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Analyzing motivations and negative implications for cancel culture engagements through natural language processing: A cross-country comparative study

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A dissertation

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A b s t r a c t

This study uses natural language processing methods to investigate text data on cancel culture to elucidate language uses that indicate the motivation for such activism in different countries and some of the negative implications of such communication on social media. Cancel culture is a kind of activism that utilizes social media to organize and reach people. In recent years, the hashtags '#Cancel_' and '#boycott', used to advance cancel culture, have become very popular. The activism has elicited a lot of media discourses, academic studies, and, especially, theoretical postulations. Many of the previous research efforts have explored the meaning of cancel culture and motivations behind it, concluding that it proceeds from the concern for social justice, driven by the woke movement that started in the USA around 2017/18 and gained worldwide spread over time. As cancel culture continues to gain global prominence, the question needs to be asked if the activism is still inspired by the goal of achieving a fairer society. This study is set to examine the similarity of cancel culture as a form of activism aimed at achieving a fairer society across different countries, as well as the motivating factors for the activism and the implication (negative) of these kinds of communication on people who engage in the conversational exchanges about it. I propose that beyond wokeness/social justice, diverse motives *drive cancel culture in the varying contexts where it is popular, some of which may be laudable, and some outright dreadful. I shall mine cancel culture data on Twitter and explore the conversations with a view to underscoring linguistically marked motivating factors that participants actively or passively attribute to their involvement in these engagements and some of the negative implications of the types of communication they are involved in the context of cancel culture engagements. The semantic markers will help to explicate the motivating factors and the implications which are bellied within the texts of the cancel culture conversations. I shall utilize various functions in natural language processing (NLP) to examine the text data to explicate the motivations for cancel culture and underscore the implication of such for society. The data for the study are user-generated comments on Twitter with cancel culture hashtags indicating their context, made between 2018 and 2022. I select the countries of South Korea, India, the Philippines, the USA, the UK, Nigeria, South Africa, and Brazil for the study. These countries represent different contexts where cancel culture is popular on Twitter and in mainstream media discourse. Text mining (TM) and natural language processing (NLP) methods are used for the analysis of this study, to examine the propositions related to the study's objective. The analyses will be implemented with R and VosViewer software. I shall conduct text similarity analysis, word network analysis, dictionary analysis, word frequencies, keyword-in-context, other text summaries, and visualizations. The analyses will help shed light on the various underlying but often unrecognized motivating factors behind cancel culture activism and the implications of negative types of communication made in the context of cancel culture engagements.*

Chapter I. Introduction and background of the study

1. Cancel culture activism in the digital social worlds

Online-based protests are popular these days. Some social media users leverage the reach of digital platforms to call for boycotts and protests, pressuring businesses and other interests associated with any person accused of some misdeeds to cut ties with the person. The businesses associated with the accused, considering the effects of a sustained negative campaign on their brand/s, may choose to take a softer landing of cutting ties with the accused person, forcing them (the accused) to lose contracts, careers, and/or jobs. This form of social media-driven activism is popularly termed cancel culture (Bakhtiari, 2020; Mishan, 2020; Brito, 2021; Norris, 2021).

Since its emergence in contemporary discourse between 2017 and 2018, cancel culture has been one of the most polarising issues (Strossen, 2020; Vareltzidi, 2022; Makridis, 2023). It props up often in popular discourses; in the media, marketing, and public relations (Bakhtiari, 2020; Mishan, 2020; Alexander, 2020; Bakhtiari, 2020). These days, businesses and celebrities are careful with their words and actions in order to safeguard their brands from the fury of cancel culture activists (Bakhtiari, 2020, Walsh, 2022). Even one of the world's richest persons, Elon Musk, long before he became Twitter's owner and CEO, has been denouncing cancel culture both in media appearances and tweets from his personal Twitter handle. For instance, on 20th May 2020, Musk tweeted, "Cancel Cancel Culture" (Ruiz & Tanno, 2020; Rogers, 2021).

Meanwhile, in the mainstream media, the term cancel culture appears frequently in news titles, reports, and opinion articles (Brito, 2021; Sossi, 2021). It is also a headline issue for many TV or online talk shows (Vogels, 2022; Walsh, 2022). On social media, cancel culture has been a reason for constant brawls among people of different ideological leanings (Clark, 2020; Porter Novelli, 2021:

8; Strossen, 2020; Pilon, 2020). In academia, it is also the focus of numerous academic research (e.g., Mishan, 2020; Ban, 2021; Norris, 2021; 2021; Clark, 2020; Cook et al, 2021; Nguyen, 2020; Ng, 2022).

Figure 1: Elon Musk's famous cancel culture tweet

However, in cancel culture's historiography, many authors have held a singular view of it as motivated mainly by the quest for social justice (Bouvier, 2020; Dudenhoefer, 2020; Romano, 2020). The term 'wokeness' was coined to represent this ideology in social media discourse (Johnson, 2020; Vissol, 2021; Johnson, 2021; Lat, 2022). The woke movement earns support mostly from the liberal progressive side of the political divide in the West, while the ideological right is said to be skeptical or hold cancel culture entirely in contempt (Swaim, 2021; Grimes, 2022; Norris, 2021; Bridges, 2021). This means that cancel culture is generally seen as a moral and culture war between the ideological Left supporting it and the Right opposing it (Nguyen, 2020; Cook et al, 2021; Norris, 2021; Bridges, 2021).

The notion of 'woke' Left versus ideological Right involving in a moral supremacy tussle as the main motivation for cancel culture is mainstream in media and academic discourse (Mishan, 2020; Ban, 2021; Norris, 2021; 2021; Clark, 2020). It has also gained wide acceptance in the mainstream media of the wider worlds of the Orient, the Americas, and Africa. News stories, news analyses, features, and scholarly discourses on the subject almost always feature the woke 'Left' versus non-woke 'Right' divide (Mishan, 2020; Carter, 2021; Alexander, 2021; Mueller, 2021; Zurcher, 2021; Fahey et al, 2022). Often, from this normative 'Left versus Right' locus, most scholars take off their studies on cancel culture (Norris, 2020; Cook et al., 2021; Clark, 2020; Trigo, 2020; Bouvier, 2020).

With increased research attention focused on the concept of cancel culture, there have been a few who are questioning its existing narratives, especially the reason why people engage in it. For instance, Ng (2020) acknowledges the pervasiveness of cancel culture driven by nationalism, but that is in faraway China. Also, there are a few other studies straying from the consensus of wokeness as the sole motivating factor for cancel culture, passively implicating different motives for cancel culture, like religion, and Christian nationalism. But in these studies - where non-woke ideology is implicated in motivation for cancel culture - one observes that mostly their author did not fully focus on studying the motivations behind cancel culture as independent variables (Cook et al., 2021: 3; Clark, 2020; Trigo, 2020; Bouvier, 2020; Dershowitz, 2020; Donnolly & Donnolly, 2021, Ng 2020).

This study questions the contemporary assumption of cancel culture as singularly driven by wokeness. As the term cancel culture gains global prominence; with calling people out, public shaming, and boycotting businesses or services getting adopted in places, it is important to question if indeed what is still being served is the same single motive cancel culture with the primary goal is achieving social justice in a fair, equal and egalitarian society, especially as most scholars, as seen in the extant literature, still view cancel culture this way (Allen, 2022; Vareltzidi, 2022; Cook et al., 2021: 3; Clark, 2020; Trigo, 2020; Bouvier, 2020; Nakamura, 2015; Clark, 2020; Nguyen, 2020; Velasco, 2020; Carter, 2021; Mueller, 2021).

Towards the set goal of this study, I shall mine text data of tweets made with '#cancel_' hashtags which I shall utilize as data to pursue a three-prong purpose for this study. The first is to examine the similarity of cancel culture conversational engagements across the different countries of South Korea, the Philippines, India, the USA, the UK, Nigeria, South Africa, and Brazil. From the point of view of information theory, similarity is defined as the commonness between two or more text documents. The greater the commonness, the higher the similarity, and vice versa (Wang and Dong, 2020; Soares, et al, 2019; Zahrotun, 2016; Zahrotun, 2016). In essence, if the themes of cancel culture conversations are similar, then the words and phrases used in the discourse will be similar. But, if the themes of the conversations are varied, then the words and phrases used in the discourse will be less similar (Gomaa & Fahmy, 2013).

The second goal is to examine the assumption of thematic unity with respect to cancel culture motivating factors. Is cancel culture indeed driven solely by wokeness in all the countries in the data? This assumption can be tested by querying the data to explicate language and communication schemas indicating the types of motivating factors for cancel culture engagements. If the motivations are similar, it means that wokeness is the principal motivation for the activism, or if they are varied, then there may other factors that are context-dependent but not yet enough highlighted in extant literature. I shall highlight these motivating factors in the analysis part of the study as part of the findings of this study.

The third goal is to query the text of the conversations to explicate conversational elements indicative of implications for negative engagements in cancel culture. Most research efforts conclude that cancel culture is good, hence fail to examine the type of harmful language used by many commenters which spread toxicity and hatred online.

Meanwhile, as already mentioned, the text data for the analysis of this study comprise comments made in the course of cancel culture engagements. Within these texts, I shall conduct analyses to explicate linguistic markers indicating the motivating factors for which the commenters involve in cancel culture engagements and the negative implications of negative types of communication that occur in the cancel culture conversational ecosystem. In essence, my focus will be on the analysis of content words and phrases contained in the comments people make under the discourse topic of cancel culture.

Comments as digital footprints left by users on social media are important sources for information retrieval (Zhang et al, 2020; Liu et al, 2018). Such data can be mined with machine learning methods and analyzed to reflect the mechanisms of the real world (Liu et al, 2013; Zhang et al, 2018). With such data, researchers are able to investigate traditional social issues from new perspectives, or even uncover new social phenomena hitherto unknown in social research (Zhang et al, 2020; Skarupova, 2014; Spaiser, 2021; Quach et al, 2022). Also, comments are relevant as research data because they are expressions of human agency (Bandura, 2001; Mishra, 2021; Batzdorfer et al, 2022). Agency is the force by which human acts out their will and volition (Liljenström, 2021). It embodies the endowments, belief systems, self-regulatory capabilities, and distributed structures and functions through which personal influence is exercised, and enables people to act freely and express opinions about certain things or issues (Taylor, 1985; Goller & Harteis, 2017). Hence, comments people make on social media are primarily judged as their opinions, worldviews, and the views of others they find important to amplify or deplore, hence expressions of their agency (Bandura 2001).

A lot of previous studies have been conducted using social media comments (Xiong & Liu, 2014; Morales et al, 2014; Segesten et al, 2020; Batzdorfer, 2022; Drivas et al, 2002). And the outcome of these studies could be used to make accurate predictions about mainstream attitudes and predilections in society (Segesten et al, 2020; Rogers, 2021; Bruns & Stieglitz, 2014; Chen et al., 2021; Durham, 2022; Ahmed et al., 2017; Campan et al., 2018).

Usually, when posts are made on popular social media sites, especially about a popular topic or hot issue, they garner comments and other engagements, like liking and sharing, in thousands or millions (Appel et al, 2020; Pennycook & Rand, 2019; Kim & Yang, 2017). The sheer number of comments on some popular posts makes it difficult for the aggregate views of the commenters to be deciphered at a glance. However, with machine learning text mining algorithms, it is now easy to analyze such comments as data (Choudhary et al, 2009; Talib et al, 2016; Gupta, et al, 2020; Li et al, 2018).

Text mining can be used to examine such large volumes of (unstructured) text data corpus looking for patterns; extracting new information, discovering contexts, identifying linguistic motifs, or transforming the text into a structured data format for further quantitative analyses (Kibble, 2013; Dinov, 2018). In text mining, therefore, researchers mainly combine techniques of data mining with information retrieval to analyze data (Kaushik, 2013; Dhawan & Zanini, 2021; Sebastiani, 2002; Dinov, 2018; Dhawan & Zanini, 2021; Torfi et al, 2021; Patel & Arasanipalai, 2021; Torfi et al, 2021).

The machine-based text processing and analysis methods not only make it possible to analyze large corpora of text easily and more accurately, but they also perform analysis unencumbered by biases that sometimes influence manual coding in qualitative research or structuring of the questionnaire in quantitative research (Basit, 2010; Li et al, 2014; Rao et al, 2015; Vaughn & Turner, 2015; Galdas, 2017; Thirsk & Clark, 2017).

For this study I shall utilize a combination of machine learning (ML) methods for the analysis of the data; like text similarity analysis, topic modeling, word network analysis, dictionaries analysis, word frequencies, keyword searches, as well as general text statistics computations, which encompass techniques for describing text corpus quantitatively (Pereira, 2017; Günther & Quandt, 2015; Welbers, et al, 2017, Abbasi and Chen 2005; Günther & Quandt, 2015; Benoit, et al, 2018).

This study is a cross-country context-based analysis. I chose eight countries from where the data for the study were obtained; three from Asia, South Korea, the Philippines, and India, one from Europe, the UK, one from North America, the USA, two from Africa, Nigeria, and South Africa, and one from South America, Brazil. My aim is to have at least a representative country in all the major continents of the world, especially countries in which cancel culture is a big issue in the mainstream media discourse. Also, the diversity of the countries in terms of history and geography will give me ample opportunity to examine the study topic across varying social contexts.

2. Purpose of study

There are three important reasons that inform the choice of this research topic. The first is to evaluate the similarity/diversity of themes in cancel culture as a way to determine if the motivation for it is about single or multiple issues. Beyond the theme of wokeness, the cancel culture crowd may actually have focused on diverse themes; that is, they fixate on varying issues that have nothing to do with the quest for woke inspired social justice. I shall analyze the data for this study to underscore the extent of statistical similarity/variation that can be found in the text of cancel culture conversations. A strong similarity will support the notion that the themes in cancel culture engagements are the same across the countries being compared, which may indicate that the motivations for cancel culture is similar across the countries.

The second reason is to evaluate the motivating factors behind cancel culture based on the conversations of the people. This is important because the foundational goal of cancel culture, which is social justice, seems to have lost steam as the activism gets popular around the world. It needs to be understood and underscored that things are changing. What exactly is changing, and what types of motivation actually drive cancel culture in the now? I acknowledge that cancel culture has evolved, and some negative and unpleasant traits can be noticed among those who involve in it, and these negative tendencies are not often researched and discussed in the literature. I shall examine these based on the communication of the people who comment on cancel culture.

The third is to explicate evidence from the data of the implications of some unpleasant motivations that have crept into cancel culture as it evolves over time. Indeed, not all types of cancel culture engagements are negative. I shall focus attention on the negative implications because they are often overlooked in cancel culture discourse due, in part, to the historical positive perception cancel culture has enjoyed in critical studies in recent years.

This study considers cancel culture as a global phenomenon. Hence, I shall evaluate the conversations of not just people in the Occidental Twitter spaces. The normative theory of cancel culture has always excluded its dynamics outside of the Occident. Little is being studied about the activism as it evolves in places like Africa and the Orient (Nakamura, 2015; Mishan, 2020; Clark, 2020; Ng, 2020; Nguyen, 2020; Velasco, 2020; Carter, 2021; Mueller, 2021). This study differs in this. I believe that a wholesome theory of cancel culture must be able to acknowledge its dynamics across multiple contexts.

3. Research questions

To stay focused on the goal of the study, some research questions are necessary as a guide. Below are the research questions that will guide my analysis of the data. I hope to be able to find an answer to each of them through the analysis:

1. Are cancel culture conversations by netizens across the different countries similar or varied to suggest similar or varied kinds of themes and motivations in their conversations?

2. What motivating factors are implicated in people's involvement in cancel culture argumentation on Twitter in the different countries in the data?

3. What are the (negative) implications of unpleasant cancel culture communications that can be explicated from the study data?

To answer the research questions, I shall conduct various types of natural language processing analysis on the study data.

1. First, I shall conduct text similarity/distance analysis to evaluate the statistical similarity of the data before comparatively visualizing them. Meanwhile, further analysis of the text data can only be possible if there is statistical evidence the data share a significant similarity in the discourse context.
2. Second, I shall conduct a latent Dirichlet allocation (LDA) to cluster the data into different topics. The topics relate groups of words to contexts. I shall explicate the motivating factors for cancel culture engagements in the context of words used under particular topics.
3. Third, I shall conduct a dictionary analysis to explicate match words in the data with a dictionary of words indicating different types of motivating factors.
4. Fourth, I shall also conduct various test statistics and visualizations like word frequencies, word network analysis, key-word-in-context analysis, and text plots, to visualize the results of the analysis.

Chapter II. The review of related literature

1. Cancel culture: understanding the phenomenon

Despite the surge in the mentions of the phrase "cancel culture" on social and mainstream media in recent years, it is not an easy concept to define. What it is or not is not commonly agreed on. Brito (2021) notes that the term itself "is vague and has become a catch-all for various situations with different degrees of severity and impact". What Brito (2021) means, therefore, is that a lot of what is called cancel culture is really not it, and a lot of what is not called cancel culture may well be it.

However, for the purpose of this study, a few definitions of cancel culture which directly relate to online call-out and boycott activism, which form the basis of this study, will be highlighted. Important among these views are the opinions of scholars who define cancel culture as a goal of getting popular personalities boycotted, ruined, and expunged from popular culture as accountability for speech or actions considered too unconscionable, egregious, inappropriate or distasteful by a critical mass of social media users (Mueller, 2021; Clark, 2020; Romano, 2020; Trigo, 2020, Kato, 2021). This view represents the mainstream notion of cancel culture activism.

A lot of the existing studies and commentaries on cancel culture reviewed for this study, especially in the Occident, extensively discuss the reasons and motivating factors for which cancel culture began, which are primarily in response to the challenges of ensuring social justice for the powerless especially when the authorities lack the political will to do so in the face of obvious infractions (Nakamura, 2015; Mishan, 2020; Dudenhoefer, 2020; Trigo, 2020; Mintz, 2021). It is appropriate, here, to note the argument of Romano (2020) who explains in great detail the frustration common people feel for the lack of consequences for the wrongdoings of the elite class, especially wrongs that affect the vulnerable and minorities.

The advent of social media offers the common people a platform to fight back. The commoners use platforms like Twitter where they have equal access to air their grievances (Hanson & Haridakis, 2008; Lee & Ma, 2012; Whiting & Williams, 2013: 366; Nielsen & Schroder, 2014). By exerting indirect pressure through boycotting, shunning, shaming, and unfollowing, they make their voices heard (Norris, 2021; Nakamura, 2015). Through '#Cancel_' and associated hashtags like '#MeToo', '#isoverparty', etc., the common people have sought and won redress for offenses that hitherto would have been ignored by the system (English, 2021: 3; Clark, 2020; Alexander, 2020).

Meanwhile, the history of cancel culture was tied from origin to social justice/woke ideology, making it almost a single-issue activism (Mendes et al 2018; Aggarwal, 2021; Greenspan, 2020; Cook et al, 2021; McGrady, 2021; McNutt, 2021). There are different sides to the woke ideology of cancel culture, though, like the black lives matter, gender equality, trans-rights, and anti-racism activisms and campaigns, etc.

There are feminist scholars who argue that cancel culture originated from the feminist-led #MeToo movement. #Metoo is a hashtag-driven movement that encouraged women victims of rape to speak up and tell their stories (Mendes et al, 2018; Aggarwal, 2021). It gained widespread attention and acceptance all over the world (Benedictis et al, 2019). The hashtag, #metoo, was used to hold people like veteran actor Bill Cosby, Hollywood producer Harvey Weinstein, and others accountable for sexual assaults against women (Greenspan, 2020).

Other commentators like Trigo (2015) Semiramis (2019), and Rabouin (2019; 2021), argue that the earliest use of the phrase cancel culture was among Black Twitter communities, around the year 2015. Black Twitter was formed as a network for sharing black experiences, especially in the United States of America. It was born out of social facts of long-standing, systemic discrimination against African Americans (Dudenhoefer, 2020; Williams, 2020; Bouvier & Machin, 2018; Sharma, 2013). Many scholars aver that the hashtag '#Cancelled' first began to circulate within these social networks where it was used to call out bad behaviors of powerful people and celebrities which were problematic and hurtful to blacks and other oppressed groups (Semiramis, 2019; Rabouin, 2021; Greenspan 2020; Cook et al, 2021; McGrady, 2021; McNutt, 2021).

Meanwhile, it was from such articles and studies like the above mentioned that cancel culture began to be associated exclusively with the wokeness movement (Romano, 2020). Many discourses related to canceling almost always end up tying it to liberals-led woke culture. For this reason, phrases like woke culture, liberal woke mobs, and leftist mobs became popular with wokeness (Vissol, 2021; Mendenhall, 2023; Levitz, 2023; Ganesh, 2023). The effort by classical leftists to dissociate wokeness as a leftist ideology has yielded little or no result (Neiman, 2023). And there has been little media coverage or acknowledgment of cancel culture being driven by other concerns, groups, or motivations.

However, it still needs to be asked if cancel has metamorphosed over the years. In academic literature, only Ng (2020) has acknowledged the pervasiveness of cancel culture driven by nationalism. But that is in faraway China. A few other scholars have implicated ideological or political persuasion in the motivation for cancel culture involvement, but they fail to fully research politics as an independent variable influencing cancel culture (Cook et al., 2021: 3; Clark, 2020; Trigo, 2020; Bouvier, 2020; Dershowitz, 2020; Donnolly & Donnolly, 2021).

2. Evaluating previous studies on cancel culture

A number of studies have been conducted by scholars trying to understand the phenomenon of cancel culture. These were done from diverse fields of academic inquiries. It is necessary to review some of these existing studies as a takeoff for this present research.

Among the early scholarly efforts made to understand cancel culture were studies conducted by Norris (2020; 2021). She sampled political science faculties from different countries about cancel culture within the academia. The result of her study shows statistically significant affirmation of the existence of cancel culture within academia (Norris, 2020: 8-11). A lot of the respondent faculties attest to being paralyzed in their work and research due to the emerging culture of intolerance in their various schools. The pressure to be politically correct, or else face the prospect of getting canceled/terminated, hampers the desire of these faculties to explore hard and sensitive research topics. They are afraid that what they research or teach, or the language they use in the classroom, etc. might trigger unexpected reactions leading to them losing their jobs (Norris, 2020: 9-11).

Norris' (2020; 2021) studies are germane in the discourse of cancel culture because, first, they debunk the argument being made by certain commentators and scholars that cancel culture does not exist (Manavis, 2020; Moore, 2021; Willingham, 2021). Secondly, it is one of the early studies that touted and generalized the liberal-progressive versus conservative divide in the cancel culture debates. Also, these two studies help in understanding how the fear of getting canceled stifles academic freedom on university campuses.

Another important study on cancel culture is Cook et al (2021) in which the researchers sought to understand the relationship between political leaning and cultural values and people's willingness to participate in cancel culture activism. The study, like Norris (2020), arrives at the binary of political Left and Right as the major drivers of cancel culture. It concludes that netizens on both sides of the political divide get involved in cancel culture provided their notion of moral rectitude is violated. In their methodology, the researchers improvised experimental instances warranting demand for canceling. They tested respondents' opinions about cancel culture based on those hypothetical instances (Cook et al, 2021: 18). The respondent, who were all citizens of the United States where the study was conducted, agreed they could participate in canceling individuals whose words or actions violated certain norms they (respondents) held dear.

Other studies like, Anderson-Lopex et al (2021) used cancel culture to examine how critical responses (comments) from a woke pro-cancel culture audience could affect television shows. Using the series, "Girls and the 100", they analyzed how audience reception affected the production of subsequent episodes of the show. The study concluded that cancel culture is not necessarily a bad thing, because the threat of cancellation by fans of the series resulted in the producers paying adequate attention to diversity and equity in subsequent episodes (Anderson-Lopex et al, 2021: 80). However, even though this study is relevant to cancel culture discourse, its analysis focused more on product management, promotion, and fandom.

Then, there is Mueller (2021) who studied psychological predictors for involvement in cancel culture behavior. This exploratory study utilized both qualitative interviews and quantitative testing to evaluate the motives behind people's participation in cancel culture. It concluded that the main motive for involving in cancel culture is not actually to ruin the accused, but rather to get them to apologize (Mueller, 2021: 10-11). The study also found that the tendency to demand an apology varies depending more on the participants' ideologies, political leanings, and gender. People who are ideologically liberal, politically leftist, and of female gender, are most likely to demand apology from the accused, according to the study.

Another study was by Ng (2022) which examines cancel culture from a critical media studies perspective. Ng (2020) tracked multiple trails to the origins of cancel practices and discourses, from Black communicative practices, celebrity and fandom cultures, consumer culture, and national politics. Her analysis moved beyond popular press accounts about the latest targets of canceling or familiar free speech debates to underscoring the different configurations of power associated with cancel culture in specific cultural and political contexts. For instance, in the United States, there is a push being orchestrated by Trump to support White Christian nationalists. On the other hand, in China, there is a rise in using cancel culture to advance the cause of Chinese nationalism.

The last studies I shall review are the discourse analyses studies conducted by Bouvier (2020) and Bouvier & Machin (2021) which analyzed cancel culture conversations vis-à-vis their use in the fight against racism. The data for this were comments made using particular hashtags like #KellyPocha #AaronMSchlossberg, #AaronSchlossberg, #KellyPocha, and #RhondaPolon, all of which were created to push back against the racist behaviors of some individuals. These accused persons' names were used to create the pushback hashtags.

The studies went further to evaluate Twitter as a platform for addressing matters of social justice, especially racism, and the finding shows that hashtags are blunt armor in the fight against social injustice because many people who involve in digital activism externalize social problems from themselves. When no one acknowledges being part of the problem, finding a solution is very difficult. So, while hashtag activism gives the participants the vicarious satisfaction of being part of something noble, nothing actually is getting done beyond just commenting and tweeting. Even the people being called-out or canceled for their racist actions are quick to deny they are racists because until their slip - considered a mistake - they do not believe themselves to be racist. Hence, cancel culture which supposedly is being used to fight against social malaise, like racism, actually distracts attention from actual and specific structural inequalities in society. But because no one owns the problem, even hashtag activism does not solve it (Bouvier, 2020; Bouvier & Machin, 2021).

