Y. (2020). How social media, movies, and TV shows interacts with young adult literature from 2015 to 2019. *Publishing Research Quarterly, 36*(4), 611–618. https://doi.org/10.1007/s12109-020-09756-8

Martens, M., Balling, G., & Higgason, K.A. (2022). #BookTokMadeMeReadIt: Young adult reading communities across an international, sociotechnical landscape. *Information and Learning Sciences, 123*(11–12), 705–722. https://doi.org/10.1108/ILS-07-2022-0086

Meservy, T.O., Fadel, K. J., Nelson, B., & Matthews, M. (2019). Production vs. consumption on social media: A Uses and Gratifications perspective [Conference paper]. Twenty-fifth Americas Conference on Information Systems, Cancun.

Murthy, D. (2008). Digital ethnography: An examination of the use of new technologies for social research. *Sociology, 42*(5), 837–855. https://doi.org/10.1177/0038038508094565

Nguyen, H.V., Huy, L.V., Nguyen, T.N., Dinh, V.S., & Tran, V.T. (2019). The role of social media in the purchase of books: Empirical evidence from Vietnam's publishing industry. *Publishing Research Quarterly, 35*(4), 704–709. https://doi.org/10.1007/s12109-019-09682-4

Peña-Fernández, S., Larrondo-Ureta, A., & Morales-i-Gras, J. (2022). Current affairs on TikTok. Virality and entertainment for digital natives. *El Profesional de La Información, 31*(1), 1–12. https://doi.org/10.3145/epi.2022.ene.06

Perreau, A. (2021). Brands on TikTok: Strategic first steps and successful execution. *Journal of Brand Strategy, 10*(3), 221–233. https://www.henrystewartpublications.com/sites/default/files/JBS10.3BrandsonTikTokStrategicfirststepsandsuccessfulexecution.pdf

P.T, A. (2023, October 5). What is the best time to post on TikTok in 2023? SocialPilot. https://www.socialpilot.co/blog/best-time-to-post-on-tiktok

Ronzhyn, A., Cardenal, A.S., & Batlle Rubio, A. (2022). Defining affordances in social media research: A literature review. *Social Media + Society, 25*(11), 3165–3188. https://doi.org/10.1177/14614448221135187

Schellewald, A. (2021). Communicative forms on TikTok: Perspectives From digital ethnography. International Journal of Communication, 15, 1437–1457. https://ijoc.org/index.php/ijoc/article/view/16414

Seaver, N. (2017). Algorithms as culture: Some tactics for the ethnography of algorithmic systems. *Big Data & Society, 4*(2), 1–12. https://doi.org/10.1177/2053951717738104

Southerton, C. (2021). Lip-syncing and saving lives: Healthcare workers on TikTok. International Journal of Communication, 15, 3248–3268. https://ijoc.org/index.php/ijoc/article/view/16900/3498

Sternlicht, A. (2023, November 29). The death of TikTok's $2 billion Creator Fund is stoking fears among influencers about the value of short-form videos on the platform. Fortune. https://fortune.com/2023/11/29/tiktok-killed-creator-fund-influencers-worry-short-form-video/

The Overstory. (2023, July 25). In Wikipedia. https://en.wikipedia.org/wiki/The_Overstory

Vallese, Z. (2023, February 27). In the three-way battle between YouTube, Reels and TikTok, creators aren't counting on a big payday. CNBC https://www.cnbc.com/2023/02/27/in-youtube-tiktok-reels-battle-creators-dont-expect-a-big-payday.html

Weinberg, D.B., & Kapelner, A. (2022). Do book consumers discriminate against Black, female, or young authors? PLoS ONE, 17(6). e0267537. https://doi.org/10.1371/journal.pone.0267537

Zarroli, J. (2021, December 31). TikTok is driving book sales. Here are some titles #BookTok recommends [Radio broadcast transcript]. NPR. https://www.npr.org/2021/12/26/1068063564/booktok-is-a-new-force-driving-book-sales-and-publishing-deals

Zeng, J., Abidin, C., & Schäfer, M.S. (2021). Research perspectives on TikTok and its legacy apps: Introduction. International Journal of Communication, 15, 3161–3172. https://ijoc.org/index.php/ijoc/article/view/14539