3. Theoretical perspectives on motivating factors for cancel culture

Despite a lot of work research already done on the subject of cancel culture, not many researchers have focused attention on the motivations for it. What exists on this question mostly are opinion articles with no valid testing or systematic examination of data. A few studies, however, partially referenced motivating factors for cancel culture. These shall I review here.

The first I shall reference is Norris' (2020; 2021), study which evaluates cancel culture as a factor of political persuasion. The study finds that, mostly, the liberal versus conservative political ideological divide is at the nexus of cancel culture activism. Most people on each side of the main political isles will be willing to cancel a person on the other side but not a person on their own side. In cultures that are liberal-oriented, like in the Occident, the tendency is to cancel people who are conservative, and in cultures that are conservative, like in some African countries, the reverse is the case (Norris, 2020: 15-18). The problem with this study, however, is that it only focused on the faculties in academia.

Another study that examines cancel culture as outshoot of political ideology is Cook et al (2021), which concludes that political ideologies, the binary of which is either Left (liberal/democrat) or Right (conservative/republican) is the major motivating force of cancel culture in the USA. They conclude from their analysis that netizens on both sides of the political divide get involved in cancel culture provided that their notion of moral rectitude is violated (Cook et al, 2021: 18). The problem with the study is that it more or less argues that the only motivation to participate in cancel culture is in defense of one's socio-political ideology; the binary of which is between progressivism and conservatism. It implies, therefore, that beyond political biases, people would not be interested in canceling others on social media. The research survey ignored the demography of those who could be neutral in the American political divide (the independents).

Also, the Mueller (2021) study used the working term "psychological predictors" to examine the motivation for people's involvement in cancel culture behavior. They conclude that the primary motivation for involving in cancel culture is just the psychological satisfaction of getting the offender to apologize. But this depends on the ideological leanings of the activists because the researchers created categories of respondents based on political persuasion and gender to understand which groups have a tendency to demand an apology from the cancel culture targets. In essence, the study measured political ideology as a motivating factor in involvement in cancel culture. It concluded that people who are liberal, and of the feminine gender are most likely to demand an apology. The main weakness of the study is that it started from the premise that the respondents' ideology is either Left or Right. In essence, it is not possible for this study to be globally contextualized, especially in contexts where strict political lines are not drawn. The sampled population for the study was entirely drawn from the United States. Also, as the researchers acknowledged, even the sampled population had a racial bias; the white population was overrepresented with regard to the proportion of all races living in the USA (Mueller, 2021: 12).

Another study by Ng (2022) more or less makes use of the same argument that political affiliation and nationalism explain participation cancel culture. In the USA, it is politics, while in China nationalism drives cancel culture. In the work done with critical methodology, Ng (2022: 73-99) discusses how the right-wing versus the left political binary in the USA which permeates the media and culture advances the discourse on cancel culture, while in China nationalistic sentiment is the basis for which cancel culture is advanced (Ng 2020: 101-136). What is important about this study is the recognition of nationalism as a motivation for involvement in cancel culture. No other previous academic study actually acknowledged or focused on this aspect of cancel culture motivations. However, the author limited her cancel culture discourse to the USA and mainland China. It is possible, however, that a look at the wider demographics of humanity in other countries could elicit more motivating factors for participation in cancel culture.

Meanwhile, other studies like Anderson-Lopex et al (2021) focus on wokeness as a motivating factor in cancel culture, same as Bouvier (2020) and Bouvier & Machin (2021) who build their study against the background of cancel culture as a core aspect of the woke movement. That is; these studies were conducted against the understanding that the grand motive for participation in cancel culture is for the advancement of woke social justice ideology. The authors did not indicate that there may be other motivating factors behind cancel culture other than wokeness.

In conclusion, there are lots of other books and articles available online written on the subject of cancel culture, many of which reached conclusions not by systematic analysis of data. They are opinions, discourses, debates, etc. often done by partisans on the many sides of the cancel culture debates (Cook et al., 2021: 3; Clark, 2020; Trigo, 2020; Bouvier, 2020; Dershowitz, 2020; Donnolly & Donnolly, 2021). The conclusions of such discourses are not presented here in this study, but I acknowledge their existence and the great insight I gained on the subject of cancel culture while reading some of them. Importantly, though, none of the existing studies focused on understanding cancel culture from the niche this study has focused on, which is to examine the motivating factor for cancel culture from a multi-contextual level.

4. Cancel culture and context

Meanwhile, since its advent in popular discourse, cancel culture has shown to be not only divisive but also a complex and multifaceted phenomenon. What is known as cancel culture differs significantly across countries possibly due to cultural, social, and political factors, even though this has not been much highlighted in existing literature. In the eight countries chosen for this study; South Korea, the Philippines, India, the USA, UK Nigeria, South Africa, and Brazil, what is considered cancel culture may vary depending on the context. Hence it is necessary to have an overview of the context and examine the unique dynamics of each and how this could yield varying motivations for cancel culture in each country. I shall, however, the context based on cultural, social, and political dynamics.

4.1. Cultural dynamics

There are many categories of cultural variability to consider in such a study as this; like values and beliefs, language, symbols, rituals, and norms (Hodder, 2013). However, two broad categorizations are important to understand in the context of this study, which are collectivist and individualistic categories of culture (Darwish & Huber, 2010).

Individualistic culture is a cultural orientation that places a high value on individual freedom, autonomy, and self-reliance. In individualistic cultures, individuals prioritize their personal goals, achievements, and self-interests over the needs of the collective or community (Darwish & Huber, 2010: 48; Hofstede & Bond, 1984). Also, there is a greater emphasis on personal accountability and self-expression (Hofstede & Bond, 1984). Hence when it comes to issues driving motivations in cancel culture in individualistic cultures, these may be rooted in issues bordering on social justice and empowerment (Saad, 2020). Cancel targets may be isolated as individuals who have to take responsibility for their actions. The campaigners who target the individual share collective agenda for the action. They only believe in the moral justification for their action.

Meanwhile, in contrast to individualistic cultures are collectivist cultures where individuals prioritize group harmony and conformity over individual goals and aspirations (Hofstede & Bond, 1984). South Korea, the Philippines, India, and Nigeria are collectivist cultures (Olowookere et.al, 2021). In these countries, it is plausible that cancel culture manifestations focus on activities that threaten the social order, or individuals focus on using cancel culture to punish those who deviate from societal expectations (Sakamoto & Miura, 2020). So, here individuals may participate in canceling someone for group interest, either cultural, social, or political.

4.2. Political and ideological divides

The political climate and ideological divisions within a country definitely affect the response of people to burning issues like cancel culture (Caprara & Vecchione, 2018; Dalton & Wattenberg, 2000; Manza & Brooks, 1999; McCarty, et al, 2006). In the USA for instance, there is a deep political divide between the ideological liberal progressives and the conservatives. The split is such that progressives mostly support and vote for the democratic party, while the conservatives mostly support the republican party (Pew Research Center, 2021; Blazina, 2022).

In South Korea, the UK, and Brazil, there is a parallel between the progressive and conservative parties also (Chae & Kim, 2010; Choo, 2019; Hayton, 2022; Giddens, 1994; Burity, 2021; Bolognesi et al, 2021). However, in South Korea, the political divide reaches beyond the ideological grounds to historical issues like the frosty relationship between South Korea and their neighbor, Japan. This historical issue follows from the Japanese colonization of South Korea and its sour aftermaths, which includes the Japanese use of Koreans as slave laborers during the second world war and how to settle the matter in the post-war era. The South Korean progressives still believe the conservatives sympathize with Japan. Hence the liberals and conservatives' positions on Japan differ on how hard the nation can go in opposing Japan (Dostal, 2017). Meanwhile, in Brazil, the liberal versus conservative divide has all been submerged into populism which grows on both sides of the political aisle (Gouvêa, et al 2021; Conniff, 2012).

In Nigeria and South Africa, the political division is not strictly divided across ideological lines, but rather along ethnic, regional, and/or religious lines (Raheem et al, 2014;). In Nigeria with diverse ethnic groups with distinct languages, cultures, and historical backgrounds, ethnicity plays a significant role in the political affiliations of ethnic groups (Uwaifo, 2016; Ezeani & Agudiegwu, 2015). The country also has a significant Muslim population in the northern regions and a substantial Christian population in the southern regions. Religious affiliations also significantly influence political alliances, policy priorities, and voting patterns (Afolabi, 2015; Oshewolo & Maren, 2015). Additionally, regional differences contribute to the political dynamics in Nigeria. The country is divided into six geopolitical zones, each with its own unique social, economic, and political characteristics (Suberu, 2002; Eze, et al, 2014). Political interests and power dynamics often revolve around regional considerations and the pursuit of regional development and influence (Owen, 2020; Demarest & Langer, 2023).

South Africa's political landscape, meanwhile, is even more diverse and complex, and multiple factors intersect to shape political divisions, which include race, socioeconomic disparities, historical legacies, and ideological differences (Grundy, 1986; Chazan et al, 1992; Ticktin, 1993; Tamir & Budiman, 2019). These factors many believe, do not operate independently, but rather interact and influence one another in South Africa (Bornman et al, 2021; Africa, 2019;).

Meanwhile in India, the political landscape is entirely different. Hindu nationalism, also known as Hindutva, has been a prominent ideology in Indian politics for several decades (Chacko 2019; Longkumer 2016; Chaturvedi 2022; Mathew, 2022). By population, Hindus are an overwhelming majority in India (Andersen, 1998; Sahgal et al, 2021). Many scholars aver that Hindu nationalism is at the nexus of Prime Minister Narendra Modi and his Bharatiya Janata Party (BJP) recent climbing and holding on to power in the country (Andersen, 1998; Vaishnav, 2019; Mehta, 2022).

Hindu nationalism is a complex blend of cultural, religious, and political beliefs, seeking to assert Hindu identity and promoting the interests of Hindus in Indian politics. Its roots can be traced to the late 19th century when it emerged as a response to colonial rule in India (Chacko 2019; Longkumer 2016; Mathew, 2022). But in recent years Hindutva has grown into some sort of militant movement (Longkumer 2016; Chaturvedi 2022). Many schools of thought posit that Hindu nationalism has contributed to social and political polarization in India (Sahoo, 2020; Ferrari, 2020). Divisions along religious lines have become more pronounced in recent years. The BJP has gained significant electoral success in recent decades, always tapping into the Hindu sentiment (Vaishnav, 2019; Mehta, 2022). The rise of Hindu nationalism, however, has led to rising intolerance, violence, and discrimination against non-Hindu communities, among other issues (Chacko 2019; Longkumer 2016; Ferrari, 2020; Chaturvedi 2022). It is not going to be surprising, therefore, if Hindu nationalism is weaponized in cancel culture to go against perceived Hindu enemies.

The review so far, on politics and ideological divides, aims at explicating that it is possible for political differences to be weaponized and exploited to go against opponents in the guise of cancel culture, especially in countries with polarized political landscapes. If this happens, cancel culture shall become a tool used for silencing dissenting voices and reinforcing domination, power, and control, or enforcing ideological conformity (Weiner, 2020; Fogle, 2021). These will antithetical to the original goal of cancel culture, which is to pursue social justice on behalf of the weak.

4.3. Social dynamics and power structures

Meanwhile, the social dynamics and power structures in different countries may affect an individual's motivations for involvement in cancel culture argumentation. In countries with deep-rooted social hierarchies and power imbalances, cancel culture can serve as a mechanism for marginalized groups to challenge systemic injustices. This factor is most pronounced in the United States of America, where people of color in general, and African Americans, in particular, feel politically and economically deprived (Alvarez et al, 2016; Starr, 2022). Also in post-apartheid South Africa, cancel culture motivations can stem from the historical context of seeking justice and redress for past wrongs against the black people (Makhubela, 2021). Conversely, in countries where social media amplifies the voices of the majority, cancel culture motivations may be driven by the desire for conformity and the fear of social backlash (Kearney et al., 2021). Exploring these social dynamics will broaden the understanding of the motivating factors that fuel cancel culture within each country.

5. Categories of motivating factors for cancel culture

Following the preliminary review of the data with the LDA analysis, I explicated six possible motivating factors for cancel culture engagements. These categories, however, are not exclusive or mutually distinct from each other. Within the data, there may be some overlap, which though will not harm the findings of this study. The categories are reviewed below:

5.1. Wokeness

Wokeness as a term of discourse presupposes actions that are motivated by convictions about woke ideology (McGrath, 2019; Cammaerts, 2022; Aerielle, 2020). In most literature, wokeness is prominently, if not exclusively, regarded as the prime motivating factor for cancel culture. It is the most discussed phenomenon associated with cancel culture (Mishan, 2020; Carter, 2021; Alexander, 2021; Mueller, 2021; Zurcher, 2021; Fahey et al, 2022). Wokeness has gained prominence in recent years, especially in discussions surrounding social justice movements. In the context of this study, wokeness refers to a heightened awareness of social and political issues related to discrimination, inequality, and oppression, particularly regarding race, gender, sexuality, and other marginalized identities (McGrath, 2019; Cammaerts, 2022). The support for or opposition to the woke forms of activism as a motivating factor for cancel culture can be implicated in conversations when the theme is about wokeness. This is evidently seen in the use of words associated with wokeness in context. Such words include “sjw”, microaggressions”, “inclusivity”, “marginalized groups”, “sexual violence”, “metoo”, “white supremacy”, etc.

5.2. Politics

Politics as a motivating factor for cancel culture presupposes all such conversations whose motivation is oriented toward using cancel culture activism as a means of gaining political power or depriving the opponent (either a person, entity, or group) of the same. In the instance of this study, individuals, groups, or businesses, may be canceled or defended based on their political views or affiliations, rather than just an honest appraisal of their moral failings (Kaufmann 2022; Bridges 2021: 7). In the context of politics-motivated cancel culture engagements, political vocabulary words are prominently used. For instance, political affiliations are mentioned as part of the justification for why a person may be canceled or defended (Norris, 2021; Bridges, 2021 Ng, 2022). Words and phrases like “democrat”, “conservative” "party“ ”politics", "elect*", "vote", "election", etc. are frequently used in these conversations.

5.3. Nationalism/patriotic sentiment

Nationalism and patriotism as motivating factors for cancel culture conversations presuppose all such conversations whose motivation is to defend the integrity of one’s nation or ethnic nationality. Here, usually, there is a cause or goal for which the activists rally in defense of the side they identify with (Ng, 2022). Nations, people, businesses, brands, or their supporters can be targeted for canceling if they come out on the opposite side; that is supporting the opposed nation or people. In these kinds of conversations, part of the goal is whipping up patriotic sentiment among the people. Words/phrases like, “our country”, “our people”, “patriotic”, “unpatriotic”, “hero”, “traitor”, “treason”, “nepotism”, etc. are frequently used in these conversations.

5.4. Normative/traditional activism

Normative or traditional forms of activism, in the context of this study, encompasses different types of traditional social change-orientated activism that have existed long before the woke ideology. In the woke era, people still tweet out in support of these forms of activism but many now try to align their goals to cancel culture. I distinguished normative/traditional activism from wokeness in this study because the vocabulary words of traditional forms of activism had existed long before the woke movement. Also, the goals of traditional activism go beyond issues of racial discrimination and oppression to include hosts of problems in society; like the environment, women's rights, girlchild rights, animal rights, bad governance, religious rights, self-determination, etc. (Thrall, 2018; Burmah, 2021). Arguably, the goal of normative activism is to fix the system or culture, but the target of woke activism is to cancel the individual, group, or entity who misbehaved. Also, traditional forms of activism tend to mobilize and have forms of existence outside of social media. Activists support their cause beyond just tweeting. They also involve in traditional modes of protesting, which include street rallies, meetings, shows, even advertising, etc. However, as already noted, in these times, some traditional activist groups do append their motive and goals to cancel culture, either to earn wider support or to trend with cancel culture hashtags. But the distinction between these two forms of activism, especially their means of mobilization and purpose are different.

5.5. Cultural/moral/ethical values

Cultural, moral, or ethical values as motivation for cancel culture presupposes all such conversations whose motive derives from the desire to redeem or restore the moral, ethical, and/or cultural values of the society (Kaufmann, 2022; Kelly, 2022). These types of conversations always hinge on the need to preserve the cultural values of the people. They are usually either in support of cancel culture or in opposition to cancel culture (Fiorazo, D. 2021; Bridges, 2021). In essence, some activists may see cancel culture as a tool in the cause of restoring of cultural and ethical norms of their society, an opportunity to eradicate noxious practices, customs, or cultural practices, while others may deem it as harmful to the norms and moral codes of their society (Shelver, 2022; Janssens et al, 2022). In these conversations, vocabularies related to moral/cultural changes, like "our culture", "our faith", "our religion", "moral", "immoral", and "custom", etc. are often used.

5.6. Free speech/freedom of expression

Free speech or freedom of expression as a motivating factor for cancel culture presupposes all such conversations whose motivation is free speech concerns. In the West, this may seem to be the preoccupation of the libertarian Right. Tweets made in the context of freedom of speech may be to defend it or criticize it. To those who advocate for free speech, cancel culture is viewed as restricting free expressions, suppressing freedom of opinion and independence of journalistic or academic inquiries. Some free speech advocates even consider cancel culture as an attack on Western civilization (Thiele, 2021; Strossen, 2020; Kaufmann, 2022: 29-32; Dershowitz, 2020; Romano, 2020). The opponents of freedom of speech would cite examples of inappropriate use of language, like incorrect gendering or reckless use of the N-word or antisemitic words, etc. (Thiele, 2021: 51). The vocabulary words associated with "free speech" in cancel culture conversations include; "freedom of expression", "censorship", "silencing", "silenced", "political correctness", "misgendering", "N-word", etc.

6. Categories of implication for negative types of cancel culture conversations

Researchers have noted some implications of negative types of online engagements (Sutherland, 2020; Vehovar & Jontes, 2021). But a lot of literature on negative online engagement focus on branding, product management, and marketing (Pfeffer, 2014; Rost, et al, 2016; Lievonen et al, 2022). Extant literature on negative communication against humans in cancel culture communication situation has been lacking.

Indeed, not all types of cancel culture engagements are negative. However, in this study, my focus is only on the negative implications because, with respect to cancel culture, the implications of negative communication are not often mentioned in extant literature despite the fact that they have real-life emotional, psychological, and sometimes physical, consequences on people who are targeted in these conversations (Vehovar & Jontes, 2021; Sutherland, 2020; Trumper, 2022: 8-10).

Unlike the categories created for motivations for cancel culture, here I do not set a threshold for significance for each category identified in the data. The only consideration given is the presence or absence of words/phrases indicating a category. The categories I draw following a preliminary review of the data include; 1. hatred/toxicity, 2. stereotyping, 3. polarization, 4. prejudice/discrimination, 5. bullying/verbal abuse, 6. mockery/shaming/trolling/name calling, and 7. Defamation/doxing/blackmail. These categories are briefly reviewed below.

6.1. Hatred/toxicity

This is when derogatory or offensive language is used to express hostility towards individuals or groups because of certain disagreements, differences, or simply because of some other attributes of the person (Laub, 2019; Mathew et al, 2019). The words which convey hatred are often intended to malign, demean, insult, or dehumanize the target, and they may contribute to a culture of discrimination, intolerance, and divisiveness. In the cancel culture context, hateful words/phrases may include, “bigot”, “idiot”, “hypocrite”, “go fuck yourself”, “go die”, “nazi”, “collaborator”, “mentally ill”, etc.

6.2. Stereotyping

These are words, terms, or phrases that perpetuate generalizations, assumptions, or oversimplified beliefs about a particular group due to possessing some differing characteristics (Kowert, 2012; Marjanovic, 2022; Daniels & Daniels, 2019; Gregory, 2020: 54).

Stereotypes can reinforce existing biases and contribute to prejudice, discrimination, and unfair treatment (Abrams, 2010; Yuen, 2019). For instance, African Americans supporting the Republican party are often sterotyped as “uncle toms” or “coons” in the cyberspace (Deavel, 2021; Pierson, 2010). In the context of cancel culture negative stereotypical words may include, “pro-”, “anti-”, “snowflakes”, “fascist”, “leftist”, “rightist”, “grifter”, “muslim”, “coon”, “extremist”, etc.

6.3. Polarization

These are words and phrases that contribute to division, conflict, and/or heightened ideological differences within society (Bail et al., 2018; Garimella and Weber, 2017; Quattrociocchi et al., 2016). Such words often evoke strong emotional responses and are used to express viewpoints that reinforce divisive narratives (Nordbrandt, 2021; Reiljan, 2020). They can exacerbate the "us versus. them" mentality and hinder constructive dialogue or understanding between different groups or individuals. Polarization words can be used to label, stereotype, or demean those who hold opposing views, fostering an environment of hostility and animosity. In cancel culture contexts, polarization words may include calling people, “ideologues”, “bigot”, “scammers”, “us”, “we”, “they”, “our enemies”, “our friends”, “opponents”, “supporters”, “haters”, or using segregation terms like “homophobes”, “racist”, “hitler”, “snowflakes”, “nazi”, etc.

6.4. Prejudice/discrimination

Online racial discrimination can be described as the denigration or exclusion of an individual or group on the basis of their ideology or other immutable characteristics (Lin & Anderson, 2012). These are words or phrases used to express prejudice, bias, or unequal treatment towards individuals or groups based on certain, and often immutable, characteristics. (Tynes et al, 2012; Maxie-Moreman & Tynes (2022). In the cancel culture context, discrimination words can include, “pro-”, “anti-”, “Muslim”, “jew”, “Whiteman”, “far-”, “radical-”, etc. When “pro-white” is used, it may be an attempt to make a targeted person be seen as a supporter of some notorious White supremacy ideology to justify prejudicial action against them. Such labels which may not even be true. Or when far-left is used, it may be to identify a person as an extremist, and for that reason, bad behavior toward him/her becomes justifiable. Prejudicial and discriminatory words are typically derogatory or offensive and contribute to a culture of discrimination and inequality (Tynes, et al, 2014; Yip et al, 2019).

6.5. Bullying/verbal abuse

Generally, online bullying means incidents where people use services of digital technology to harass, threaten, humiliate, or otherwise hassle other online users (Hinduja & Patchin, 2020; Ferrara, et al, 2018; Craig et al, 2020). Typically, online connectivity opens up a social media user to other users from all over the world, and this is not always a good thing (Hamm et al, 2015; Hinduja & Patchin, 2020). Some of the users feel free to post or send whatever they want online without considering how such content can cause harm. For instance, a young person can send hurtful texts to others or spread rumors using smartphones or tablets (Hamm et al, 2015; Ferrara, et al, 2018). In the context of cancel culture, words and/or phrases are used which are derogatory, demeaning, or hurtful, with the aim to belittle, intimidate, or humiliate a targeted person. Often these words are meant to assert power and control and are made with the intent to cause emotional distress or harm (Notar et al, 2013; Hamm et al, 2015, Hinduja & Patchin, 2020). Some bullying terms that can found online include words like “clowns”, "stupid", "ugly", "fat", “fat ass”, "worthless", “dimwit”, “self-loathing”, etc.

6.6. Mockery/shaming/trolling/name-calling

Mockery and trolling are posts or comments online made to deliberately upset others (Griffiths, 2014; Golf-Papez & Veer, 2017; Sun & Fichman, 2019; Kaplan, 2021). They are often context-dependent and are made by perpetrators who are pseudo-sincere, intentional, provocative, and repetitive (Sun & Fichman, 2018). Barzotti et al (2021) say that the aim of mockery is to attack fundamental human honor and respect, while Herring et al (2002: 373) opine that online trolls like to lure others into often pointless and time-consuming discussions. Also, Morrissey (2010: 77) states that, among other things, online trolls produce intentionally false or incorrect utterances with the high-order intention to elicit from a target a particular response, generally negative or violent. Thus, it appears trolling is an act of intentionally provoking and/or antagonizing users in an online environment, which creates an often desirable, sometimes predictable, outcome for the troll. Phillips (2015) observes the cross-national diversity of online trolling and mentions various motivations for trolling behaviors in countries like Australia, the USA, and the UK.

Meanwhile, in the context of cancel culture, mockery, shaming, trolling, and name calling can involve people using derogatory names or labels, ridiculing or making fun of someone's mannerisms, speech, or behavior in order to demean and embarrass them. It can involve sarcastic comments, mimicry, or sarcasm meant to demean or diminish a person's worth. In cancel culture context, “magat”, “qanon”, “snowflakes”, “NPC”, “talking head”, “remoaner”, “slut”, “karen”, “mob”, “rapist”, “fool”, “stupid”, “clown*” etc.

6.7. Defamation/doxing/blackmail

Doxing is an intentional public release on the Internet of personal information about an individual by a third party, often with the intent to humiliate, threaten, intimidate, or punish the identified individual (Douglas, 2016;). Blackmail are words or phrases whose intent is to manipulate and control another person’s actions by exploiting their fear of potential consequences for toeing a particular line of action (Mattise, 2015; Anderson & Wood, 2021). Blackmail could also be emotional done by making the target feel guilty for certain words or actions when they ought not to. The person attempting the blackmail may leverage on verbal or written threats, accusations, or promises in order to coerce the target into a particular behavior. In the cancel culture context, doxing and blackmail words include, “dox”, “doxing”, “doxxing”, “doxxed”, “doxed”, “ashamed of”, “hidden agenda’, “traitor”, “race hustler”, etc.

Chapter III. Study methodology

1. Opinion mining and natural language processing

The analytical methodology for this study is text mining (ML) and natural language processing (NLP), which are aspects of machine learning dealing with text analysis. I shall use ML algorithms to mine and analyze opinions people express on social media about cancel culture to understand the motivations driving their participation in these kinds of online engagements.

The sheer number of comments on some popular posts especially on popular sites like Twitter makes it difficult for the aggregate views of the commenters to be deciphered at a glance. However, with machine learning text mining algorithms, it is possible to analyze such comments as data (Choudhary et al, 2009; Talib et al, 2016; Gupta, et al, 2020; Li et al, 2018). With text mining, it is possible to examine large volumes of (unstructured) text data; looking for patterns, extracting new information, discovering context, identifying linguistic motifs, or transforming the text into a structured data format for further quantitative analyses (Dinov, 2018, Kaushik, 2013; Jacobi et al, 2016; Dhawan & Zanini, 2021; Sebastiani, 2002; Dinov, 2018; Dhawan & Zanini, 2021; Torfi et al, 2021; Patel & Arasanipalai, 2021; Torfi et al, 2021).

In summary, text analysis process involves the basic steps below; 1. selecting the data, scrapping/importing the data, 2. preprocessing the data by removing the noise in them, like punctuation, stopwords, etc., 3. constructing a document-term matrix (DTM) from the input document, and 4. using machine learning techniques for varius analysis like prediction, clustering, classification, similarity search, network/sentiment analysis, forecasting, etc. (Dinov, 2018; Patel & Arasanipalai, 2021).

2. Data selection and collection

As stated in the literature review, there is no agreement among scholars as to when the term cancel culture was coined, or, even, when the activism itself started. However, there is evidence in the literature that the use of cancel culture hashtags had become common on Twitter by 2017, and the term had become ubiquitous on the platform by 2018. Hence, in this study tweets made on cancel culture within the timeline between 2018 and 2022 were scrapped from Twitter for analysis.

Meanwhile, cancel culture on Twitter is associated with numerous hashtags, like #IsOverParty, #RIPJKRowling, #HasJustineLandedYet, #MeToo, etc., some of which trended for other reasons before they became associated with cancel culture. But, among the many hashtags associated with cancel culture, two are prominent, typical, and specific to its activism and conversations, which are #cancel_ and #boycott_. These two hashtags are sometimes used independently or together in tweets, and sometimes they are used with other cancel-culture-related hashtags. For instance, there are hashtags like #canceldavechappelle, #boycottdavechappelle, #cancelauntjemima, #cancelkorea #boycottFCMB, #boycottJKRowling, #boycottSnowdrop, etc. For this study, comments made on Twitter in which the two hashtags, #cancel_ and/or #boycott_ were used as key hashtags of the tweet were collected. For non-English speaking entities, like South Korea and Brazil, direct translations of these hashtags - for example #취소문화 and 보이곳운동 in Korean - were used in creating the script for the scrapping of the data.

Below are a few samples of cancel culture tweets collected for the analysis of this study.

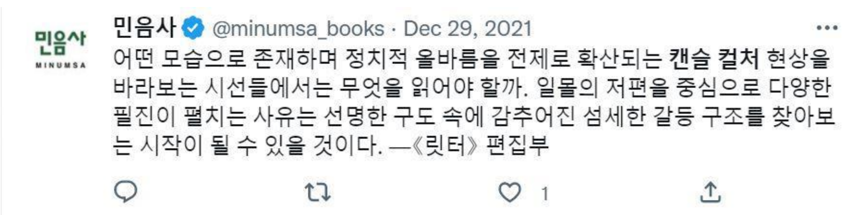

Figure 2: Examples of cancel culture tweets with different hashtags and on various issues

Meanwhile, permission for scrapping the data was obtained from Twitter, with access granted via Twitter academic API v2, the endpoint of which allows for precise, complete, and unbiased data access to researchers (Twitter, 2022). The script for scrapping the data was created with the 'academictwitteR' package in R (Barrie & Ho, 2022), designed to query the Twitter academic research product track.

Furthermore, each tweet on Twitter is a rich data record containing multiple metadata fields, including timestamp, location, language, and additional information derived from the users' profiles. In this study, however, I am interested in the text (content) of the tweets and the geotag (countries) where the tweeters are located at the time of tweeting. Hence, the query script was created with an argument to return data that met these specific criteria (Barrie & Ho, 2022).

The text content of the tweets from the South Korean Twitter space was mostly written in Korean. Those from India and the Philippines were written with a lot of code-switching between Hindi or Tagalog and English. Those written in Brazil were mostly written in Portuguese. So, I created a text translation script to translate all the tweets' content into English using Google's NLP API with the authorization accessed through the 'googleLanguageR' package in R.

The translation conducted by the app does very well, especially with regard to the content words. All the keywords and content words in the original languages were most accurately translated into English. An example is presented below of a tweet from Korea data that the machine translated into English. The content words in the translated version of the tweet were closely matched with the original version.

Tweet

Translation

Brad Jeong

@joom1217

-Brad

Mar 21

Line 1, Seolhwa Mungok Station, Dalseong-gun, Daegu

Relay one-person protest

YoonSeokYeolDeathKimGunHeeSpecial Prosecutor

B e g g i n g D i p l o m a c y HumiliationDiplomacy Indigenization

Boycott BOYCOTTJAPAN

Ilcheongmo

Daegu Citizens' Gathering for the Liquidation of Japanese Remnants

Democratic Rights Party Members

Figure 3: Sample of a non-English tweet and its translation with Google Translation API

3. Data presentation

The data scrapped for analysis consists of a document corpus containing eight variables as seen below.

```
> colnames(thesis_quantanaly_corp)
[1] "source"            "country"           "id"                "conversation_id"
[5] "text"              "lang"              "author_id"         "created_at"
[9] "in_reply_to_user_id"
```

Figure 4: Variables of the data used for the analysis

The document corpus consists of 196721 rows. Two variables out of the nine in the data were important for our analysis, which are "text and "country"; they were selected for further analysis. After tokenizing the text variable, the tokenized features were 261289 which became the final data used for this study. The breakdown of the features per country is presented in Table 1 below:

Table 1: Summary of features (words) in the study data

Country	No of Features
South Korea	19241
Philippines	14062
India	61474
United States	109802
United Kingdom	77815
Nigeria	26768
South Africa	16627
Brazil	24004
Total	261289

Note: the result here excludes punctuation.

4. Data preprocessing

Meanwhile, as mentioned above, the content of the text data was dense and very noisy; containing not just sentences but also HTML tags, abbreviations, honorifics, domain-specific words, and sometimes, emoji, special characters, and digits. For the analysis of the text to produce a meaningful result, the data needed to be cleaned properly before using them. The steps taken for cleaning and arranging the data – explained in detail in Dinov (2018: 661-671), Eisenstein (2018), and Watanabe et al. (2023) – are presented below:

a. Noise removal – to remove digits, special characters, and pieces of irrelevant texts from the data corpus before conducting analysis with them. The quanteda package in R is used to evaluate and remove irrelevant texts from the corpus.

b. Lowercasing – when necessary, to lowercase the text data before analysis is conducted with them. The quanteda and tidytext packages have arguments for lowercasing texts in a corpus.

c. Tokenizing – when necessary, to break the corpus of text into a sequence of discrete tokens of words. Both quanteda and VosViewer have inbuilt functions to tokenize text. Some word positional analyses, like bag-of-word analysis, can be performed upon tokenizing the corpus.

d. Filtering – to remove words that are irrelevant for text analysis. Usually, stopwords, URLs, and HTMLs are redundant, having little or no analytical value for text mining. They are removed before conducting some types of analysis. Both the quanteda and VosViewer have functions for filtering and removing stopwords from the text data corpus.

e. Document Term Matrix (DTM) – a matrix of text in which each row represents a document, and each column represents a term. DTM provides a numerical representation of the textual data and enables various computational analyses

5. Data analysis methods

5.1. Document similarity: Text similarity analysis

The text similarity measure is a type of unsupervised text clustering technique that splits and classifies text/documents into several groups based on their similarities (Manning et al, 2008; Han et al, 2012). It is used to compare a piece of text with another to find the similarity between them. It's used basically to determine the degree of closeness of text documents (Radev, 2016; Metcalf & Casey, 2016).

In this study, the essence of the similarity analysis is to underscore how the data for the study are related in the discourse context. The context supposed to be shared by all the conversations is cancel culture, irrespective of where the data is obtained from. The similarity test is conducted to confirm the assumption of basic similarity of the cancel culture discourse in the data, which will determine if the data is suitable for further analyses or not. That is; the analysis will determine if the text data are comparable or not. If they are unrelated in context ($2.9 \geq \cos\ \theta \geq 0$), then further analysis will not be conducted with the data.

Secondly, the similarity analysis is used to provide some clue into the consistency or unity of cancel culture conversations across the varying contexts and invariably the similarity of the motivating factors for the cancel culture activism. The text similarity analysis will identify semantic consistency in the language used in cancel culture conversations.

The similarity function I shall utilize is the cosine similarity, which I shall implement in R. And three assumptions are being made here depending on the result of the analysis:

1. If the text from the various countries are highly similar *(($1.0 \geq \cos\ \theta \geq 0.7$))* it suggests that a lot of the lexicons used in cancel culture engagements are similar. Hence, the context of the discourse/ conversations in the data is similar. So, further analysis is possible as the data can be compared. It may also mean that the issues in the conversation are generally similar, invariably similar motivating factors for which the issues are discussed. If individuals, organizations, or groups of interlocutors across different locations use similar words, phrases, or word collocations across multiple planes of communication, this indicates consistency in their reasoning, hence consistency in the motivations for which they participate in the conversations.

2. If the text is less similar *($0.69 \geq \cos\ \theta \geq 0.3$),* it suggests that the context of the conversation is similar to an extent because the discourse is still about cancel culture, but the similarity is weak, which suggests that a lot of the lexicons in the data are not commonly used among the countries being compared. This also suggests that even though the tweets are about cancel culture, the issues the tweeters fixate on vary, and invariably the motivating factors for their involvement. That is to say, for example, in one country, the conversations about cancel culture are centered on wokeness, while in another country they are

centered on cultural values. In this kind of outcome, it is possible to perform further analysis of the data, but the focus will be to understand the points of divergence.

3. If the texts are almost or perfectly dissimilar *($0.29 > \cos\ \theta \geq 0$)*, it means the contexts of the discourse in the documents are entirely different. It is possible that one corpus is about medicine and another is about cancel culture. Therefore, further analysis of the two data corpora is not possible, since they do not share the same discourse context.

5.2. Motivating factors for participation in cancel culture conversations

The approach I shall use to explicate and explain the motivating factors of cancel culture shall be conducted in a number of steps using different machine learning methods; Latent Dirichlet allocation (LDA), word network/wordcloud analysis, dictionary analysis, word frequencies, and keyword-in-context analysis. The software I shall use for the analyses here is R and VOSViewer. R, together with relevant text mining packages built in it, shall be utilized for statistical analysis, classification, categorization, and sometimes visualization of relationships, while VOSViewer mapping will be used for visualizing word network analysis.

5.2.1. LDA analysis

The LDA is a method useful for identifying hidden patterns like topics/themes in a large document corpus. LDA is a probabilistic topic modeling technique that assumes documents are generated from a mixture of latent topics. It discovers underlying topics in a collection of documents and assigns probabilities to each topic for each document (Landauer, et al, 2009; Bellegarda, 2007; Manning et al, 2008; Cvitanic, 2016; Jacobi et al, 2016; Cheng, et al, 2021). LDA is particularly useful for tasks such as document clustering and topic identification. It provides a way to uncover the latent thematic structure in a corpus. The LDA computation is done for the categorization and classification which places words into meaningful units that cluster around topics and themes. These topics and themes will suggest what the document is all about (Landauer, et al, 2009; Cvitanic, 2016; Cheng, et al, 2021).

I will conduct the LDA analysis on the entire data set. The script for the classification will be designed to extract eight dimensions in total from the LDA analysis. That is, I seek at least six topics from which prominent cancel culture motivating factors can be implied. The LDA, meanwhile, does not propose or give names to topics emanating from its analysis, but these can be inferred in relation to the meanings of the words clustered together under each topic. I will name the topics according to the semantic proximity of most words which stand together to describe a particular motivating factor.

5.2.2. Dictionary analysis

In dictionary analysis, dictionaries or lexicons are used to analyze and interpret text data (Welbers, et al, 2017). This process involves mapping words or phrases in a text to predefined categories or labels present in the dictionary. The dictionary typically contains a list of words or expressions along with their associated meanings, sentiments, emotions, or other relevant information. Broadly, patterns are used to count how often these concepts occur in text data. Hence, dictionary analysis is a deductive approach, because it defines a priori what codes are measured and how (Welbers, et al, 2017: 12). A lot of prior studies have utilized dictionary methods, which is a computationally simple but effective approach to making deductions from the data (Welbers, et al, 2017: 12).

Among the dictionaries in use in the quanteda package is the LIWC dictionary (Pennebaker et al, 2007) which I chose for this study. But the LIWC dictionary does not have all the categories for the analysis of our data. Fortunately, the quanteda has a function to supplement the existing dictionary corpora. So, I used the dictionary function to modify the features to suit the purpose of this research. For instance, the dictionary of political words used in this study is modified to include the words, “conservative", “democrat”, “liberal”, “left wing”, “right wing”, "politics”, "democracy", "vote", "election”, "campaign", "rig", "power", "alt-Right", “alt-Left”, “party”, "win", “lose”, “right to vote”, etc.

Meanwhile, the dictionary analysis conducted here aims to find words that indicate motivating factors for cancel culture as well as negative implications of some kinds of cancel culture conversational engagements. The analysis examines the data for the presence of terms associated with one another in specific semantic sphere to be identified as motivating factors which can be grouped according to the categories from the LDA analysis. For instance, “politics” is considered a motivating factor for cancel culture, and is a category identified following the LDA analysis. The dictionary analysis will involve matching “politics” vocabulary words in the dictionary with the data to explicate politics as a motivation for cancel culture. If there are significant matches, then the fact is established.

I set a threshold for each category to be considered significantly represented in the data to *0.4%*, except the data from the United Kingdom which has a large internal variance, which I set at *0.3%*. In essence, a category is considered significantly represented in the data if there are matches of up to 4 percent of the dictionary features in the data. I consider this significant because a lot of normal conversations involve words which are very unrelated in their contexts and hence have low pragmatic analytical value.

5.2.3. Word network/cloud analysis

The wordcloud/network analysis is used to underscore how words cluster around key issues in a word network. With word network analysis, it is possible to identify issues in the conversations by identifying the clusters of high-frequency word nodes appearing in the same context (van Eck et al, 2008; van Eck & Waltman, 2010). Semantically, the themes and motivating factors for which people engage in conversations can be inferred by examining word clusters and nodes in the word network. For word network analysis, I shall use the VosViewer software, the output which is basically focused on visualization.

The Vos mapping technique requires a similarity matrix as input (Waltman and van Eck, 2007), but unlike other similarity functions like cosine and the Jaccard index, its mapping uses a similarity measure that is based on word association strength (Van Eck and Waltman, 2007b; Van Eck et al., 2006). Using the association strength, the similarity between two items is calculated as proportional to the ratio between, on the one hand, the observed number of their co-occurrences, and on the other hand the expected number of their co-occurrences under the assumption that their occurrences are statistically independent (van Eck & Waltman, 2010). The VosViewer was fundamentally designed for bibliometric network analysis, but can also handle textual data and create visualizations of keyword networks based on word co-occurrences in the text data (van Eck & Waltman, 2010).

Using the VosViewer mapping on the Philippines data, for example, five-issue clusters are observed, with several nodes within each cluster. In each cluster are nodes closely related in the corpus due to similarity defined by the frequency of their co-occurrence in the data corpus. By this mapping, the theme of the conversations in each cluster can be deciphered. For, instance, a yellow cluster has words like, "cancelkorea", "philippine", "korea", "racism", "apologize", "cancelracism", "korean", etc. It is easily understood that the nodes in this cluster are conversations about Korea and the Philippines in relation to allegations of racism. And since two nations are involved, we can make an assumption that nationalistic tendency is involved as a motivating factor in these cancel culture conversations. However, the proof of nationalism in the Philippines will need to be verified using the dictionary analysis.

5.2.4. Word frequencies

Word frequencies are used to place documents onto a single dimension, which makes it possible for their frequencies to be conveniently computed (Slapin & Proksch, 2008). There are a number of word frequency approaches in NLP literature (Welbers, et al, 2017; Benoit, 2018; Chen Meurers, 2016; Yang, & Eum, 2018). However, in this study, Slapin & Proksch (2008) wordfish scaling model, written in R and implementable with quanteda, is preferred. It can be used to estimate the word frequencies of documents.

Wordfish is a statistical scaling model based on Poisson naive Bayes model. It assumes that the frequencies of words in text data are generated by a Poisson process. The word positions in the text are estimated using an expectation-maximization algorithm. The programme utilizes a scaling technique, and unlike other word frequency programmes, it does not need any anchoring documents to perform analysis. Instead, it relies on a statistical model of word counts (Slapin & Proksch, 2008: 708).

Further, wordfish can visualize the estimated word weights (estimated beta) versus word fixed effects (estimated psi) for each word used in the analysis. Confidence intervals for estimated positions are generated from a parametric bootstrap (Slapin & Proksch, 2008: 705). In the visualization, frequent words (e.g., conjunctions, articles, prepositions, etc.) do not discriminate between parameters (e.g. party manifestos) because they do not contain any domain dependent (e.g. political) meaning. Therefore, they have large fixed effects associated with weights close to zero. In contrast, words that are mentioned more infrequently, are more likely to be part of politically relevant language and discriminate between the parameters (e.g. manifestos of political parties). These words therefore have smaller fixed effects associated with either positive or negative weights, depending on how words position the parameters (party manifestoes), either on the left or on the right (Slapin & Proksch, 2008: 715).

With wordfish, it is possible to analyze the degree to which the estimates capture the dimension under investigation by estimating the word-discrimination parameters. For example, words related to foreign policy should presumably receive a great deal of weight when examining foreign policy texts. If otherwise, the source of the data is suspect (Slapin & Proksch, 712).

Meanwhile, for better estimation, Slapin & Proksch (2008) suggest that the researcher should first define the dimensions he aims to analyze and ensure to use only documents that contain information relevant to that dimension. And only documents which deal with the dimension and issue of interest should be compared.

5.2.5. Keyword-in-context

The keyword-in-context (KWIC) is a tool used to generate a list of all instances of a search term in a corpus in the form of a concordance (Russell, et al 2017). It is useful in displaying words or phrases in the context they are used within a given corpus of text (Russell, et al 2017; Howe, 2020). It works by extracting a small section of text (usually sentences) from a larger corpus, centered on a particular keyword or phrase of interest, and displaying them in the context of other words, according to concordance (Russell, et al 2017; Welbers, et al, 2017). KWIC is useful in finding the frequency of a word or phrase in a corpus. It can also distinguish different word classes such as nouns, verbs, and adjectives; as well as complex linguistic structures such as passives, split infinitives, etc. It can be used to sort, filter and randomize concordance lines and also to perform statistical analysis comparing the use of a search term in different corpora. In the case of this study, individual tweets are examined in the context of particular keywords from our dictionary to make it obvious how the keywords are used in the speech contexts.

Table 2: Measures used for semantic classification of text

Latent Dirichlet Allocation	Clusters words according to topics, semantic inference can be made here on the themes emanating from the data, and based on the topics motivating factors can be predicted
Word cloud analysis	Clusters words according to the frequency of co-occurrence with other words. Clusters can represent themes and issues to which the keyword nodes relate. These can be exemplified in determining the most common motivating factors for the evolving conversations.
Dictionary analysis	Keywords from the text are matched against a dictionary of words related to particular types of motivating factors. A significant match indicates such category of motivating factor is evident in the data.
Word frequencies	Computes frequencies for the use of keywords in the text. Wordfish frequency method used in this study is generated by a Poisson process, and the word positions are estimated using expectation maximum algorithm.
Keyword in context	Generates a list of instances of a search term in a corpus in the form of a concordance. It displays the words or phrases in the context they are within a given corpus of text. The motivating factors for the discourse indicated in the dictionary analysis can be confirmed here to truly exist here by evaluating the literal words used in the conversations.

Chapter IV. Findings and analysis of the data

1. Investigating the mutuality of cancel culture conversations

The analysis conducted here is to underscore the similarity or commonness of language use among cancel culture tweeters in various countries. For each pair of countries, a significant similarity indicates that there is a high commonality in the themes and topics in the cancel culture conversations. We can assume, based on this, that cancel culture ideas and conversations among Twitter users in these paired countries are basically centered on similar themes. Since in the literature, wokeness ideology is advanced as the primary motivating factor for cancel culture engagement, if most countries' data exhibit high similarity, it means those existing studies are correct which suggests that wokeness primarily drives cancel culture activism. If not, then we can assume that there are other factors involved in cancel culture activism not yet amply explored in research. These can be explored from within the data of the present study.

The similarity measure I use for the analysis here is cosine similarity; to conduct a pairwise comparison between pairs of countries in the study data. For this analysis, I selected 10000 words from the data from each of the countries, in order to have a proportional representation. The result of the analysis is presented in Table 3 below:

Table 3: Text similarity analysis of the text corpora from the eight countries in the data

	S/Korea	India	Philippines	USA	UK	Nigeria	S/Africa	Brazil
S/Korea	1.0000	0.095	0.159	0.155	0.147	0.217	0.0861	0.285
India	0.0951	1.0000	0.150	0.142	0.142	0.190	0.0895	0.119
Philippines	0.1592	0.1502	1.000	0.840	0.579	0.758	0.7054	0.699
USA	0.1553	0.1420	0.840	1.000	0.499	0.789	0.8989	0.851
UK	0.1468	0.1420	0.579	0.499	1.000	0.679	0.1215	0.201
Nigeria	0.2168	0.1896	0.758	0.789	0.679	1.000	0.5894	0.621
S/Africa	0.0861	0.0895	0.705	0.899	0.122	0.589	1.0000	0.889
Brazil	0.2852	0.1187	0.699	0.851	0.201	0.621	0.8885	1.000

Method = "cosine", [Note: stopwords, URLs, and HTMLs removed before the similarity analysis was conducted]

As seen in the result in Table 3, there is evidence within the data that between some countries, the themes in cancel culture conversations are very similar due commonness of words used in the context of cancel culture conversations. In some other countries, there is some sort of average similarity between the pairs due to less commonness of the words used by the tweeters in the countries. And then, in some others, there is a very low similarity between them, because there is even much less commonness among the words used in these conversations.

1.1. High similarity

The pairs of countries with high text similarity include the Philippines paired with the USA, Nigeria, South Africa, and vice versa (see Table 3). The text data of the conversational engagements about cancel culture in these countries paired against each other share a commonness of about or higher than 70 percent of the content words *($1.0 \geq \cos\theta \geq 0.7$)*. As Table 3 shows, the pairwise similarity score of the USA corpus with the Philippines is 0.840, with Nigeria is 0.789, South Africa is 0.899, and Brazil is 0.851. Also, the pairwise similarity of the Philippines corpus with Nigeria is 0.758, with South Africa is 0.705. And the similarity of the South corpus with Brazil is 0.889.

What high similarity of the words in the data indicates is that a lot of the content words used in the conversations are similar or the data from the two countries share a lot of words in common. It is probable, therefore, that the cancel culture conversations in these countries speak to common key issues because of semantic closeness, and perhaps indicate that the tweeters share similar motivations because they speak about the same issues. I shall choose a pair of countries; the USA and Brazil *(pairwise similarity = 0.851)* for further analysis to exemplify what high similarity indicates in the context of this study. Table 4 shows the top ten words that appear in the USA data *(n-target)* compared with Brazil data (*n-reference*). As seen in the Table only two words "dave" and "chappelle" are not used at all in Brazil. However, the high X^2

values for most words with respect to the target corpus (the USA), indicates excessively high use of the top words in the target country compared with Brazil, but what is important is that most of the top words used in the USA are also used in Brazil, which justifies the high correlation of words used in the context of cancel culture conversations among tweeters in both countries.

Table 4: Text_stat keyness result comparing words used in the USA and Brazil

	feature	chi2	p	n_target	n_reference	ratio
1	cancel	2279.725550239	0.0000000000000000000000	42100	2752	15.297965
2	culture	931.022004360	0.0000000000000000000000	39057	3744	10.431891
3	boycot	3404.416240604	0.0000000000000000000000	24335	265	91.830189
4	people	−0.769215382	0.3804598897866959816838	11130	1807	6.159380
5	dave	741.747484958	0.0000000000000000000000	4648	0	Inf
6	chappelle	693.332448608	0.0000000000000000000000	4346	0	Inf
7	woke	634.898709941	0.0000000000000000000000	4286	23	186.347826
8	trump	413.252909820	0.0000000000000000000000	2846	19	149.789474
9	think	−160.973963612	0.0000000000000000000000	2766	738	3.747967
10	right	−24.712133008	0.0000006656381252856391	2737	548	4.994526

In total, there are just about 514 words not common between the two countries, 309 words used exclusively in the USA and 205 words used exclusively in Brazil. In the USA, some of such exclusive words include; “chapelle”, “beg”, “gop, “nomore”, “mob”, “georgia”, “@cnn”, “donors”, “nfl”, “nba”, “tuckercarlson”, “runoff”, “whining”, “comedians”, “democrats”, etc., while in Brazil they include; ”kcafavmusicvideo”, “marilia”, “militancy”, “mendoca”, “bbb21”, “biphobic”, “bolsonaro”, “anitta”, “fatphobic”, “brazilian”, “militant”, etc. Tables 5 and 6 below show examples of top ten words used exclusively in each country and not in the other.

Table 5: Top ten words used in the USA but not Brazil

	feature	chi2	p	n_target	n_reference	ratio
1	chappelle	722.40622	0.0000000000000000000000	683	0	Inf
2	begged	118.15908	0.0000000000000000000000	112	0	Inf
3	gop	111.82613	0.0000000000000000000000	106	0	Inf
4	plans	90.71873	0.0000000000000000000000	86	0	Inf
5	nomore	89.66346	0.0000000000000000000000	85	0	Inf
6	mob	88.60820	0.0000000000000000000000	84	0	Inf
7	georgia	84.38725	0.0000000000000000000000	80	0	Inf
8	@cnn	69.61512	0.0000000000000001110223	66	0	Inf
9	donors	67.50497	0.0000000000000002220446	64	0	Inf
10	@nfl	56.95477	0.0000000000000446309656	54	0	Inf

Table 6: Top ten words used in Brazil but not in USA

	feature	chi2	p	n_target	n_reference	ratio
1	#kcafavmusicvideo	-112.91378	0.0000000000000000000000	0	119	Inf
2	marília	-103.42059	0.0000000000000000000000	0	109	Inf
3	militancy	-88.23327	0.0000000000000000000000	0	93	Inf
4	mendonça	-81.58950	0.0000000000000000000000	0	86	Inf
5	#bbb21	-79.69135	0.0000000000000000000000	0	84	Inf
6	biphobic	-75.89517	0.0000000000000000000000	0	80	Inf
7	bolsonaro	-73.04812	0.0000000000000000000000	0	77	Inf
8	anitta	-56.91628	0.0000000000000455191440	0	60	Inf
9	fatphobic	-56.91628	0.0000000000000455191440	0	60	Inf
10	brazilian	-52.17209	0.0000000000005084821453	0	55	Inf

As Tables 5 and 6 show, the words used in the cancel culture context that are peculiar to each country are either names of political personalities or private individuals who became popular as cancel culture targets, or names of businesses, brands, entities, or institutions which became associated with cancel culture in each country. Beyond those, we can see wordsthat are peculiar coinages, like “nomore” in the USA, and “victimism” and “bolsominion”, etc. in Brazil. These words are not regular dictionary words, and, probably, their use is restricted to each country’s discourse.

Further, a pair of wordcloud visualization, presented below in Figure 5 show the representation of the top fifty words used in the USA and Brazil data. These show that both countries share a lot of top words in common, which include words like; “cancel”, “hate”, “see”, “culture”, “people”, “right”, “good”, “think”, “time”, “will”, “now”, “much”, “shit”, “someone”, “know”, “everyone”, “one”, “make”, “still”, “never”, “also”, “go”, “just”, “like”, “said”, “can”, “thing”, etc. The commonness of words like these is the reason for the very high text similarity between the two countries, which also suggests a semantic similarity of key issues tweeters care about in the cancel culture discourse in both countries.

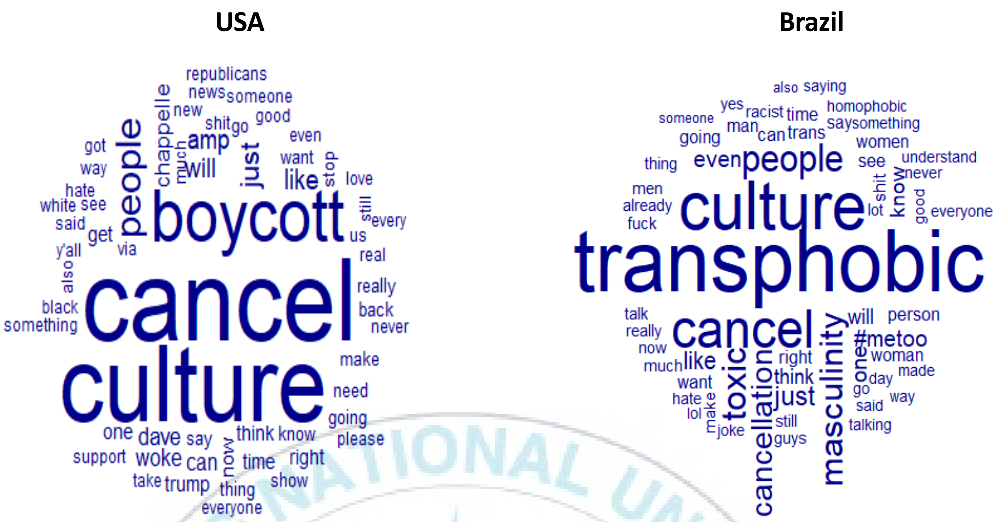

Figure 5: Wordcloud visualization of 50 most used words in the USA and Brazil indicating high similarity

1.2. Average similarity

The pairs of countries with average similarity according to the analysis include the UK paired with the USA, the Philippines, Nigeria, and vice versa. Between these pairs of countries, the similarity of the content words used in cancel culture tweets is between 69 and 30 percent *(0.69 ≥ cos θ ≥ 0.3).* In essence, the pairwise similarity fluctuates around the statistical average. For example, the similarity between the pair of the UK and the USA is 0.499, the UK and the Philippine is 0.579, and the UK and Nigeria 0.679. Also, the similarity between the Philippines and Brazil is 0.699.

The text statistic keyness Tables 7a and 7b below is used to show an example of how words are used in the countries with average similarity. The Tables show the result from the UK and Philippines data *(pairwise similarity = 0.579).* As the Table 7a shows, seven out of top ten words used in the UK *(n_target)* conversations are also spoken, but to a lesser extent, in the Philippines *(n_reference)*. These words are "jk_rowling", "media", "uk", "social", "sign", "israel", and "boycott". However, words like "brexit", "ukchange", "piersmorgan", (top 7th, 8th, and 10th respectively) are used in the UK but not mentioned at all in any cancel culture tweet originating from the Philippines. The high X^2 with respect to the target country (UK) is because of the excessive use of these top words in the UK compared to the Philippines.

Table 7a: Upper section of text_stat keyness result comparing words used in the UK versus the Philippines

	feature	*chi2*	*p*	*n_target*	*n_reference*	*ratio*
1	jk_rowling	449.89641	0.0000000000000000000	4745	2	2372.50000
2	media	93.36920	0.0000000000000000000	1880	48	39.16667
3	uk	88.56603	0.0000000000000000000	996	3	332.00000
4	social	77.08554	0.0000000000000000000	1508	37	40.75676
5	sign	71.65488	0.0000000000000000000	999	12	83.25000
6	israel	59.53047	0.0000000000000001199041	648	1	648.00000
7	brexit	59.41915	0.0000000000000001276756	625	0	Inf
8	ukchange	56.92024	0.0000000000000004540812	598	0	Inf
9	#boycott	55.03242	0.0000000000000011857182	1705	66	25.83333
10	piersmorgan	51.49002	0.0000000000000071964656	541	0	Inf

Meanwhile, it is at the lower end of the Table (7b) that the evidence of disparity responsible for the average score in the similarity between the two countries is clearly observed. The lower end of the table (Table 7b) shows some examples of the many words that are not commonly used between the two countries. For example, words like "filipinos", "nellygbasco", "gmaxtape", "mainedcm", and "cancelkorea", etc., which are very popular in cancel culture tweets in the Philippines are unknown and not used at all in the UK. The presence of many words used in the Philippines and not at all or less used in the UK accounts for the high negative X^2 values with respect to the UK.

Table 7b: Lower section of text_stat keyness result comparing words used in the UK versus the Philippines

	feature	*chi2*	*p*	*n_target*	*n_reference*	*ratio*
8047	filipinos	-1767.164	0	0	168	0.000000000
8048	nellygbasco	-1903.949	0	0	181	0.000000000
8049	gmaxtape	-2619.530	0	0	249	0.000000000
8050	adn	-2792.891	0	3	269	0.011152416
8051	stay	-2887.705	0	175	421	0.415676960
8052	mam	-3198.437	0	6	311	0.019292605
8053	aldenrichards02	-3348.976	0	4	323	0.012383901
8054	mainedcm	-3482.644	0	0	331	0.000000000
8055	po	-5707.593	0	4	547	0.007312614
8056	cancelkorea	-10469.577	0	0	994	0.000000000

Meanwhile, a visualization of the top fifty words used in both countries as seen in Figure 6 below also shows that cancel culture tweets in both countries do not share a lot of top words in common. Among the top words they have in common are; “boycott”, “cancel”, “culture”, “people”, “will”, “never”, “one”, “right”, “time”, “like”, “want”, “think”, “can”, “support”, etc.

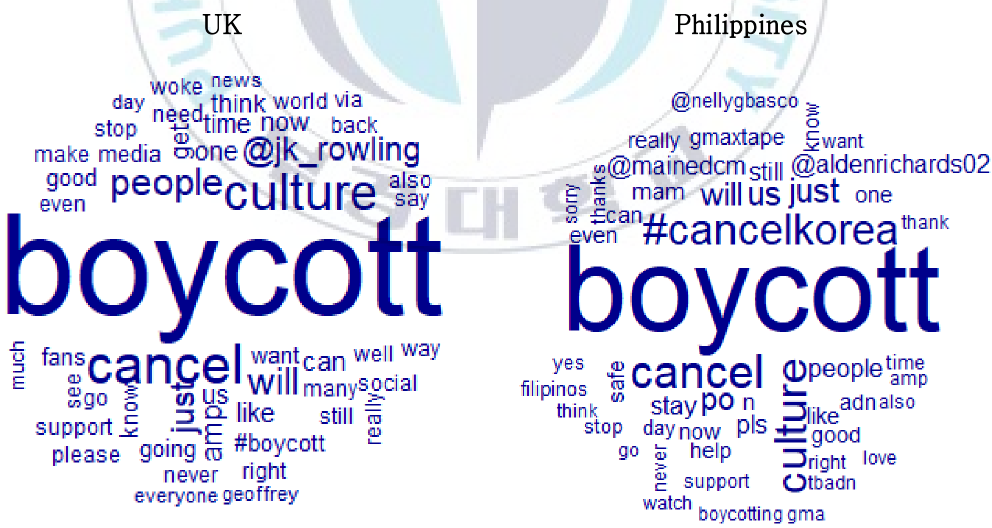

Figure 6: Wordcloud visualization of 50 most used words in the UK and the Philippines indicating average similarity

The results of these analyses suggest that the theme and motivations for cancel culture conversations between the pairs of countries with average similarity are somewhat similar and some lexicons are commonly used, but the commonness is weak. It is, therefore, plausible that even though the tweets are all about cancel culture, the issues the tweeters fixate on vary, and invariably the motivating factors for their involvement in these engagements vary. With this kind of outcome, it is possible to perform further analysis of the data focusing on understanding and underscoring the points of divergence between these pair of countries.

1.3. Low similarity

Meanwhile, the pairs of countries where the similarity of the data is very low, below 30 percent $(0.29 \geq \cos\theta \geq 0)$ include South Korea with all the other countries and vice versa; India with all the other countries and vice versa; the UK with South Africa and vice versa, and the UK with Brazil and vice versa. Using South Korea as an example, the pairwise similarity between South Korea and the Philippines is 0.0951, India is 0.159, the USA is 0.155, the UK is 0.147, Nigeria is 0.217, South Africa is 0.0861, and Brazil is 0.285.

I shall further use the pairing between South Korea and India to explicate and underscore the language use of tweeters in the countries with low similarity. Between South Korea and India, there are just a few cancel culture related content words that are used in common. The text statistic keyness Table (8a) below shows that many top words in cancel culture tweets in South Korea are not often used at all in India. Among the top ten words used in South Korea, the words “lee”, “korea”, “korean” did not show up at all from India data. Even with some of the words they share in common like “kim”, “comfort”, “park”, and “sexual”, there is a big disparity between their use in both countries. The X^2 is so high for each of these words with respect to the target country (South Korea).

Table 8a: Upper section of text_stat keyness result comparing words used in South Korea versus India

	feature	chi2	p	n_target	n_reference	ratio
1	kim	2895.2265	0	1654	1	1654.000000
2	omfort	2530.6034	0	1453	4	363.250000
3	party	1750.3021	0	1265	140	9.035714
4	lee	1727.4075	0	987	0	Inf
5	korea	1366.2613	0	781	0	Inf
6	park	1258.4936	0	728	4	182.000000
7	sexual	1201.1369	0	1468	524	2.801527
8	movement	1159.7883	0	1710	757	2.258917
9	korean	998.4360	0	571	0	Inf
10	japanese	994.4698	0	573	2	286.500000

Meanwhile, at the lower end of Table (8b), the disparity in the use of words is even more obvious. Out of the ten most used words in India, six are not used at all in South Korea. Words like hashtags "boycottbollywood", "boycottchhapaak", "bollywood", and "istandwithdeepika" are exclusively used in India's Twitter-sphere. Also, even for the words that are common, the disparity in their use between the two countries is so wide that for each word, the X^2 is highly negative with respect to the target country (South Korea).

Table 8b: Lower section of text_stat keyness result comparing words used in South Korea versus India

	feature	chi2	p	n_target	n_reference	ratio
6768	deepika	-552.0011	0	0	962	0.0000000000
6769	india	-586.2339	0	1	1026	0.0009746589
6770	boycott	-593.2342	0	53	1255	0.0422310757
6771	hai	-631.3761	0	0	1100	0.0000000000
6772	film	-727.6378	0	38	1430	0.0265734266
6773	standwithdeepika	-821.9559	0	0	1431	0.0000000000
6774	deepikapadukone	-961.4665	0	0	1673	0.0000000000
6775	bollywood	-1208.5652	0	0	2101	0.0000000000
6776	boycottchhapaak	-3656.3410	0	0	6298	0.0000000000
6777	boycottbollywood	-5602.8584	0	0	9581	0.0000000000

Meanwhile, below I present a word cloud visualization of 50 top words used in South Korea and India cancel culture engagements. As shown in the visualization, the two countries' data share a few words in common which include "metoo", "women", "will", "case", "times", "like", "movement", etc. However, they still differ a lot more in that Korean tweeters are fixated on issues like, "japan", "comfortwoman", "korean", "victim", while their Indian counterparts are fixated on issues like "hindu", "india", "film", "justice", "movie", etc.

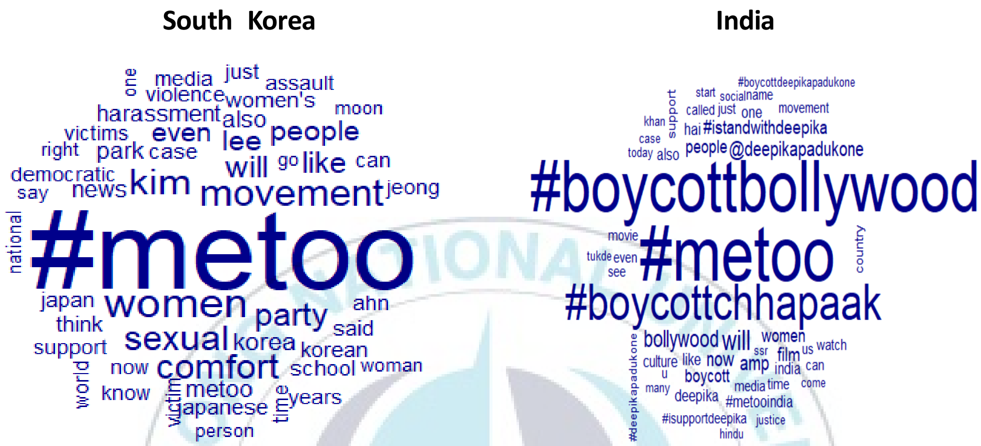

Figure 7: Wordcloud visualization of 50 most used words in South Korea and India indicating low similarity

What the low pairwise similarity between the text corpora from the countries like South Korea and India indicates, therefore, is that the tweeters in these countries rarely use words that are common to each other. In essence, the themes of cancel culture conversations among the people in each context vary strongly. And it is also very possible that their views are divergent as well as the motivation for which they involve in cancel culture engagements.

1.4. Summary of the finding on the mutuality of the cancel culture conversations

Table 4 below summarizes the findings of the similarity analysis conducted for this study. It shows the categories of similarity of the data corpora among the countries in the study data; the highly similar, the averagely similar, and the lowly similar. Between each pair of the Philippines and the USA, Nigeria, South Africa, Brazil, and vice versa, there are lots of words commonly used in cancel culture tweets. Semantically this suggests that the themes in the cancel culture discourse in these countries are similar, and it is probable they are motivated by common concerns for which they engage in the conversations. Between the pairs of the UK and the Philippines, the USA, and Nigeria, there is an average level of similarity. This will suggest that some of the themes in cancel culture conversations are similar and some themes are dissimilar. It could also suggest varying concerns for involvement in cancel culture conversations, especially with respect to the UK which varies with all the other countries. Between the pairs of South Korea and India with all the countries, as well as the UK and each of South Africa and Brazil, there is a low level of similarity, which will suggest that the themes in cancel culture conversations between these pairs of countries are completely dissimilar. Also, it is probable that the concerns for which the interlocutors in the countries involved in cancel culture vary. The next analysis of the second research question will focus on understanding these points.

Table 9: Explaining the categories of similarity in the data according to cosine strength

Similarity	Countries	Cosine
Highly similar	The Philippines, the USA, Nigeria, South Africa, and Brazil [all with each other]	*(1.0 ≥ cos θ ≥ 0.7)*
Averagely similar	UK with the Philippines, USA, and Nigeria [and vice versa]	*(0.69 ≥ cos θ ≥ 0.3)*
Lowly similar	South Korea with all the countries [and vice versa] India with all the countries [and vice versa] UK with South Africa and Brazil [and vice versa]	*(0.29 ≥ cos θ ≥ 0)*

2. Explicating the motivations for cancel culture

I took several analysis steps in explicating the motivating factors for the interlocutors involved in cancel culture engagements on Twitter. The first step is the LDA analysis, followed by the dictionary analysis, the word network analysis, the word frequency analysis and finally, the keyword-in-context analysis. The goal is to group and pragmatically analyze these to exemplify how their relationship help to establish an underlying motivation for the cancel culture tweets.

2.1. Presentation of the result of the LDA analysis

I used the LDA analysis to cluster the words in the data to different topics/themes to identify the latent thematic relationship among them. The dimensions I chose for the LDA implementation are eight (8), in order to give room for meaningful topic categories to emerge from the analysis. The result of the LDA analysis is presented in Table 10 below.

Table 10: The result of cancel culture LDA analysis of the text data

	topic1	topic2	topic3	topic4	topic5	topic6	topic7	topic8
[1,]	"#metoo"	"@jk_rowling"	"woke"	"right"	"like"	"amp"	"#boycottbollywood	"will"
[2,]	"women"	'"will''	"transphobic"	"woke"	"dave"	"via"	"#boycottchhapaak"	"media"
[3,]	"movement"	"us"	"just"	"like"	"chappelle"	"#boycott"	"will"	"fans"
[4,]	"sexual"	"trump"	"like"	"think"	"shame"	"will"	"bollywood"	"just"
[5,]	"victims"	"party"	"know"	"just"	"get"	"rally"	"film"	"get"
[6,]	"woman"	"vote"	"wokeness"	"amp"	"shit"	"companies"	"#metoo"	"game"
[7,]	"kim"	"america"	"toxic"	"can"	"really"	"can"	"@deepikapadukone"	"time"
[8,]	"back"	"news"	"hate"	"china"	"now"	"business"	"movie"	"social"
[9,]	"case"	"republican"	"masculinity"	"say"	"petition"	"support"	"now"	"now"
[10,]	"comfort"	"time"	"can"	"thing"	"one"	"products"	"#deepika"	"going"
[11,]	"violence"	"America"	"will"	"want"	"show"	"support"	"watch"	"amp"
[12,]	"harassment"	"election	"twitter"	"speech"	"got"	"money"	"hai"	"go"
[13,]	"victims"	"god"	"want"	"things"	"fuck"	"stop"	"country"	"well"
[14,]	"years"	"fox"	"man"	"way"	"know"	"sign"	"deepika"	"can"
[15,]	"victim"	"japan"	"still"	"someone"	"thing"	"patriot"	"wrong	"one"

From the result of the LDA, it is possible to explicate six different categories which thematically indicate of various motivating factors for cancel culture engagements. I shall group these themes under associative keywords. The first keyword is "Wokeness" ideology, which I decided on based on the presence of words like "metoo,", "women", "movement", "violence", "harassment", etc. as seen under "topic 1". These words are predominantly used in the context of woke discourse. Hence, those who use them in cancel culture engagements are directly or indirectly motivated by the idea of social justice advanced through wokeness ideology.

The second keyword is "Politics", which I decided on based on the presence of words like "trump", "election", "republican", "party", “vote”, etc., as seen under “topic 2”. These keywords are normally used in the context of politics. Those who use them in cancel culture engagements do more just advocate for social justice. In most instances, they use their involvement in cancel culture to advance their political goals.

The third keyword is “Moral/ethical/cultural values” which I decided on based on the presence of words like “right”, “wrong”, “movie”, “shame”, “film”, “show”, “bollywood”, “fans”, etc. as seen under “topic 4” and “topic 7”. These are words associated with ethics and morality on one hand, and cultural values or culture industry on the other. When one uses these words in the context of cancel culture engagements, it is possible that they are advancing opinions in defense of the ethical, moral, or cultural values of their society.

The fourth is “Normative/traditional activism”, which I decided on based on the presence of words like “petition”, “support”, “stop”, “rally”, “sign”, “please”, etc., as seen under “topic 5” and “topic 6”. Those who tweet out these words in the context of cancel culture participate in one form of normative activism which they try to associate with cancel culture. Often, they use cancel culture hashtags in order to trend their cause on Twitter. Such causes may include human rights, animal rights, environment activism, etc.

The fifth is “Nationalism/patriotism”, which I decided on based on the presence of words like “country”, “china”, “america”, “japan”, “nation”, “patriot”, etc., as seen under “topic 6” and “topic 7”. These are words normally associated with nationalism and patriotism. It is plausible, therefore, that those who use these words in cancel culture engagement are advancing nationalistic sentiment among their readers. They may be participating in canceling someone not for social justice reason, as it were, but for the sake of their nation or their nation’s interest. In the context of such conversations, words are used which inspire patriotism and nationalism.

The last is “Free speech” rights, which I decided on based on the presence of words like “right”, “free”, “speech”, etc. as seen under “topic 4”. Free speech advocates have traditionally been opponents of cancel culture. These ones usually tweet words that express concerns about the limitation on free speech posed by cancel culture. However, what is important is that while tweeting or replying to tweets with #cancel_ hashtags, their motivation is to advance conversations about free speech on social media.

In the table 11 below, the summary of topics and the words thematically associated with them are presented.

Table 11: Keywords for motivating factors selected for further analysis following LDA

	Motivating factors	Related topics	Associated words
1.	Wokeness	Topic 1	“metoo,”, “victims”, “women”, “movement”, “harassment”, etc.
2.	Politics	Topic 2	“trump”, “election”, “republican”, “party”, “vote’, etc
.3.	Moral/cultural/ethical values	Topics 4 & 7	“right”, “wrong”, “movie”, “shame”, “film”, “show”, “bollywood”, “fans”, etc.,
4.	Normative/traditional activism	Topic 5	“petition”, “support”, “stop”, “rally”, “sign”, “please”, etc
5.	Nationalism/patriotism	Topics 6 & 7	“country”, “china”, “america”, “japan”, “patriotism”, etc.
6.	Free speech	Topic 4	“right”, “free”, “speech”, etc.

2.2. Dictionary analysis: Explicating different kinds of motivating for cancel culture

I shall conduct a dictionary analysis to search for the features/words associated with the keywords “Wokeness”, “Politics”, “Moral/ethical/cultural values”, “Normative/traditional activism”, “Nationalism/patriotism”, and “Free speech” within the research data. That is; with the analysis, I shall examine the study data to find matches with terms in the dictionary that suggest motivations for cancel culture related to these keywords. With every match between the dictionary and data features, the statistical function will make a count. I set the threshold of significance for each motivation category at 4% in all the text from each country, except the UK which I set at 3%. When computed, the 4% threshold for South

Korea data is 289 words, for India is 783, for the Philippines is 134, for the USA is 208, for the UK is 585, for Nigeria is 337, for South Africa is 144, and for Brazil is 236. The detailed result of the analysis is seen in Table 12 below.

Table 12: The result of the analysis of the dictionary of keywords based on the motivating factors for cancel culture

Docs	Wokeness	Politics	Nationalism	Cult/Ethics	Normative	Free/Spch	Unmatchd	theshhld
S/Korea	1931	1312	367	105	487	105	53809	>*0.4*(289)
India	814	590	1217	3181	207	365	189404	>*0.4*(783)
Philippines	160	194	422	1180	34	65	31542	>*0.4*(134)
USA	688	708	246	2226	93	367	48414	>*0.4*(208)
UK	926	1771	822	1308	631	496	192837	>*0.3*(595)
Nigeria	501	843	650	1771	301	176	80238	>*0.4*(337)
S/Africa	296	198	127	3169	113	137	32031	>*0.4*(144)
Brazil	1109	439	155	3101	204	198	54005	>*0.1*(236)

As seen in the dictionary analysis, (in Table 12), people get involved in cancel culture engagements over varying motivating factors as the keywords they use in their engagements suggest, and there is a pattern of it across the countries. I shall explain these varying motivations for cancel culture by clustering the keywords using the word networks in VosViewer.

2.2.1. The motivation for cancel culture in South Korea

In South Korea where the significance threshold is *289* words, the dictionary analysis indicates that the motivating factor for which people are most likely to involve in cancel culture engagement is Wokeness ideology (with 1931 words matched with the dictionary), then Politics (with 1312 words matched), Nationalistic/patriotic sentiment (367 matched) and various forms of Normative/traditional activism (487 matched). However, issues bordering on Cultural/moral/ethical values (105), as well as Free speech (105) are not significantly represented as major motivating factors for cancel culture engagement among South Korean tweeters.

The result of the dictionary analysis of the data is consistent with the word network analysis conducted in VosViewer, which also shows four major clusters of keywords closely related by co-occurrence in the same context. As seen in Figure 8 below, the first cluster has keyword nodes like “metoo”, “sexual violence”, “sexual assault”, “violence”, “schoolmetoo”, “society”, etc. This cluster is about the metoo movement which is a core aspect of wokeness activism. The second cluster has keyword nodes like “Korea”, “Japan”, “apology”, “Abe”, “compensation”, “trade”, “conflict”, “prostitution”, “apology”, “compensation”, etc. This cluster is about Korean nationalism related to historical issues between South Korea and Japan. The third cluster has keyword nodes like “feminism”, “feminists”, “sexism”, “rape”, “bookstagram”, “sex discrimination”, etc. This cluster has to do with Normative/traditional feminist activism mostly driven by Korean feminists. The fourth keyword node has words like “party”, “country”, “democracy”, “change”, “corruption”, “moon jae in”, etc. This cluster has to do with the local politics of South Korea. Those who tweet with political words in South Korea have an interest in using cancel culture to advance their political views.

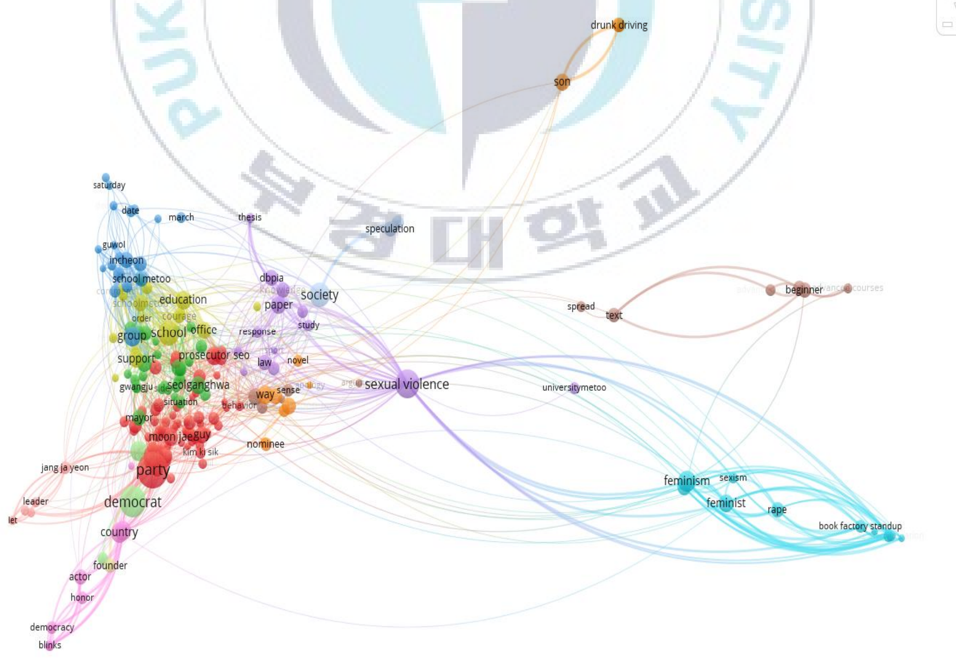

Figure 8: Word network analysis of cancel culture text data from South Korea

From the word network analysis of the South Korea data, it is seen, that Wokeness, Politics, Nationalism, and feminism-driven Normative activism are the prominent motivating factors driving cancel culture engagements in South Korea. Wokeness ideology is used to fight against sexual violence against women, Nationalism is mostly deployed in relation to South Korea's historical issues with Japan, Politics is implicated when netizens air political views with cancel culture hashtags, and Normative activism represents other forms of activism, especially traditional feminist actions now associated with cancel culture.

An observation can be made here that the key wokeness/social justice concerns like transgender activism, BlackLivesMatter (BLM), freedom of speech, historical racism, and white supremacy discourse among others, which underpin cancel culture discourse in the West are not often the prime issues in woke conversations in South Korea. The wokeness ideology-related conversations center on sexual exploitation of women in particular and gender equality in general.

Table 13: Motivating factors for cancel culture engagements in South Korea

	Motivating factors	associated terms/ keyword nodes
1.	Wokeness	metoo, sexual violence, sexual assault, schoolmetoo, stigmabase, metoo, etc
2.	Politics	party, democratic party, country, democracy, moon jae in, etc
3.	Nationalism/patriotism	korea, Japan, apology, Abe, compensation, trade, conflict, prostitution, apology, compensation, etc.
4.	Normative/traditional activism	feminists, feminism, rape, bookstagram, student, girl, gyeonggi, korean, sex, etc

2.2.2. The motivation for cancel culture in India

In India with a significance threshold of *783*, the Wokeness ideology (814) is significantly represented as a motivating factor for cancel culture engagements, as well as Nationalism/patriotism (1217), and Cultural/moral/ethical values (3181). Politics (590), Normative/traditional activism (207), and Free speech concerns (365) are not significantly represented. That is to say, in India, the dictionary analysis shows that there are three important motivating factors for people getting involved in cancel culture interlocutions, and these include Wokeness ideology, Nationalism/patriotism, and concerns for the Cultural/moral/ ethical values of their society.

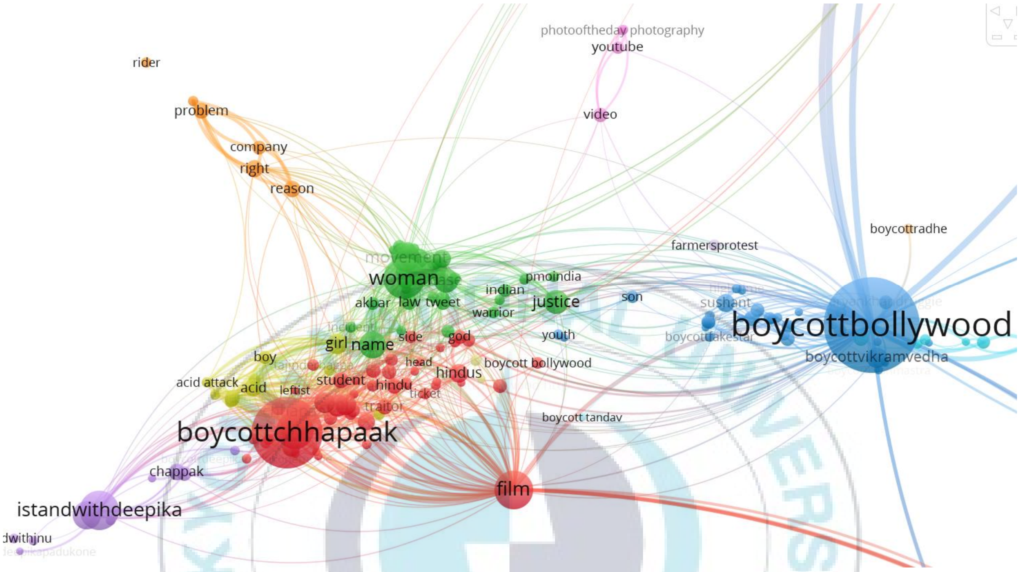

Figure 9: The word network analysis of cancel culture text data from India

The result of dictionary analysis of India data is also consistent with word network analysis which shows three main keyword clusters. As seen in Figure 9 below, the first cluster is centered on the country's film industry with "boycootbollywood", "film", "gods", "nepotism", "sushantsinghrajput", "hightime", "bollywoodmafia" being among the larger nodes. Collectively these nodes speak to Indian netizens' concerns about how the country's culture is being misrepresented in Indian movies. Such tweets call for canceling movies that misrepresent Indian culture. The second cluster is around keywords like "woman", "metoo", "campaign", "movement", "justice", "sexual harassment", "law", "timesup", "mjakbar", "allegation", "justice", etc. These nodes are related to the wokeness campaign in India. The third cluster is around the keywords "hindu", "hindustan", "god", "nepotism", "traitor", "indian", etc. These nodes speak to Hindu (Indian) nationalism. Netizens involved in these conversations agitate for the supremacy of Hindu identity in India. They usually call for canceling of individuals or entities who are considered to have betrayed the Hindu ways of life.

It can also be observed with the India data that wokeness-driven cancel culture engagements in this country are not a lot about transgender activism, BLM, freedom of speech, historical racism, or issues of white supremacy like in the West. The woke conversations in India, like in South Korea, center on the treatment of women within the Indian culture, especially on the question of sexual exploitation and harassment.

Table 14: Motivating factors for cancel culture engagements in India

	Motivating factors	associated terms/ keyword nodes
1.	Wokeness	woman, metoo, campaign, movement, justice, sexual harassment, law, timesup, mjakbar, allegation, justice, etc.
2.	Nationalism/patriotism	Hindu, hindustan, god, nationalism, traitor, nepotism, etc.
3.	Cultural/moral/ethical values	boycootbollywood, film, gods, nepotism, goddess, sushantsinghrajput, hightime, bollywoodmafia, etc

2.2.3. The motivation for cancel culture in the Philippines

In the Philippines with a significance threshold of *134,* Wokeness ideology (160) is significantly represented as one of the main motivating factors for involvement in cancel culture engagements, as well as Politics (194), Nationalism/patriotism (422), and consideration for Cultural/moral/ethical values of the society (1180). On the other hand, Normative/traditional activism (34) and Free speech concerns (65) are not significantly represented. That is; the result of the analysis shows four significant categories of motivating factors for involvement in cancel culture engagements in the Philippines, which are Wokeness, Politics, Nationalism, and concerns for the Cultural/Moral/Ethical values of the society.

Meanwhile, the result of the word network analysis conducted on the data from the Philippines is consistent with the finding of the dictionary analysis. As can be seen in the visualization in Figure 10 below, the result of the network analysis produced five major keyword clusters. The first cluster has keyword nodes like "boycottgmaxtape", "tbadn", "laban", aldub", "alden", "nellygbasco", "maine", etc. This cluster has keywords addressing Cultural/moral/ethical concerns focused on a popular TV series, Aldub, in the Philippines. In the discourse context of the TV show, both supporters and traducers argue over some moral issues, for which cancel culture tweets go viral. The second cluster has keyword nodes like; "filippines", "cancelKorea" "canceltoxickorean", "racism", "apologisetofilipinos", "country", "pinoy", etc. This cluster relates to Nationalism/patriotism, and not necessarily wokeness. They are tweets made in a sustained effort to cancel patronage of South Korean brands in the Philippines over allegations of racism made by some Filipinos against some South Koreans. Meanwhile, the third cluster has keywords nodes like "duterte", "vote", "country", "election", etc. It is a cluster of keywords associated with politics in the country. Those who tweet with these keywords use cancel culture to influence the country's local politics. Then the last cluster has keywords nodes like, "metoo", "woman", "justice", etc. This cluster speaks to the metoo movement, which is driven by wokeness ideology.

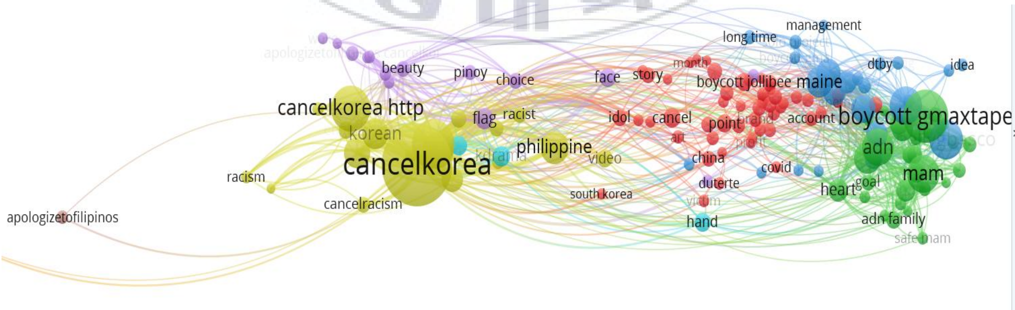

Figure 10: The word network analysis of cancel culture text data from the Philippines

Meanwhile, the analysis so far also shows that, as in South Korea and India, woke-related cancel culture conversations in the

Philippines center mostly on sexual exploitation of women and women's rights. The other wokeness hot topics like transgender, BLM, or white supremacy do not gain enough traction to be among the top issues motivating cancel culture conversations in the Philippines.

Table 15: Motivating factors for cancel culture engagements in the Philippines.

	Motivating factors	associated terms/ keyword nodes
1.	Wokeness	woke, metoo, woman, justice, etc.
2.	Politics	duterte, vote, country, election, etc
3	Nationalism/patriotism	filippinos, cancelKorea, canceltoxickorean, racism, apologisetofilipinos, country, pinoy, etc.
4.	Cultural/moral/ethical values	boycottgmaxtape, tbadn, laban, aldub, alden, nellygbasco, maine, etc

2.2.4. The motivation for cancel culture in the USA

In the USA where the threshold for the significance is set at *208*, Wokeness (688), Politics (708), Nationalism/Patriotism (246), consideration for Cultural/Moral/Ethical values (2226), and Free speech (367) are all significantly represented as motivating factors for cancel culture engagement. On the other hand, words related to Normative/Traditional forms of activism (65) are not significantly expressed in cancel culture conversations in the country. That is; the analysis shows that in the USA cancel culture conversations encompass a lot of issues and motivating factors; from Wokeness, Politics, Nationalism/patriotism, and concerns for Cultural/moral/ethical values, and Free speech. But the Normative/traditional activism types like the popular "bds", "animal rights", "climate change" activism, et cetera, are not so popular in cancel culture conversations in the USA as they are, for instance, in the UK.

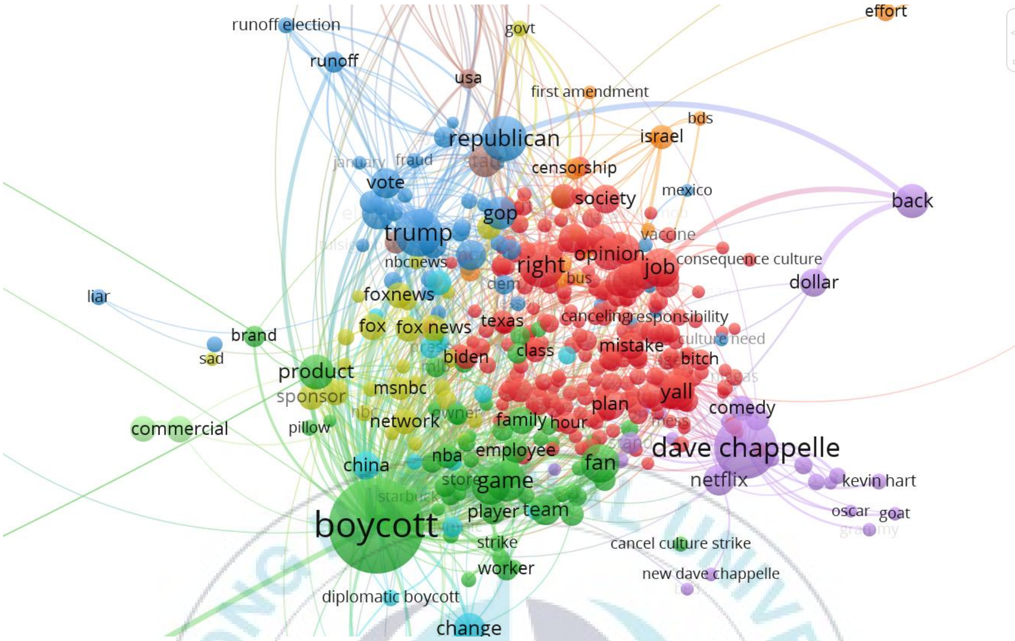

Figure 11: The word network analysis of cancel culture text data from the USA

Meanwhile, from the word network analysis of the USA data, seven main topic clusters emerged. The first cluster has words like “boycott”, “cancel culture”, “product”, “brand”, “nfl”, “team”, “fan”, “culture war” etc. These keyword nodes are related to Wokeness conversations about boycotting brands and businesses alleged to have been involved in conducts that infringed on the rights of minority groups. The second cluster has words like “trump”, “republican”, “democrat”, “gop”, “left”, “biden”, “dem”, “whitehouse”, “election”, “fraud”, “runoff”, etc. These are cancel culture conversations made in the context of promoting political preferences. Here the motivation for the conversation, therefore, is in advancing the political or ideologies of the tweeters. The third cluster has words like “freedom”, “opinion”, “right”, “free speech”, “wokemob”, “joerogan”, “censorship”, “political correctness”, “first amendment”, etc. These are cancel culture conversations made in defense of free speech. The fourth cluster has words like “dave chappelle”, “netflix”, “grammy”, “comedy”, “oscar”, “kevin hart”, etc. This cluster is also about Wokeness but related particularly to the entertainment industry, where comedians like Dave Chapelle and Kevin Hart have faced cancellation campaigns against them for alleged homophobic behavior. Also, a lot of tweets are made which condemn awards like Grammies and Oscars for virtue signaling during their annual award ceremonies. Such conversations are captured under this cluster. Meanwhile, the fifth cluster has words like "china", "nba", "russia", "nfl", "diplomaticboycott", "cop" and etc. This cluster is about nationalism; the conversations focus on boycotting foreign nations like China or Russia, and/or businesses and brands associated with them. Usually, the arguments made in these tweets are that these nations involve in human rights violations or anti-democratic practices, but the nationalistic undertone is always obvious in them. The sixth cluster has keywords "metoo", "resistance", "accountability", "takeaknee", "blm", "nomore". This cluster is also about Wokeness focused on issues of sexual exploitation of women and treatment of black people in the USA, especially in the form of police brutality which had led to the formation of groups like Black Lives Matter. Then, there is the seventh cluster with words like "statue", "mob", "dr seuss", "culture shift", "culture war", "cult", etc. which are used in expressing concerns for the Cultural/moral/ethical values of the country. Some of the tweeters believe and tweet about these norms being eroded by wokeness ideology.

Table 16: Motivating factors for cancel culture engagements in the USA.

	Motivating factors	associated terms/ keyword nodes
1.	Wokeness	metoo, resistance, accountability, takeaknee, blm, nomore, boycott, culture war, woke mob, wokeness, consequence, mistake, netflix, grammy, comedy, oscar, grammies, kevin hart, etc
2.	Nationalism/patriotism	china/russia, nba, nfl, diplomatic boycott, cop, product, brand, team, etc
3.	Cultural/moral/ethical values	religion, judeochristian, vulgar, immoral, dr seuss, culture shift, statue, values, movies, obscenity, hollywood, etc
4.	Free speech	freedom, first amendment, opinion, right, free speech, wokemob, joerogan, censorship, political correctness, etc

2.2.5. The motivation for cancel culture in the UK

Also, in the data from the UK with a threshold of *595 (0.3%)*, Wokeness (926) is significantly represented as a motivating factor for involving in cancel culture engagements, as well as Politics (1771), Nationalism/patriotism (822), concerns for Cultural/moral/ethical values, (1308), and causes around Normative/traditional types of activism (631). However, Free speech (496) does not rank high in the United Kingdom as a prominent motivating factor for which people involve in cancel culture conversational engagements.

Also, the result of the word network analysis of the UK data produced five clusters which are consistent with the result of the dictionary analysis, from which the motivating factors for cancel culture can be explicated. The first cluster has keyword nodes like "sign petition", "animal cruelty", "trophy hunting", "wildlife", "abuse", etc. Here, the conversations are about Normative/traditional activism concerning wildlife abuses and protection. The second cluster has keyword nodes like "Israel", "pledge", "apartheid", "palestine", "bdsmovement", "divestment", "human right", etc. Here also the conversations are about normative activism dedicated to Israel versus Palestine conflict. The boycott campaign, known as BDS, had existed long before the advent of social justice concept of online boycott activism. Meanwhile, the third cluster has keywords nodes like "culture war", "agenda", "woke", "commonsense", "truth", etc. This cluster is made up of conversations driven mostly by the Wokeness agenda. Then the fourth cluster has keywords like "china", "korea", "Indonesia" "dogtrade", "dog", "petition", "winterolympics", etc. the keyword-in-context analyses conducted with some of these keywords indicate that the conversations are made in the context of dog meat trade and consumption culture in some Asian countries. These conversations, therefore, are about Normative activism about animal rights, but with a special focus on the dog meat trade going on in South East Asia for which campaigners call for the boycott of countries like China, South Korea, and Indonesia where activists believe the culture is endemic.

Then the fifth cluster has words like “brexit”, “conservatives”, “farage‘’, “snp”, “ukip”, “labour”, “remainers”, “boris”, “remoaners”. The conversations with these keywords are had about individuals and organizations involved in UK politics. Hence, it is easy to understand that the underlying motivation is politics and power. Meanwhile, there is also a minor cluster of keywords with nodes like “respect”, “integrity”, religion", "westernculture", "vulgar", "immoral", etc. This cluster are tweets made in the context of concerns for Cultural/moral/ethical values of the country. However, the significantly represented theme of Nationalism/patriotism is not evidently represented as a cluster in the word network, analysis. This is perhaps because tweets with nationalistic terms were not consistently made within specific contexts that could form an independent cluster in the word network.

Figure 12: The word network analysis of cancel culture text data from the UK

It can be seen from the analysis of the data that people involved in cancel culture conversations in the United Kingdom are concerned about varying issues. There are conversations in the context of woke ideology, as well as animal rights, the Israeli versus Palestine conflict, dog meat trade in Asia for which the conversation focused on boycotting the Pyeongchang Winter Olympics which was held in 2018 in South Korea. There were also conversations motivated by politics, especially those related to the fractious plebiscite on Britain exiting (Brexit) from the European Union, as well as conversations made about concerns for the Cultural/moral/ethical values of the country.

Table 17: Motivating factors for cancel culture engagements in the UK.

	Motivating factors	associated terms/ keyword nodes
1.	Wokeness	culture war, stigmabase, woke, truth, gender, women, sexual harassment, social justice, misogyny, meto, ideology, outrage, etc.
2.	Normative/traditional activism	wildlife, animal rights, animal cruelty, trophy hunting, abuse, planet, pledge, apartheid, israel, palestine, bds movement, divestment, human right, korea, indonesia, dogtrade, petition, etc.
3.	Politics	remainer, voter, poll, borisjohnson, election, remainer, remoaner, farage, ukip, propagandists, etc.
4.	Cultural/moral/ ethical values	respect, integrity, religion, westernculture, vulgar, immoral, etc

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2.2.6. The motivation for cancel culture in Nigeria

In Nigeria with a significance threshold of *337 (0.4)*, Wokeness (501), Politics (843), Nationalism/Patriotism (650), and concerns for the Cultural/Moral/Ethical values of society (1771) are major motivational factors for people involving in cancel culture argumentations. Traditional/Normative modes of activism (301) and concerns for Free speech (176) are not strongly linked to conversations about cancel culture in Nigeria.

With Nigeria data, the analysis of the word network is also consistent with the result of the dictionary analysis. The result shows four main clusters of keyword nodes. The first cluster has nodes like “cancel culture”, “woke”, “outrage”, “career”, “madness”, “racism”, “trash”, “violence”, etc. These are Wokeness motivated tweets, but evidently, most of the tweeters have a negative sentiment of wokeness ideology, hence the use of negative terms in the context of woke tweets. The second cluster comprise keyword nodes like “election”, “electionboycott”, “totalboycott”, “ipob”, “nnamdikanu”, “pvc”, “pdp”, “apc”, “buhari”, “debate”, “violence”, etc. This cluster is about Politics. The names used in these tweets are entities and persons involved in Nigerian politics. The tweeters use cancel culture hashtags to advance their political positions. Meanwhile, the third cluster has keyword nodes like, “justiceforsylvester”, “school”, “father”, “law”, “dowen college”, “student”, “death”, “family”, “child”, “police”, etc. This viral hashtag seems spontaneous following a tragic event leading to the death of a child, “sylvester”. The tweets made in this context called for accountability and legal inquiries into the death. So, I categorize this cluster under Ethical considerations. Then the fourth cluster has keywords nodes like “South Africa”, “company”, “xenophobia”, “violence”, “xenophobic violence”, “attack”, “mtn”, “dstv”, “shoprite”, etc. This cluster contains tweets made in response to claims of xenophobic attacks against Nigerians living in South Africa. From the keyword-in-context analysis, it is observed that most of these tweets call for boycott of South Africa businesses in Nigeria. So, these tweeters are largely motivated by Nationalism towards their country.

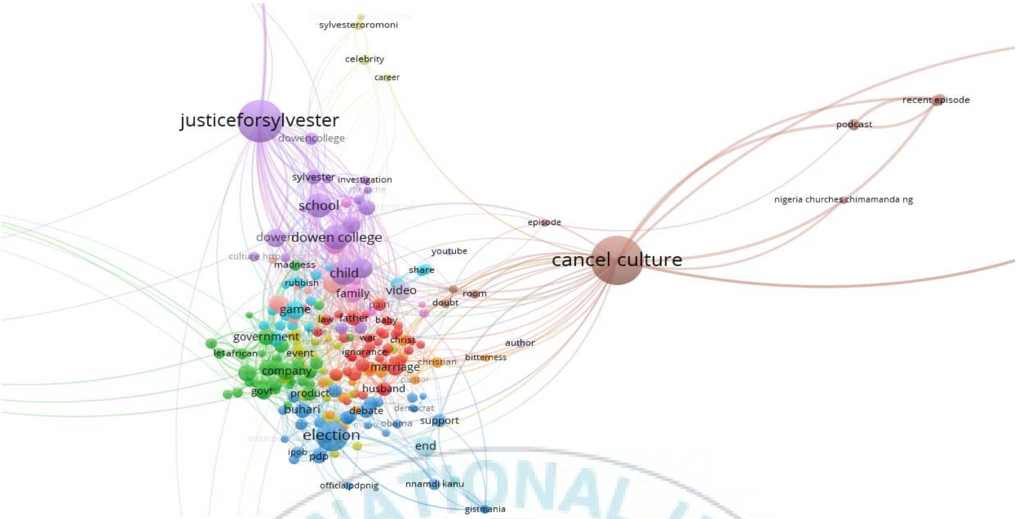

Figure 13: The word network analysis of cancel culture text data from Nigeria

The analysis here, therefore, shows that in Nigeria cancel culture conversations are made on the bases of Wokeness ideology, but mostly to oppose it. Also, Political affiliations, Nationalistic/patriotic sentiments, and consideration for the Cultural, Moral, and Ethical values of the society are the main motivating factors for which people tweet out opinions about canceling and boycotting people, institutions, and brands.

Table 18: Motivating factors for cancel culture engagements in Nigeria.

	Motivating factors	**associated terms/ keyword nodes**
1.	Wokeness	woke, wokeness, outrage, career, justice, madness, racism, trash, chimamanda, violence, etc
2.	Politics	election boycott, ipob, nnamdi kanu, pvc, pdp, apc, buhari, violence, etc.
3.	Cultural/moral/ethical values	Justice, school, dowen college, sylvesteroromoni, student, death, family, police, etc
4.	Nationalism/patriotism	company, xenophobia, violence, xenophobic violence, attack, mtn, dstv, shoprite, etc

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2.2.7. The motivation for cancel culture in South Africa

In South Africa, with a threshold of *144 (0.3)*, Wokeness (296) is significantly represented as a motivating factor for cancel culture conversations, as well Politics (198) and concerns for Cultural/Moral/Ethical values of society (3169). However, motivation factors like Nationalism/Patriotism (127), Normative/Traditional activism (113), and Free speech (137) are not strongly associated with cancel culture engagements.

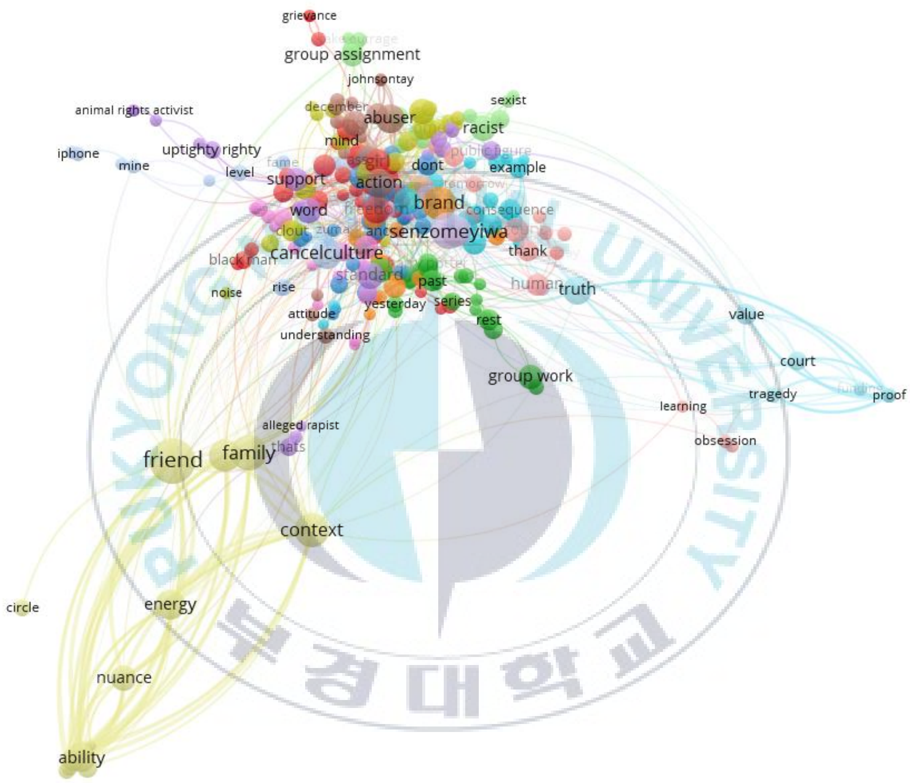

Figure 14: The word network analysis of cancel culture text data from South Africa

The word network analysis of the data from South Africa produced six main clusters of keyword nodes. The first cluster has nodes like "racism", "whiteman", "cancel culture", "charge", "message", "rise", "history", etc. These words appear together to indicate wokeness conversations related to the history of white people. So, the motivating factor for these cancel culture conversations is Wokeness ideology related to racism by white people. The second cluster contains the words “freedom”, “conversation”, “context”, “fear”, “platform”, “single story”, “shame”, etc. A keyword-in-context analysis conducted on some of these words indicates they were used in the context of freedom of expression in the face of the increasing popularity of cancel culture activism. So, here the motivating actor is Free speech. This is understood because even though Free speech is not significantly represented based on the dictionary analysis, it is below the threshold of 144 for South Africa by just 7 points. Then the third cluster has keyword nodes like “senzomeyiwa”, “abuse”, “death”, “pain”, “career”, “song”, “truth”, “court”, etc. Also, a keyword-in-context analysis conducted on some of these keywords indicates that they were used in the context of a person, Senzo Meyiwa’s death. A cancel culture campaign was raised against persons alleged to have had a hand in his death, and the campaign lasted for a long time. So, in this context, the motivating factor for cancel culture conversations is ethical values. A lot of the tweeters want justice to be done in honor of the dead. The context of the conversations is not implicitly about wokeness ideology nor were the words used in the conversations related to wokeness. Meanwhile, a fourth cluster has keyword nodes like “brand”, “pressure”, “action”, “movement”, “allegation”, “trump”, “racist”, etc. The words used in this cluster indicate conversations made in the context of wokeness; this time they were focused on taking action against businesses associating their brands with targets accused of racist tendencies. The fifth cluster has keyword nodes like “attention”, “clout”, “cause”, “job”, “girl”, “fear”, “noise”, “fake outrage”, etc. A keyword-in-context analysis conducted with some of these keywords also indicates that most of these conversations are about people having conversations on the moral aspects of cancel culture, especially about those who use activism to seek “attention” or chase “clout” on social media. I categorized this under concerns Moral values of the society.

Table 19: Motivating factors for cancel culture engagements in South Africa.

	Motivating factors	associated terms/ keyword nodes
1.	Wokeness	whiteman, charge, message, rise, history, context, fear, shame, pressure, action, movement, allegation, racist, tragedy, feminism, gender, fear, noise, etc.
2.	Politics	Government, national crisis, right-wing, liberal, libtard, socialism, etc.
3.	Cultural/moral/ethical values	attention, clout, cause, job, girl, fear, noise, fake outrage, abuse, senzomeyiwa, death, pain, career, song, truth, court, etc.

2.2.8. The motivation for cancel culture in Brazil

In the data from Brazil, which has a significance threshold of *236*, Wokeness (1109), Politics (439), and concerns for Cultural/moral/ethical values of society (3101) are important factors for which people are motivated to engage in cancel culture conversations. However, Nationalism/patriotism (155) and other forms of Normative/tradiitonal activism (204), and concerns for Free speech (198) are not strong motivating factor for people's involvement in cancel culture engagements.

Meanwhile, the word network analysis of the Brazil data produced six clusters of keywords nodes which are consistent with the result of the word network analysis of the Brazil data. The first cluster has keyword nodes like "metoo", "feminism", "victim", "movement", "brazil", "image", "man", "woman" etc. This cluster exemplifies words used in the context of Wokeness conversations. So, the main motivating factor behind these conversations is Wokeness ideology. The second cluster has keyword nodes like "toxic masculinity", "masculinity", "view", "story", "country", "violence", "debate", "attention", "daughter", etc. This cluster too is about Wokeness ideology made in the narrower context of toxic masculinity and its effects. The third cluster has keyword nodes like "hate", "crowd", "canceling", "culture", "comment", "consequence", "idiot", etc. These nodes are also about Wokeness ideology, but they are related to campaigns against social justice warriors. In essence, this cluster represents the opinions of woke cancel culture dissenters. The fourth cluster has words like "country", "government", "bolsonaro", "law", "brazilian", "state", "bolsominion", "communism", “lula”, “democracy”, “vote”, etc. This cluster contain words used in the context of Politics. The fifth and final main cluster has keyword nodes like “decadence”, “cult”, “prejudice”, “oppressor”, “horror,” “jkrolling”, “oscars”, “injustice”, “victimization”, “carnival”, etc. These are words used to express concerns for the Cultural/moral/ethical values of the society.

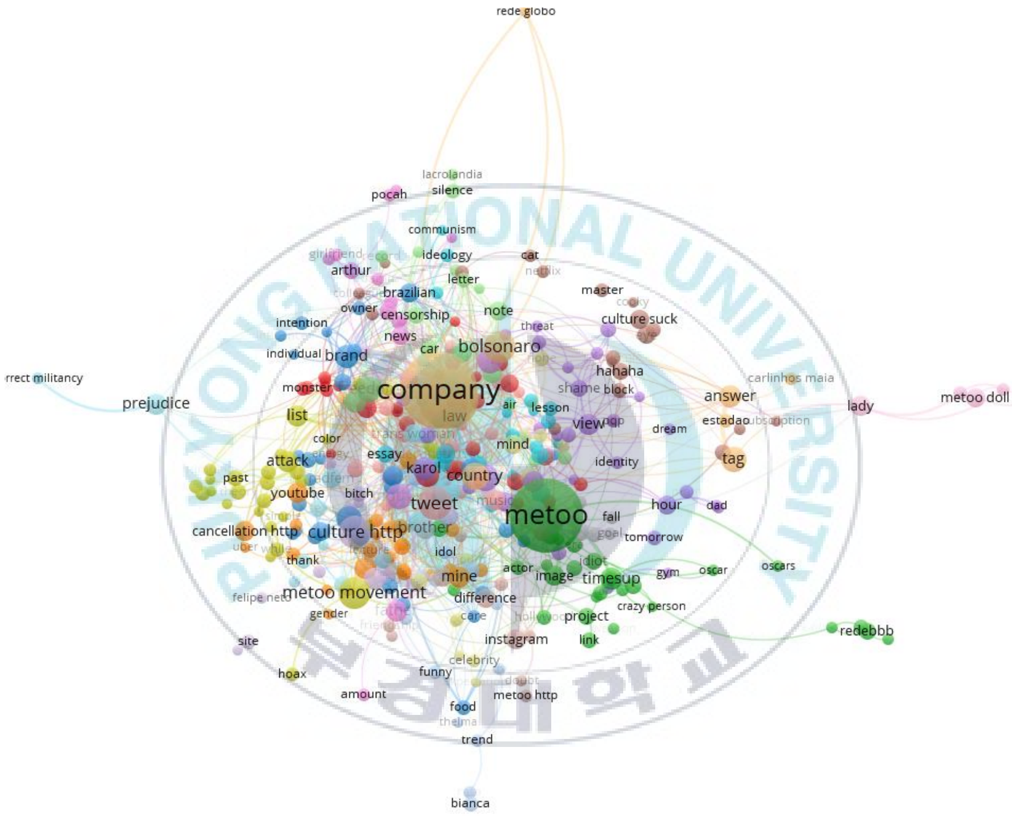

Figure 15: The word network analysis of cancel culture text data from Brazil

As seen from the analysis, much of the cancel culture conversations in Brazil are made about the Wokeness ideology, Politics, and the questions of Cultural/moral/ethical values regarding cancel culture. It is important to note the divergencies of wokeness discourse in Brazil. There are conversations around the keyword “metoo” with associated nodes like “victim”, “movement”, “image”, “man”, and “woman” used in the context of victimhood of sexual violence. There are those conversations around “toxic masculinity” with other keywords like “masculinity”, “brazil”, “story”, “violence”, “debate”, “daughter”, etc., used in the context of toxic masculinity discourse in Brazil. Then there are conversations around the keyword “hate” with associated nodes like “crowd”, “canceling culture”, “comment”, “consequence”, “idiot”, etc. these are conversations around consequences in cancel culture. Even, there are smaller clusters of keyword nodes with conversations around “boycott”, “business”, “nonsense”, “product”, “brand”, etc., which suggest brands and businesses being boycotted or canceled due to their stance on wokeness activism. Wokeness is indeed a strong motivating factor engagement in cancel culture in Brazil.

Table 20: Motivating factors for cancel culture engagements in Brazil.

	Motivating factors	Associated terms/ keyword nodes
1.	Wokeness	feminism, victim, movement, man, woman, toxic masculinity, view, story, violence, debate, attention, daughter, crowd, canceling, culture, consequence, idiot, business, product, brand, action, woman, metoo movement, etc.
2.	Politics	Country, government, bolsonaro, law, Brazilian, state, bolsominion, communism, lula, democracy, etc.
3.	Cultural/moral/ethical values	Decadence, cult, prejudice, oppressor, jkrolling, Oscars, injustice, victimization, carnival, movie, hate, etc

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2.3. Explaining the motivating factors for cancel culture

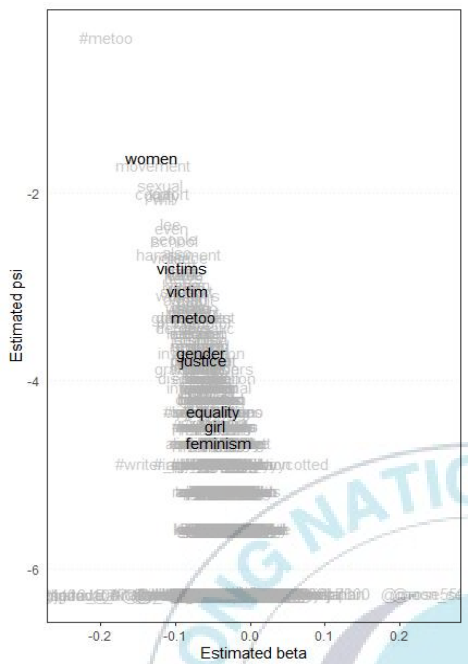
In this section of the analysis, I shall use wordfish frequency scores and keyword-in-context analysis to evaluate how words were used in cancel culture engagements inspired by different motivating factors.

2.3.1. Wokeness

From the result of the dictionary and word network analysis, wokeness as a motivating factor for cancel culture engagements is implicated in all the countries in our data; South Korea, India, the Philippines, the USA, the UK, Nigeria, South Africa, and Brazil. These are cancel culture tweets inspired by the idea of social justice as espoused by Wokeness ideology. Since the inception of cancel culture activism, it has been associated, sometimes exclusively, with Wokeness. The findings of this study reinforce the notion that wokeness ideology inspires a lot of those involved in cancel culture activism, irrespective of the country they live in.

Some of the wokeness words and phrases used in cancel culture tweets include "sexual harassment", "social justice", “lgbtq”, "misogyny", "victim", "metoo", "sexual assault", "outrage", "sjw", “gender”, “homophobia”, “women", “transgender”, “justice”, “misogyny”, “girl”, “metoo campaign”, “woke ideology”, “sexual orientation”, “sexual assault”, “racism”, “intolerance”, “tolerance”, “virtue signaling”, “weaponizing”, “bigot”, “bisexual”, “survivor”, “molestation”, “climate justice”, “crt”, etc.

However, the use of these words varies depending on the prevalent mainstream culture and understanding of Wokeness ideology in each country. For instance, in countries like South Korea, India, and the Philippines, wokeness words are used mostly in the context of sexual exploitation of women and girls. Hence, in South Korea top wokeness cancel culture words/phrases are “women”, “victims”, “metoo”, “feminism”, “justice”, “oppression”, and “weaponization”. This can be seen in Figure 16a below, which visualizes word frequencies of wokeness terms used in South Korea data, as seen in the data. In the Philippines, the top wokeness words are “women” and “girl”. This is also seen in Figure 16b. And in India, the top words/phrases associated with wokeness include, “justice”, “women”, “girl”, “victims”, “bigot”, “metoo”, “outrage”, and “feminist”. This is seen in Figure 17. In essence, the wokeness discourse in South Korea, India, and the Philippines speaks specifically to the sexual exploitation of women and girls who are disproportionately the victims of sexual exploitation. A lot of the tweets made in the context of wokeness in these countries are about the sexual exploitation of women.



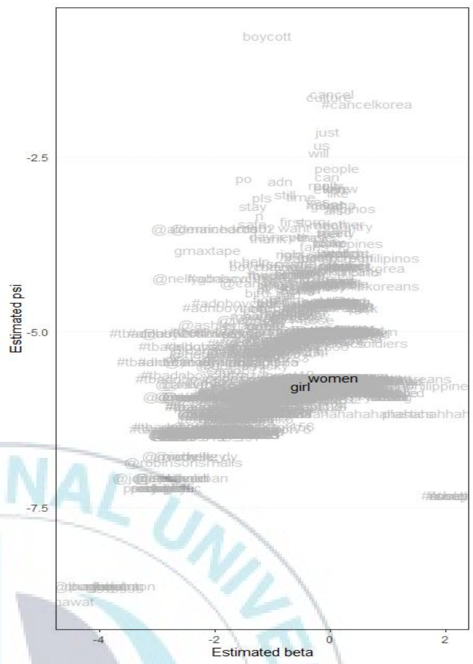


Figure 16a and 16b: Top wokeness words in South Korea and the Philippines data

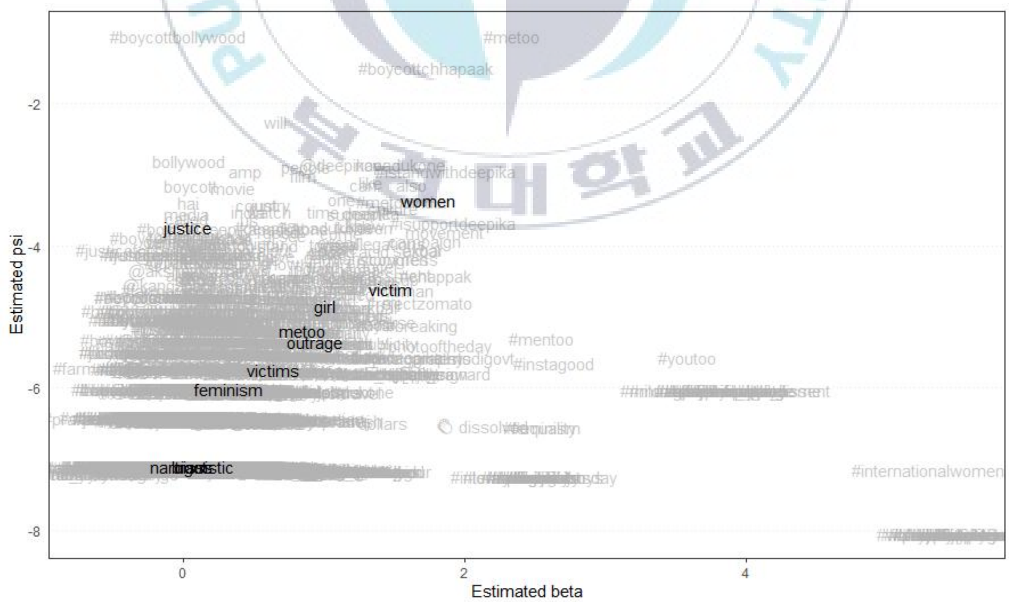


Figure 17: Top wokeness words in India data

Generally speaking, therefore, wokeness in South Korea, India, and the Philippines is not significantly associated with discourses on racism and gay and transgender rights. No popular personality or institution in these countries gets canceled for xenophobic or homophobic acts. In fact, it seems that tweeters in these countries care less or not at all about racism and LGBTQ+ issues.

A keyword-in-context analysis to view how the keyword "metoo" is associated with wokeness motivation for cancel culture engagements in South Korea is seen in Table 21 below. Within the comments, as seen in the Table, the tweeters used words like "victims", "women", "violence", "silence", "Yongwha High School", "petition", "desecrating people", "metoo gangsters", "easy girls", as well as mentioned political words like "party", "democratic", "Moom Jae-in", "general election" etc. These tweets not only explicate how wokeness issues motivate cancel culture, but also how cancel culture is easily used to pursue other goals like political influencing.

Table 21: Sample of keywords-in-context of the word "metoo" from South Korea data.

[650, 18]	#How are the victims living after	**metoo**	#withyou#Violence against women STOP
236, 13]	nightmare that broke the silence of Catholic'	**MeToo**	'.." I could never forget
[3148, 2]	The	**MeToo**	Party habitually steals the name of the Democratic
[3193, 7]	Yonghwa Girls' High School School	**MeToo**	, please continue with the petition calling for
[3195, 1	desecrating people? Aren't the dirty habitual	**metoo**	gangsters afraid of the sky? Moon Jae-in
[3217, 47]	palace Frustrated again with a false	**metoo**	... In this general election I
3373, 18]	woman, using a new tool called [	**MeToo**]	I guess he's using easy girls to
[3401, 33]	the same time, stealing lies..	**MeToo**	. violence.. Can I live with

Meanwhile, in countries of Nigeria and South Africa, added to issues of women and girls' rights, wokeness discourse also revolves around racism. The top words for wokeness in Nigeria include "women", "feminism", "racism", "justice", and "outrage", as seen in Figure 18a. And the top words for wokeness in South Africa include "outrage", "women", "gender", and "racism", as seen in Figure 18b. In essence, in Nigeria and South Africa, there is considerable interest in the discourse of racism related to wokeness. This is easy to understand because the African tweeter audience would naturally show interest in the global Black Lives Matter movement in the aftermath of the death of the African American, George Floyd at the hand of a white police officer on May 25, 2020.

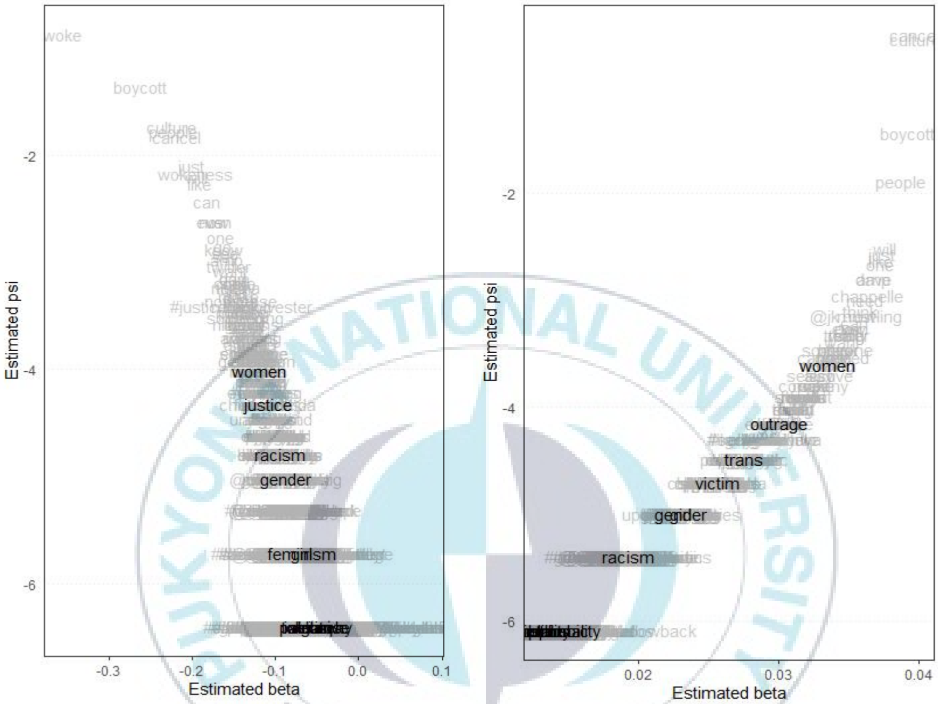


Figure 18a and 18b: Top wokeness words used in Nigeria and South Africa data

Meanwhile, in the United States, United Kingdom, and Brazil, the issues associated with wokeness conversations include issues about wokeness, racism, and LGBTQ+ rights. In the USA, the top words used in wokeness-inspired engagements include “women”, “victim”, “victims”, “metoo”, “racism”, “social justice”, ”girl”, “lgbtq”, “diversity”, “homophobic”, “feminism”, “narcissistic“, “bigot”, and “oppression”. In the United Kingdom, the top wokeness words include “racism”, “women”, “trans”, “outrage”, and “Islamophobia”. And in Brazil, the top wokeness words include “women”, “transphobic”, “metoo”, “victims”, “girl”, “racism”, “intolerance”, “equity”, and “toxic masculinity”. An example of wokeness as discourse motivated by three key issues of sexual exploitation, racism, and LGBTQ+ rights is seen in Figure 19, which shows the word scores for wokeness words used in the USA.

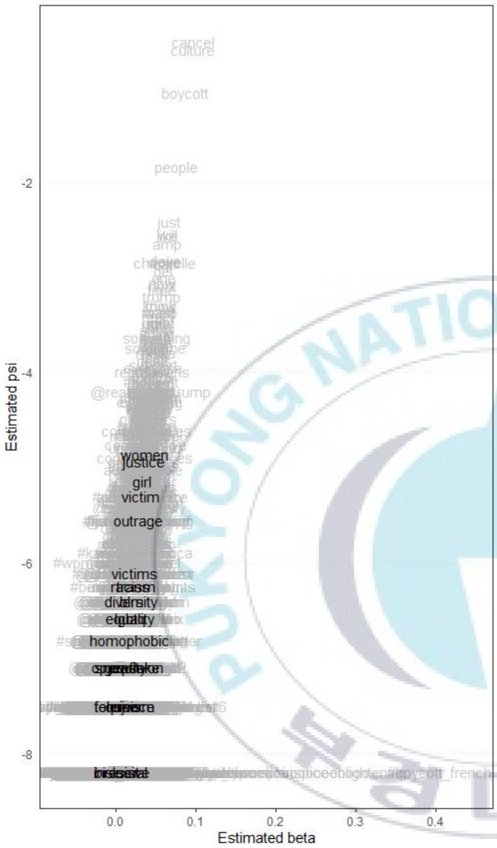


Figure 19: Top wokeness words used in the USA data

Also, a keyword-in-context analysis conducted on the United Kingdom data to view how the keyword “trans” is associated with wokeness motivation for cancel culture engagement is seen below in Table 22. Within the comments, as seen in the Table, the tweeters mentioned keywords like “safety”, “violence”, “boycott”, “athletes”, “games”, “compete”, “women”, “woke”, “climate”, “diverse”, “trans rights”, “human rights”, “inclusive”, “culture”, etc. These words indicate various kinds of conversations about wokeness, including references to protecting trans women vying to compete in the female category at the Olympic games. The tweeters share varying opinions on the issue as expected. But it is understood here that the conversations are about wokeness and the focus was on women, racism, and the rights of transgender people.

Table 22: Sample of keywords-in-context of the word, "trans" from the USA data.

[641002, 34]Disinformation. That has a huge impact on | **Trans** | people's safety& amp; violence against
[478102, 14]cancel your TV licence in support of the | **trans** | boycott of the@BBC (Neither did i
[619102, 3] @MahyarTousi The | **trans** | community will be planning a boycott asap I'm
[226712, 4]@thereclaimparty All non | **Trans** | athletes should boycott any games that allows trans
[226712, 12] athletes should boycott any games that allows | **trans** | athletes to compete against women.
[255610, 80]condemned countries who want to execute | **trans** | and gays. We shd boycott the countries
[503412, 42]are some vile people in this world. | **Trans** | rights are human rights
[511910, 19]together and boycott any sports event when a | **trans** | person is involved, It's the only way
[659712, 8] In our current woke climate and diverse | **trans** | inclusive culture; from this moment I now
[682512, 47]their junk down your throat and insist a | **trans** | individual is now a woman.

2.3.2. Nationalism/patriotism

One of the key findings of this study so far is that many people have turned cancel culture into a tool for advancing extraneous interests like nationalism and patriotism. This aspect of motivation for cancel culture is not often spoken about in cancel culture discourse. From the result of the dictionary and word network analysis, Nationalism/patriotism is implicated as a major motivating factor for cancel culture in the countries of South Korea, India, the Philippines, the USA, the UK, and Nigeria. Only in South Africa and Brazil is cancel culture not significantly motivated by nationalistic/patriotic sentiment.

Some of the words and phrases used in the context of nationalism/patriotism motivated cancel culture tweets include "country", "national", "national culture", "our country", "our people", "love our country", "hate our country", "statesman", "xenophobia", "unpatriotic", "national language", "nation", "identity", "patriot", "patriotic", "national history", "nepotist", "nepotism", "republic", "tribe", "nationalist sentiment", etc.

In the data from South Korea, top nationalism/patriotism words include, "national", "country", "republic", "identity", and "patriot", with numerous references to “japan”. This is seen in Figure 20 below. In India, top nationalism/patriotism words include, “country”, “hindu”, nepotism, “national”, “nation”, and “identity”. In the Philippines, top nationalism/patriotism words include, “country”, “flag”, and “pinoy” with numerous references to “korea”. In the USA, top Nationalism/patriotism words used include “country”, “constitution”, “nation”, “patriotic”, “national”, and “flag” with numerous references to Russia and China. In Nigeria, to Nationalism/patriotic words include “country”, “national”, and “patriotic” with numerous references to South Africa.

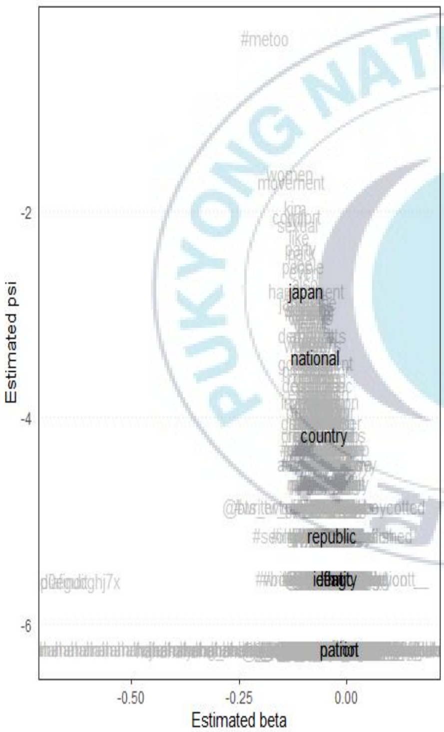


Figure 20: Top nationalism/patriotism words used in South Korea data

There is usually a historical or contemporary reason for which netizens are motivated to tweet for boycotting or canceling a country or businesses and brands originating from it. From the keyword-in-context analysis conducted on the data for this study, it is seen that in South Korea the campaign to cancel Japan and Japanese brands is popular, and it was motivated by a trade dispute arising over disagreements between the two countries on compensation for Koreans who were used for slave labor by Japan during the second world war. The South Koreans protested and called for canceling Japan purely out of loyalty to their own country. In the Philippines, nationalism/patriotism tweets were mostly made against South Korea/Koreans with trending hashtags like #cancelkorea and #racistkorea. These hashtags trended over allegations of racial discrimination by some South Koreans against Filipinos. The Filipinos initiated a cancel culture campaign as a national rallying call in responce to these allegations.

Meanwhile, In the USA, nationalism-motivated tweets are made mostly against China and Russia. There are many reasons for this; political, economic, and, sometimes, human rights issues. In the UK, nationalism-motivated tweets were made against the backdrop of Britain's exit from the European Union. Both sides who opposed each other in the plebiscite leading to Brexit would also tweet against each other, campaigning to cancel each other. In Nigeria, Nationalism/patriotism motivated cancel culture tweets arose over accusations of homophobia against Nigerians living in South Africa. In response to these allegations, Nigerian netizens would tweet calls for canceling South Africa and companies from there doing business in Nigeria. Meanwhile, in India, nationalism/patriotism motivation for cancel culture is championed by ethnic Hindus who usually target non-Hindus celebrities, and sometimes Pakistanis. These ones would frequently call for boycotting of businesses, brands, and people especially in Bollywood (mostly Muslim directors and actors) who are alleged to have disrespected the Hindu — the people, culture, religions, or gods.

A keyword-in-context analysis conducted on the India data to view how the keyword "hindu" is associated with nationalistic/patriotic sentiment as motivation for cancel culture is seen below in Table 23. Within the comments, as seen in the Table, the tweeters mentioned keywords like "Bollywood", "hindu", "muslim", “blasphemous”, “insult”, “religion”, “boycott”, “mighty Hindu empire”, “national”, “movie”, “portray”, “Gods”, “Goddesses”, “cow”, etc. These are words and phrases used to espouse Hindu supremacy and call for censure against people accused of harboring anti-Hindu sentiments.

Table 23: Sample of keywords-in-context of the word, “hindu” from India data.

[131100, 6]	#BoycottBollywood Negative role for	**Hindu**	and Police Inspector for Muslim.
[151100, 11]	@zomato is equally responsible for hurting	**hindu**	sentiments. No place for blasphemous
[379100, 20]	for brother-in-law who will insult our	**Hindu**	religion now we all unki ga
[382100, 34]	Khan gang, then we all	**Hindu**	brothers will definitely boycott them too
[421100, 20]	better to learn about the mighty	**Hindu**	empire that historians have kept us
[608100, 9]	#Boycott every film that portrays our	**Hindu**	Gods and Goddesses as funny characters
[84310, 12]	national movie, which intentionally hurts	**hindu**	feelings, now starts #boycottvikramvedha
[91910, 7]	The writer of Raksha Bandhan derided	**Hindu**	sentiments by mocking cows while
[1358, 25]	Bollywood's furious people dare to insult	**Hindu**	religion? Those angry people need
[1378, 6]	@Devils_Angel21 Only such#movie spoils	**Hindu**	girls. And attracts Muslim boys

2.3.3. Politics

From the result of the dictionary and word network analysis, politics as a key motivating factor for cancel culture is implicated in all the countries in the data. This presupposes all conversations made with cancel culture hashtags with overt or subtle intent on gaining or sustaining political power. Such tweets often call for canceling individual politicians, political organizations, entities, agencies, or persons who have political influence. Such views can be openly or subtly expressed within the text of the tweets.

From the result of the dictionary and word network analysis, politics is implicated as a major motivating factor for cancel culture in the countries of South Korea, the Philippines, the USA, the UK, South Africa, Nigeria, and Brazil. Only in India is cancel culture not significantly motivated by an interest to advance political views.

Some words popularly used in politics-motivated tweets include “politics”, "ruling party", "opposition party”, "democrat”, conservative", "constitution", "republic", "states", "politics", "elect", "vote", "rightwing", "leftwing", "liberal", "leftist", "rightist", "election", "campaigns", "ballot", "poll", "candidate", "centrist", "partisan", "rig", "people power", "alt-Right", "win election", "extreme left", and "politics", "communist", "socialist", etc.

In the data from South Korea, the top politics words used in cancel culture conversational contexts include, “party”, “politics”, “candidate”, “election”, “election”, “states”, “progressive”, and “incumbent”. In the Philippines, the top politics words include, “election” and “vote”. In the USA, the top politics words include “vote”, “party”, “election”, “liberal”, “state”, “socialist”, “constitution”, “propaganda”, “identity”, “republic”, and “patriot”. This is seen in Figure 21 below, which shows a visualization of the top words used in polities motivated tweets in the USA. In Nigeria, meanwhile, the top politics words include “election”, “party”, “vote”, “progressive”, and “liberal”. In Brazil, the top politics words are “party”, “leftist”, “judicial”, “election”, and “franchise”.

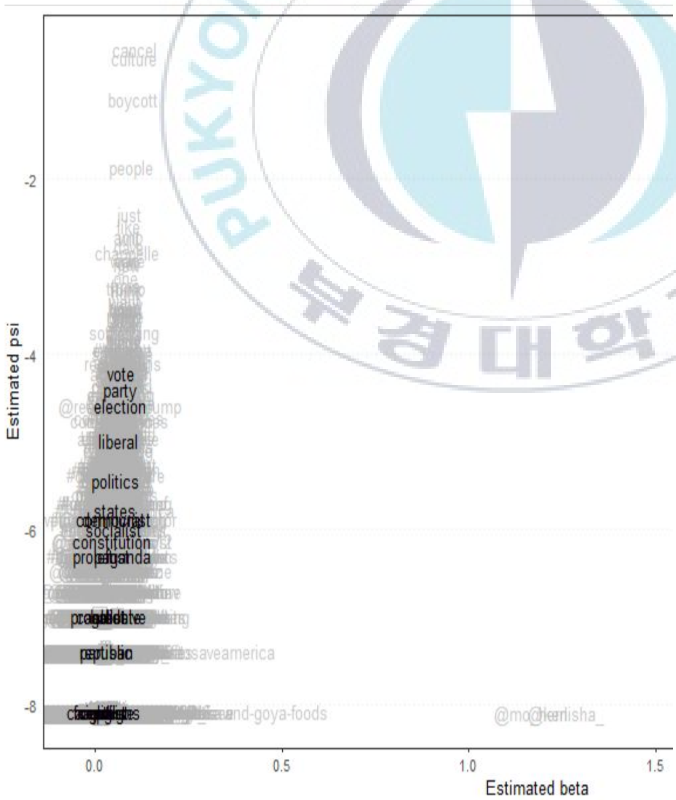


Figure 21: Top politics words used in the USA data

Meanwhile, an example I shall make of cancel culture activism motivated by politics using keyword-in-context analysis is drawn from Brazil data, as seen in Table 24 which shows a keyword-in-context analysis done with the keyword “vote”.

Table 24: Sample of keywords-in-context of the word, “vote” from Brazil data.

[103294, 30]	for a better Brazil, we can't	**vote**	for@jairbolsonaro#EleNao He preaches hatred, violence
[143542, 35]	Juliette's Biphobic speech. If you're going to	**vote**	, use another criterion because if
[143573, 24]	was homophobic. I didn't want Gil to	**vote**	for Rodolffo because of homophobic speech.
[144672, 14	docu-series style you decide where we	**vote**	to skin or stone the transphobic old woman
[150143, 4]	Thanks to the	**vote**	, we have a TRANS councilor in a
[163873, 5]	HELP!!!	**VOTE**	AGAINST THIS PL! She is totally transphobic
[167993, 5]	Uncle Claudio had my	**vote**	for councilor until he took an extremely transphobic
[180393, 12]	volleyball, transphobic than only she, will	**vote**	for Bolsonaro. Tell me something new.
[232763, 46]	, but if one day I need to	**vote**	, it will be against him. So
[232763, 57]	will be against him. So I didn't	**vote**	because the other one was even more transphobic

Within the comments, as seen in Table 24, the tweeters mentioned important keywords like “Brazil”, “jairbolsonaro”, “hatred”, “violence”, “homophobic”, “speech”, “trans”, “councilor” etc. These are words and phrases used to persuade other people to hold or change political views, support particular political candidates, or vote in a certain way in an election. So, the underlying motive for these tweets is to gain or sustain political power.

2.3.4. Cultural/moral/ethical values

Cultural/moral/ethical values concerns motivate some people to get involved in cancel culture. These are engagements whose undertones are cultural/moral/ethical concerns made in the context of cancel culture.

From the result of the dictionary and word network analysis, cancel culture tweets made about Cultural/moral/ethical values are a lot in the countries of India, the Philippines, the USA, the UK, Nigeria, and Brazil. Only in South Korea are words related to culture, morals, and ethical values not frequently used in cancel culture tweets.

Some words popularly used in cultural, moral, and ethical value-motivated tweets include "religion", "western", "vulgar", "nudity", "immoral", "drugs", "disgusting", "inhuman", "christian", "Islam", "budhism", "judeochristian", "haram", "values", "teachings", "movies", "root", “tripiţaka”, “agama”, "nakedness", "obscenity", "bible", "quran", "god", "goddess", "bollywood", "nollywood", "hollywood", etc.

In India data, the top words used in cultural/moral/ethical values motivated tweet include “religion”, “god”, “culture”, “goddess”, “drugs”, “disgusting”, “western”, and “obscenity”. In the Philippine data, the top words in this category are “religion”, and “movies”. In the USA data, the top words include “god”, “bible”, “Christian”, “values”, and “root”. In the UK, the top words are “god”, “western”, and “culture”. In Nigeria data, the top words are “god”, “christian”, and “western”. And in Brazil data, the tops words are “god”, “hollywood”, “christian”, and “root”.

Figure 22a and 22b: Top culture/moral/ethical words used in the India and UK data

An example I shall make of cancel culture activism motivated by cultural/moral/ethical concerns using keyword-in-context analysis will be drawn from Nigeria data, as seen in Table 25 below, which presents a keyword-in-context analysis done with the keyword "christian".

Table 25: Sample of keywords-in-context of the word, "christian" from Nigeria data.

[242614, 42]	nt talking to non-Christians. If a	**Christian**	is comfortable seeing Christ as gay, that
[242614, 53]	seeing Christ as gay, that ain't no	**Christian**	
[675613, 10]	people are beginning to drag the	**Christian**	faith into all these and doubting if the
[693413,38]	your voice in this woke world as a	**Christian**	
[83765, 24]	Heck, you're not even safe as a	**Christian**	residing there and if you must attend
[91233, 2]	A	**Christian**	can't outrightly be woke. If you watch
[91233, 46]	So it will be wrong for a	**Christian**	to leave Christ-like standards and be woke!
[98803, 8]	As I grow older, I would rather have	**Christian**	traditional values over woke generation
[98832, 4]	Don't be that	**Christian**	who mocks biblical principles because of woke
[103562, 39]	woke.. you can quit being a	**christian**	and stop being a fool.
[107752, 7]	@alanfryerm There is a culture of	**Christian**	hatred within the Liberal rank.

Within the comments, as seen in Table 25, the tweeters mentioned important keywords like “non-christians”, “Christ”, “gay”, “faith”, “woke”, “wrong”, “christ-like standards”, “traditional values”, “biblical principles” “culture”, “hatred”, “liberal”, etc. These words were used in cancel culture conversational context but with the major concern being the traditional/Christian values of the society which the commenters seem to argue are not in tandem with the woke ideology. For example, in line [98832, 4], the commenter posted, “Don't be that Christian who mocks biblical principles cos of woke…”, and in line [98803, 8] another commenter wrote, “As I grow older, I would rather have Christian traditional values over woke generation…” In essence, while these comments were made in the context of cancel culture, the primary motive behind them was to defend the traditional Christian values which the commenters believe are in conflict with the wokeness ideology.

2.3.5. Normative/traditional activism

Normative or traditional forms of activism have been popular prior to the advent of woke movement, and involve various forms of protesting against individuals, governments, policies, and institutions; like street protests, rallies, petitions, etc. Since the advent of cancel culture, some traditional forms of activism have become associated with it, with activists advocating online with #cancel and #boycott hashtags but retaining their primary modes of expression, like protests, rallies, petitioning and etc. That is; these modes of activism are limited to online shaming and boycotting and advocating for canceling an individual’s access to career and civic life.

Among all the countries in the study data, normative forms of activism are significantly explicated only in South Korea and the United Kingdom. In the countries of India, the Philippines, the USA, Nigeria, South Africa, and Brazil cancel culture engagements advancing Normative/traditional forms of activism are not very common.

Some of the words popularly used in Normative/traditional activism include “human rights”, “hunger strike”, “sit-in”, “non-profit”, “civil disobedience”, “advocacy”, “dissident”, “resistance”, “direct action”, “activism", "activist", "solidarity", "feminism", "feminist", "girl child", "gender equality", "bds", "workers”, “animal rights", "women’s right", "exploitation", "molestation”, “march", "apartheid", "global warming”, etc.

In South Korea top words related to normative activism include “feminist”, “feminist”, “activist”, and “molestation”, while in the United Kingdom, the top words related to normative activism include “apartheid”, “solidarity”, “activist”, “exploitation”, “march”, and “bds”. This shows that in South Korea the traditional feminist activism about sexual exploitation of women got woven into cancel culture. In the UK, however, issues like bds, exploitation of labor, feminism, and even animals right, gets woven into cancel culture.

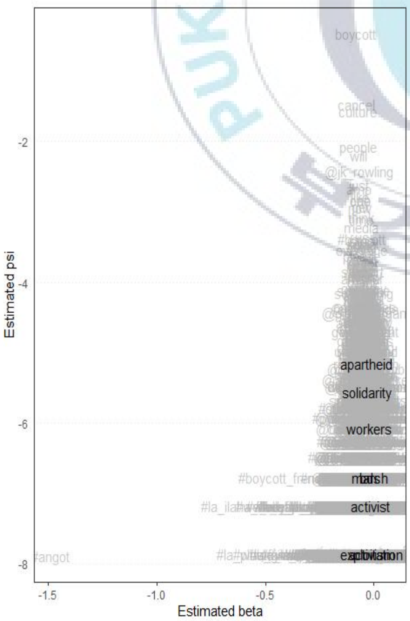


Figure 23: Top normative activism words used in the UK data

For cancel culture activism motivated by normative/traditional activism, I use keyword-in-context analysis of the keyword "apartheid" drawn from UK data as an example of feature conversations. As can be seen in Table 26 below, the word "apartheid" is not related to South Africa but to the political conflict between Israel and Palestine. It is used to draw a parallel between what happened in South Africa and what is happening between Israel and Palestine with Israel being the accused occupier. In essence, these conversations are not primarily about wokeness social justice; they are made in furtherance of BDS movement activism which has been in existence since 2005.

Table 26: Sample of keyword-in-context of the word, "apartheid" from the UK data.

[495102, 11] tube maps with stickers saying' Boycott Israeli | **Apartheid** | ' is fine?@TfL@SadiqKhan
[72013, 22] BDS campaign that eventually brought an end to | **apartheid** | . It will be the same in regard
[72013, 33] will be the same in regard to Israeli | **apartheid** | & amp; the brutal, illegal occupation
[79210, 30]happy to deliberately conflate opposition to Israeli | **apartheid** | & ethnic cleansing. Jew hate
[118810, 45]Help convince PUMA to end support for Israeli | **apartheid** | !
[143412, 12]it's time to end your support for Israeli | **apartheid** | oppressing millions of Palestinians.
[143710, 11] did! Boycott Divest and Sanction Israel! | Apartheid | state.
[157310, 41]to boycott Israel. Good riddance. Another | **apartheid** | enabler hits the dust.
[164712, 19] Boycott ANYTHING originates from the | **apartheid** | occupying zionist state of israel.
[203712, 5] Israel is currently an | **apartheid** | racist rogue state and we shouldn't be afraid

Within the comments, as seen in Table 26, the tweeters mentioned keywords like "boycott", "Israeli", "BDS", "campaign", "illegal occupation", "opposition", "ethnic cleansing", "jew hate", "oppressing", "Palestinians", "sanction", "divest", "zionist", "racist", "rogue", etc. These are words and phrases used in the context of the existing conflict between Israel and Palestine. Even though the tweets, which were made in the context of cancel culture, were actually about the traditional protest against the state of Israel inspired by the BDS movement. This is a typical situation where an existing cause of civil disobedience is coopted into cancel culture by the convenience of using the #cancel or #boycott hashtags.

2.3.6. Free speech

From the result of dictionary analysis, Free speech as a motivation for cancel culture engagement is significantly explicated in the data from the United States of America. That is the only country where cancel culture is debated strongly in the context of free speech. In other countries in the data, the tweeters do not fixate a lot on freedom of speech in the context of cancel culture.

Some words popularly used in free speech-motivated tweets include; "free speech", "censorship", "censor", "censoring", "civil", "liberty", "hate speech", "politically correct", "correctness", "silencing", "chilling effect, “freedom of expression", “second amendment”, etc.

In the USA, the top words/phrases used by people who tweet about free speech in the context of cancel culture are “speech”, “free”, “correct”, “censor”, “censoring”, “censorship”, “correctness”, and “silencing”. This is seen in Figure 24 below.

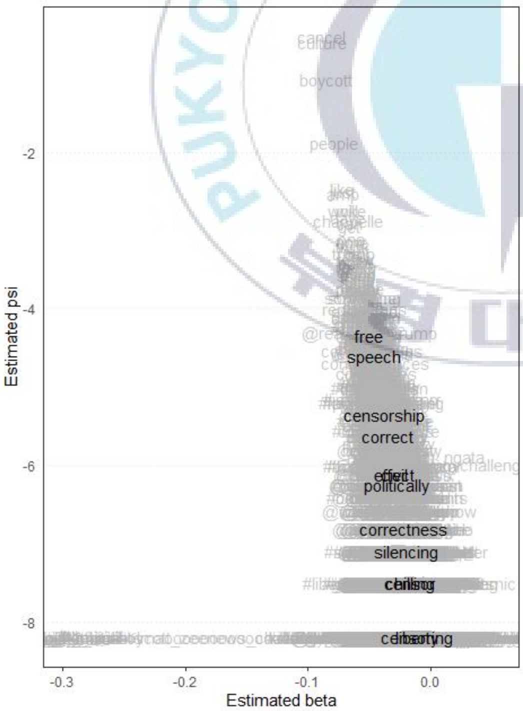


Figure 24: Top Free speech words used in the USA data

To exemplify free speech-motivated tweets in the context of cancel culture, I conduct a keyword-in-context analysis using the keyword “censorship”, from the USA data. As can be seen in Table 27 below, the tweeters mentioned words relevant to free speech discourse like “independent thinker”, “injustice”, “BLM”, “nazi”, “cancel culture”, “CCP (China)”, “hate”, “American Right”, “silence”, “criminal”, “sjw”, “demand censorship”, “woke leftists”, “support their views”, “conservatives”, “unAmerican”, “The Right”, “banning books”, “silent killer”, “have an opinion”, “spoke out against”, “book”, “fascists”, etc. These words and phrases were used by the tweeters to express their concerns about the challenge of maintaining the tradition of free speech in the era of cancel culture. These tweets, therefore, are motivated by the desire to defend the rights of people to freely express themselves in the cancel culture era.

Table 27: Sample of keywords-in-context of the word, “censorship” from the USA data.

[573111, 27]	balance that our country thrived on,	**censorship**	is happening both sides with one using
[6521, 8]	@kenklippenstein@Cernovich, the alleged" anti	**+censorship**	,"" independent thinker gawd,
[671311, 18]	I see corruption and injustice. I think	**censorship**	and cancel culture are the new norm.
[76381, 19]	; BLM (like nazi brownshirts),	**censorship**	, cancel culture, rioting, tearing down
[7736, 30]	hate CCP are not as demanding of	**censorship**	as people who hate the American Right
[77471, 6]	Hollywood's Silence on Cancel Culture	**Censorship**	Is Darn Near Criminal
[78252, 8	Cancel Culture: SJWs at Spotify Demand	**Censorship**	of Network's Newest Star Joe Rogan
[7929, 28]	latest example of" woke leftists" demanding	**censorship**	and cancel culture to support
[8984, 26]	growing up it was the conservatives pushing for	**censorship**	and what would come be
[90121, 12]	to me) is just another form of	**censorship**	, but none of y'all ready to admit
[94612, 7	ah guy who openly supports	**censorship**	and cancel culture trying not to get cancelled
[96062, 6]	@kburton40@Alyssa_Milano No, because	**censorship**	sucks even when you do it. Cancel
[10566, 9]	@WeThePeople021 Cancel Culture& amp;	**censorship**	are unAmerican when ever practiced,
[113401, 14]	points what do you mean by	**censorship**	? The Right is currently banning books across
[116981, 27]	their flies, they scream and cry about	**censorship**	and cancel culture. Fuck off, Clay
[118181, 3]	@JordanSimone38@SotDPodcast	**Censorship**	is the silent killer in this cancel culture
[119262, 18]	you dont defend hate speech,	**censorship**	rises to include most speech like cancel culture
[125202, 4]	Cancel culture means	**censorship**	now. No one can have an opinion
[145081, 34]	spoke out against cancel culture and	**censorship**	. The book gets more relevant witheach
[145942, 83]	not unilateral, fascist, cancel Culture,	**censorship**	mentality.

2.4. Summary of the result of motivating factors for cancel culture

In conclusion, the result of the analysis of the data for this study has shown that there are various motivating factors for which people get involved in cancel culture engagements on Twitter. Wokeness ideology and politics are the most popular factors. They inspire tweeters in all the countries where the data was obtained; South Korea, India, the Philippines, the United States of America, the United Kingdom, Nigeria, South Africa, and the Philippines.

Meanwhile, nationalism is also a prominent motivation for involvement in cancel culture. People are willing to cancel celebrities or brands that they believe hold loyalty to a foreign nation, or call for brands to be canceled in their country for being affiliated with a country, ethnic group, or nationality against which a cancel culture campaign has been raised. This is observed in South Korea, India, the Philippines, the USA, the UK, and Nigeria. Only in Brazil and South Africa is nationalism not strongly explicated as a motivating factor for cancel culture.

Concerns for cultural, moral or ethical rectitude in society is also an important reason for people's involvement in cancel culture engagements. This is seen in India, the Philippines, the United States of America, South Africa, the United Kingdom, Nigeria, South Africa, and Brazil. Only in South Korea is this not a major motivating factor for people getting involved in cancel culture campaigns.

Meanwhile, normative kinds of activism linked to cancel culture is popular only in the UK and South Korea, where activism like feminist actions, global warming, animal rights, DBS activism, etc., have become incorporated into cancel culture causes.

Finally, the concerns for free speech and freedom of expression have been a motivating factor for a lot of people getting involved in cancel culture argumentations. This aspect of cancel culture discourse is popular in the USA. In other countries, tweets motivated by the desire to defend free speech are not significantly represented in the data for this study.

Table 28: Summary of motivation for involvement in cancel culture conversations

	Wokeness	Politics	Nationalism	Cultural /moral/ethical concerns	Normative activism	Free speech
Countries in	South Korea, India, USA, UK, South Africa, Philippines, India, Nigeria,	South Korea, Philippines, USA, UK, Nigeria, South Africa, Brazil	South Korea, India, Philippines, USA UK, Nigeria	India, Philippines, USA, UK, Nigeria, South Africa, Brazil	South Korea, UK	USA
Countries out		India	South Africa Brazil	South Korea	South Korea, Philippines, USA, India, Nigeria, South Africa	South Korea, Philippines, India, UK, Nigeria, South Africa, Brazil
Associated keywords	"sjw" "lgbtq" "misogyny" "victim" "metoo" "sexual" "assault" "homophobia" "women" "transgender" "girl" "metoo" campaign" "woke" "ideology", "racism" "intolerance", "crt" etc	."democrat" "states" "politics" "elect" "vote" "right-wing" "leftwing" "liberal" "leftist" "rightist" "election" "campaigns" "ballot" "poll" "candidate" "centrist" "partisan" "rig" "alt-Right" "communist" "socialist" etc.	"country" "national" "patriotic" "statesman" "nation" "identity" "patriot" "patriotic" "national" history" "nepotism" "tribe",	"religion" "vulgar" "immoral" "drugs" "disgusting" "inhuman" "christian" "Islam" "Buddhism" "haram" "values" "teachings" "movies" "tripiṭaka", "agama" "obscenity" "bible" "quran" "god" "goddess" Etc.	"human rights" "hunger strike" "sit-in" "non-violent "civil disobedience" "advocacy" "resistance" "solidarity" "feminism", "girl child" "bds", "animal rights", "women's right", "apartheid", "global warming", etc.	"free speech" "censorship" "censor" "censoring" "civil" "liberty" "hate speech" "politically correct" "silencing" "chilling effect" "freedom of expression" etc.

3. Explicating the implications of negative cancel culture conversations

3.1. Result of the dictionary analysis, keyword in context and wordfish analysis

The dictionary analysis, keyword-in-context, and word frequencies are used to examine the implications of the use of certain words in the context of cancel culture communication. The dictionary analysis is applied to the data to find matches of words that indicate different types of words signifying different types of implications. Table 12 below shows the result of the dictionary analysis. The result is further interppreted together with wordfish/frequency and keyword-in-context analyses.

Table 29: Analysis of words indicating different negative implications of cancel culture.

docs	Hatred/tox	Stereotyping	Polarization	Discrimination	Bullying	Mockery	Blackmail	Unmatched
S/Korea	38	9	81	70	28	17	0	57531
India	706	53	146	306	67	52	215	194094
Philippines	171	8	80	9	71	14	0	33108
USA	201	38	139	76	62	67	8	51525
UK	583	68	360	383	155	150	26	196356
Nigeria	200	23	91	71	129	143	3	83593
S/Africa	117	10	80	15	46	65	0	35660
Brazil	308	27	133	15	47	28	0	58425

3.1.1. Hatred/toxicity

Hatred and toxicity are infused into cancel culture engagements when words are used which express deep-seated resentment and/or bias against another person/s or group/s. Expressions of hatred and toxicity are indicated in the use of words like “bigot”, “hate”, “punish”, “fuck yourself”, “go die”, “hater”, “mentally ill”, “shame on you”, “stooge”, “nazi”, “hypocrite”, “collaborator”, “pedo”, “idiot”, “shameless”, “rubbish”, “fight”, etc. Such words could cause emotional harm and sometimes could motivate people to inflict physical harm on a person they are used against. A hearer would interpret the use of these words to mean hostility and hatred.

In our analysis, however, the data returned positive result for the use of these words in all the countries in the data. In South Korea, 138 words showed up, for India 706, for the Philippines 171, the USA 201, UK 583, Nigeria 200, South Africa 117, and Brazil 308. Below in Figures 25a and 25b are visualizations of top hatred and toxicity words from a sample of ten thousand words taken from each country.

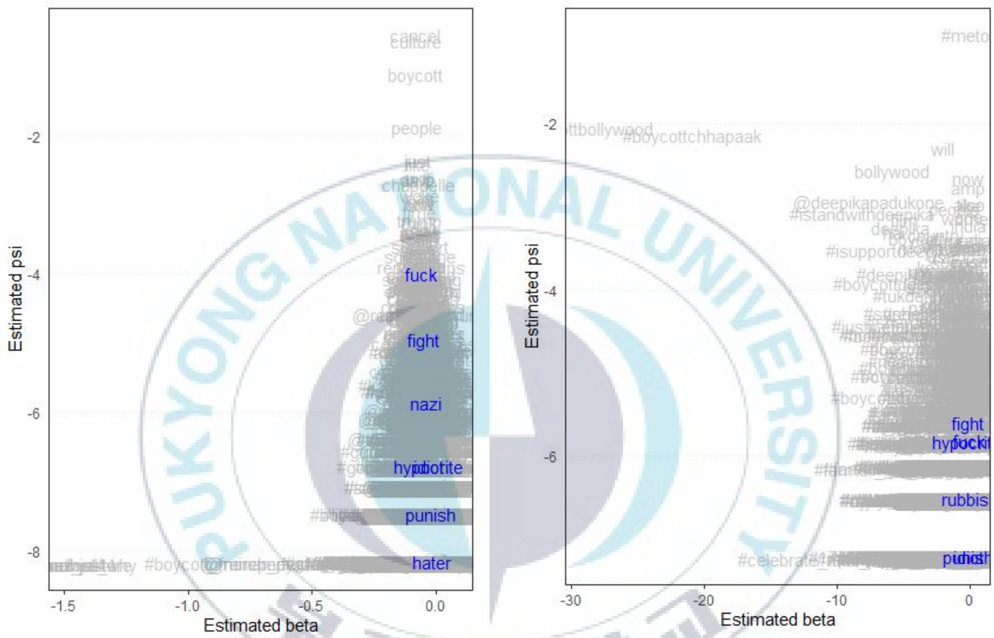


Figure 25a & 25b: Top hatred/toxicity words used in the USA and India sample data

Tables 30 and 31 below are examples of keyword-in-context analysis taken from Brazil and UK data respectively of tweeters using the keywords “hypocrite”/“nazi” and “idiot” in comments which convey hatred and toxicity in the course of cancel culture conversations.

Table 30: Sample of keywords-in-context of the words, "nazi" and "hypocrite" from Brazil data.

[539513, 32]	or just giving rise to being labeled a	hypocrite	etc.
[540314, 49]	of reports are real, I'm not a	hypocrite	, our society is
[551115, 23]	website and anyone who doesn't read it is	Nazi	
[169343, 41]	to transsexual-themed pornography, the	hypocrite	is the main nutrient of cigenderism.
[170873, 1	the cheeky right is quiet. Then the	hypocrite	is me.
[172143, 47]	other women, you are nothing but a	hypocrite	and a shame for feminist movement!
[139693, 2]	this	idiot	here wants to play a cool leftist but
[150109, 26]	cool, it has to be a real	idiot	
[150453, 47]	accept your own bisexuality and a fucking	idiot	. And the trans guy who is willing

Table 31: Sample of keywords-in-context of the words, "nazi" and "bigot" from UK data.

[96812, 36]	show than the government, and yet this	idiot	is employed by the same people, you
[106413, 35]	on their bigotry. Demand to be a	bigot	and there is an infinite well of ostracism
[166310, 3]	Whenever a	bigot	/ TERF/ homophobe/ racist etc vows
[236414, 14]	run until his death in run by a	Nazi	: a proper Nazi who joined the Swedish [236414,
[345616, 23]	a proper Nazi who joined the Swedish	Nazi	party in. So boycott them.@JuliaHB1
[269210, 26]	company. Or are you a racist,	bigot	and far right white male supremacist too?
[404711, 2	it in layman's terms. What a callous	idiot	boycott his pub I wouldn't give him my
[458413, 6]	@Swamy39 Boycott ths	idiot	completely, he is the biggest
[533312, 3]	@Nigel_Farage You	idiot	. Now you have lead us away from
[541311, 5]	Vine is an absolute	idiot	, we should boycott his stupid shows.
[57711, 2]	ask yourself when you turned into a racist	idiot	
[613911, 24]	and Islamophobic people by the simple term'	bigot	Life was much simpler back then

As seen in the keyword-in-context result in Tables 20 and 31, these words are used in the same context with even more egregious and negative-sentiment words like "pornography", "cisgenderism", "cheeky", "shame", "leftist", "bisexuality", "fucking", "bigotry", "ostracism", "TERF", "homophobe", "racist', "far right", "white male", "supremacist", "callous", "stupid", "Islamophobic", etc. These are words that portend negative implications for their target no matter the context they are used.

3.1.2. Stereotyping

Stereotypes are infused in cancel culture engagements through intentional use of words that express oversimplified and generalized beliefs or ideas about a particular group of people. "Stereotyping" expressions are indicated in the use of words like "snowflakes' which is used to mean liberals; "fascist" used to mean right-wingers; "jihadist" used to generalize about Muslims, etc. Other words in the dictionary for "stereotyping" include "karen", "leftist", "ignorant", "rightist", "grifter", "faggot", "extremist", "blacks", "whites", and "asians". Stereotypes in cancel culture can be used to classify and belittle another person. Such words also could cause psychological harm and distress to the hearer.

Meanwhile, the dictionary analysis of the stereotype words in the study returned positive for all the countries. In South Korea data, 9 words showed up, in India data 53, in the Philippines 8, in the USA 38, the UK 68, Nigeria 23, South Africa 10, and Brazil 27. Below in Figures 26a and 26b are visualizations of top stereotyping words from the UK and Nigeria data; words taken from a sample of ten thousand words from each country.

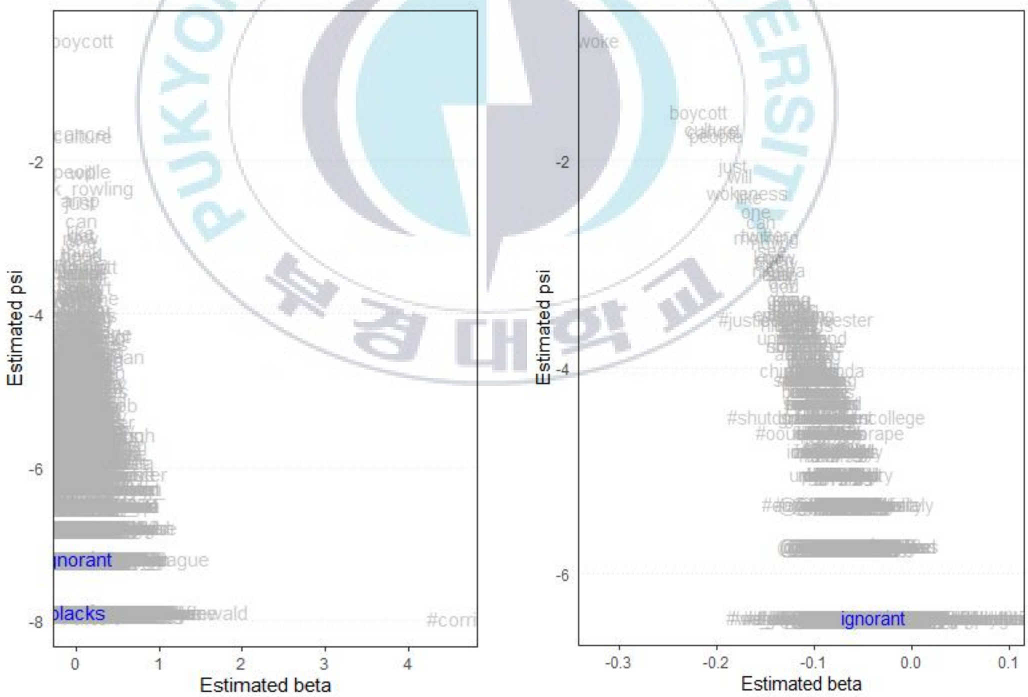


Figure 26a & 26b: Top stereotyping words used in the UK and Nigeria data

Tables 32 and 33 are examples of keyword-in-context analysis taken from the Philippines and Nigeria data of tweeters using the keywords “Asians”, “snowflake”, “fascists”, “ignorant”, and “whites” to cast stereotype labels on other persons or races in the course of cancel culture conversations.

Table 32: Keyword-in-context analysis with words “fascist”, “asians”, and “ignorant” in cancel culture tweets from the Philippines

[294, 41]	line, she is as bad as any	**fascist**	could be.
[1928, 7]	The Evolution of Twitter Innocent/	**ignorant**	tweets Call out culture Cancel
03710, 12]	and tropical country, there are so many	**snowflakes**	in the Philippines#cancelkorea
[7038, 12]	and tropical country, there are so many	**snowflakes**	in the Philippines#cancelkorea
[80571, 26]	looked down on Filipinos and other South East	**Asians**	. You claim to be a Kpop stan
[81201, 40]	SEA countries which they call" jungle	**asians**	" because of our looks smh xenophobia
[8261, 9]	enough calling Filipinos black of	**asians**	. We are not defined by color because
26161, 17]	as" woke mentality" and being"	**snowflakes**	"? What did you do in
[17586, 8]	Devil in boycott genshin wtf? These	**snowflakes**	are always like that as long as they

Table 33: Keyword-in-context analysis with words, “leftist”, “ignorant”, “whites”, and “extremist” in tweets from Nigeria

[460105, 21]	I can't never support	**leftist**	leaning of Abortions, socialism, cancel culture
[103414, 2]	An	**ignorant**	, entitled generation and cancel culture.
[132514, 5]	Chimamanda Adichie Is An	**Extremist**	Misleading Lot Of Our Girls-Presidential
[164813, 12]	its a Culture war. Woke,	**Fascist**	Misandrists posing as Feminists, Simps, Predators
[207014,	a boycott of delta airlines. This	**ignorant**	fools never wish us well.
[268713, 31]	you know that we have more	**ignorant**	and daft people in this country than learned
[491314, 19]	on earth is bothered by the" All	**Whites**	" tag. White people should stop getting
[500615, 4]	surpressed by American	**leftist**	ideologies& amp; wokeness culture, exported
[598511, 8	What did we ever do to the	**whites**	? If they hated us so fucking much
[652812, 12]	its a Culture war. Woke,	**Fascist**	Misandrists posing as Feminists, Simps and Predators
[85133, 58]	at least the old baba will not be	**ignorant**	& amp; still argue blindly

As seen in the keyword-in-context result (Tables 33 and 33) these stereotype words are used in the same context as “cancelkorea”, “looked down on”, “other South East Asians”, “our looks”, “xenophobia”, “calling Filipinos black of”, “woke mentality", ”devil“, ”abortions“, ”socialism“, ”misleading“, ”culture war“, ”misandrists“, ”feminists“, ”simps“, ”predators“, ”fools“, ”daft people“, ”hated“, ”fucking“, ”argue blindly“, etc. All these words have negative connotations no matter the context they are used in.

3.1.3. Polarization

Polarization is infused in cancel culture engagements when words are used which are divisive and aimed at pitching people against each other. Expressions of polarization are indicated in the use of words like “ideologues”, “indoctrinated”, “divided”, “propagandist”, “scammer”, “homophobe”, “racist”, “hitler”, “snowflakes”, “evil”, “nazi”, “disagree”, “unite against”, “whiteness”, “blasphemer”, “elite globalist”, “nationalist”, “meltdown”, “islamophobe”, “misogynist”, etc. These are words that are capable of polarizing opinions of people and ensuring there is constant wrangling among them.

The keyword-in-context analysis of the data for polarization words returned positive for the use of these words in all the countries. From South Korea data, 81 words were returned, from India 146, from the Philippines 80, from the USA 139, from UK 360, from Nigeria 91, from South Africa 80, and from Brazil 133. Below in figure 27a and 27b are visualizations of top polarization words used in India and UK matching our dictionary, taken from a sample of ten thousand words.

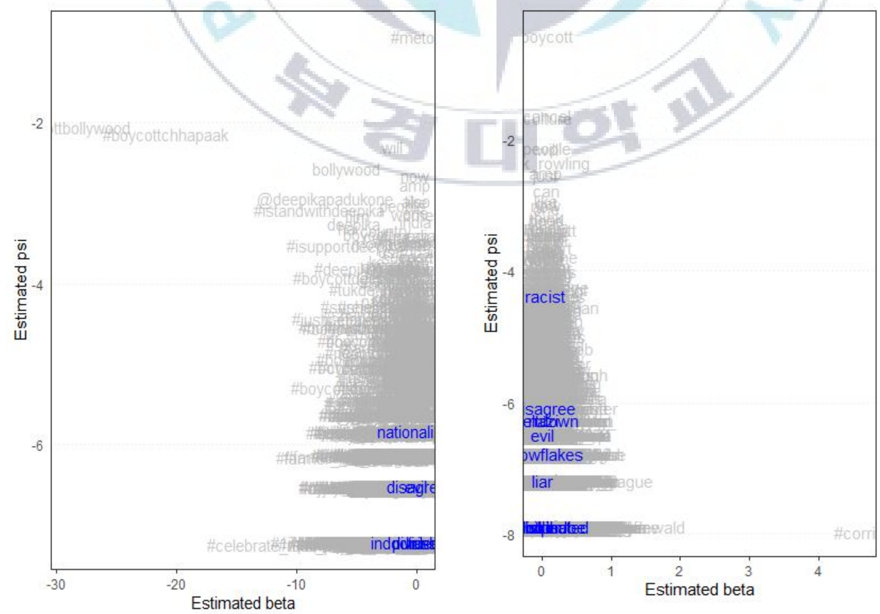


Figure 27a & 27b: Top polarization words used in the India and the UK data

Table 34, also, is an example of keyword-in-context analysis taken from South African data of tweeters using the polarization keywords like calling others "Hilter", "globalist", "snowflakes", "elite", and "racists" while passing comments on Twitter in cancel culture conversational context.

Figure 34: Keyword-in-context analysis with words, "hitler", "racist", "globalist", "elite", and "snowflakes" in from South Africa

[246107, 36]	of Zille to compare black leaders to genocidal	Hitler	So, there is a precedent being
[270106, 55	clouding our judgement. I abhor racism and	racist	behavior!
[273105, 11]	Lying, cancelculture agendas by socialist lefties	GLOBALIST	elite
[273105, 12]	cancel culture agendas by socialist lefties	GLOBALIST	elite
[314106, 27]	old man with dementia to be handled by	GLOBALIST	
[417105, 20]	follow you to learn from you. I disagree with	elite	, with a lot of what you say.
[593104, 55]	cancel culture' are the ones calling ppl	snowflakes	
[91617, 50]	people effected by the offensive view of the	elite	
[94118, 20]	follow you to learn from you. I	disagree	with a lot of what you say.
[111717, 55]	cancel culture' are the ones calling ppl	snowflakes	
135619, 15]	cancelled AFTER doubling down on a non apologetic	racist	homophobe. Cancel culture
[135619, 30]	responsibility which punctures your unbridled	racist	homophobic, sexist privilege.
[158018, 45]	of a miniscule group of academics in uber	elite	US institutions?)

As seen in the keyword-context-analysis, (Table 34) these words are used in the same contexts as words like "genocidal", "abhor", "lying", "socialist lefties", 'old man with dementia", "offensive view", "nonapologetic", "homophobe", "homophobic, "sexist", "miniscule group of". These words and expressions are very negative and are always used with negative connotations irrespective of the discourse context.

3.1.4. Prejudice/discrimination

Discrimination is infused in cancel culture engagements when words are used to express prejudice or bias about certain individuals or groups. Expressions of discrimination are indicated in the use of words like "pro-", "anti-", "Muslim", "jew", "whiteman", "far-", "blacks", "whites", "asians". These words are signifiers used to cluster people under groups or categories which can be discriminated against. Anybody who is associated with any of the groups is discriminable.

In the keyword-in-context analysis, the data returned positive results for the use of discrimination words in all the countries. For South Korea, 70 words were returned, India, 306, the Philippines 9, the USA 76, the UK 383, Nigeria, 71, South Africa, and Brazil, 15 words. Below in figure 28a and 28b are visualizations of top prejudice/discrimination words used in Brazil and South Africa matching our dictionary, taken from a sample of ten thousand words.

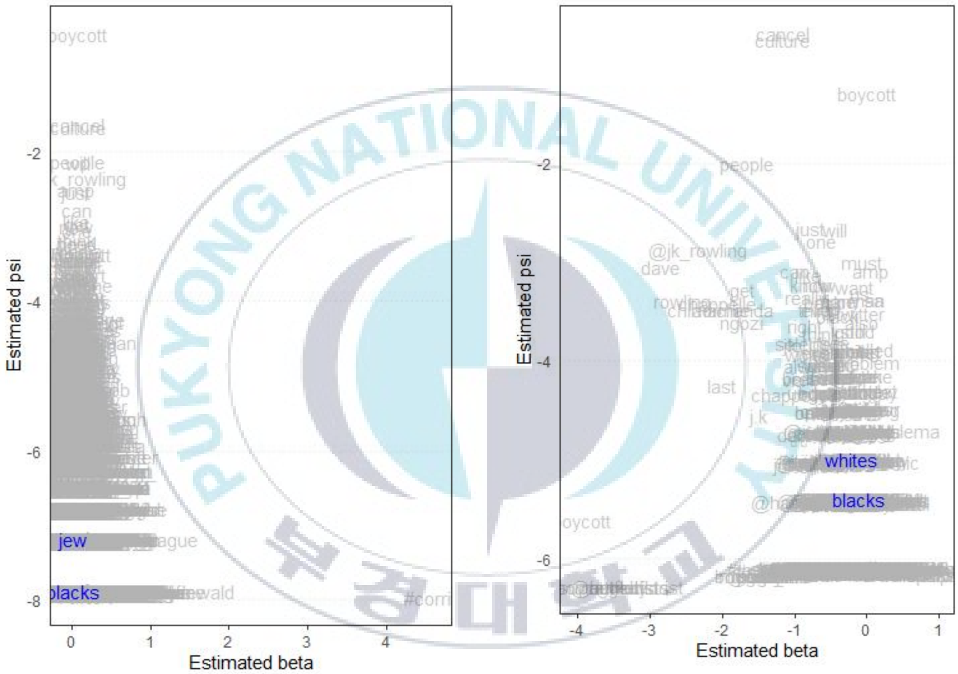


Figure 28a & 28b: Top prejudice/discrimination words used in Brazil and South Africa data

Tables 35 and 36 show the results of the keyword-in-context analysis conducted with the USA and Indian data. The discrimination terms applied in the analysis are “anti-”, “Asians”, and “Muslim”.

Table 35: Keyword-in-context analysis with words, “anti-”, “asians”, “Muslim”, and “snowflakes” from tweets in the USA.

[128211, 33] Watch as their enrollment slides. Pathetic | **anti-** | American college student union.
[3080, 33] But Shane Gillis has repeatedly called | **Asians** | chinks on several occasions as a grown
[8877, 20] dont be disingenuous. They're an anti | **Muslim** | hate group. And please dont
[104901, 8] Jim Murray has been reduced to writing | **anti-** | " cancel culture" rants in the Daily
[11573, 39] on, stop trying to bring your shitty | **anti-** | " cancel culture" motives into
[121662, 37] a race wars: blacks, browns, | **asians** | , are the targets! Beware
[18761, 54] anti-vaxxed Twitter- liberal, cancel culture, | **pro-** | vaccinated
[25729, 15] who push unethical, racist, misogynistic, | **anti-** | lgbtqia ideals and practices, it's
[27002, 14] be asked not to tell jokes athat include | **Asians** | ???? Yes the cancel culture
[275882, 8] Ethan Van Sciver can shout kill all | **asians** | DAYS after a fucking racist masacre and he
[28788, 11] culture will be like" making fun of | **Asians** | wasn't racist back in the day it's just

Table 36: Keyword-in-context analysis with words, "anti-" and "muslim" in tweets made in India.

[131100, 11]Negative role for Hindu and Police Inspector | **Muslim** | .The image Muslim always good
[136610, 11] Bollywood love story happen without a Hindu | **Muslim** | ? If you are making, then also
[1378, 11] movie spoils Hindu girls. And attracts | **Muslim** | boys to marry them
[2508, 10] it drugs consumption and trafficking, murder, | **anti-** | nationalism or drink& amp;
[4103, 2] | **Muslim** | Superstar" my foot.#Boycott
[5432, 12] south indian movie not belong to mugal | **muslim** |they always show in movies Hinduism's bad
[6373, 8] She is a Hindu Married to a | **Muslim** | and became his toy
[84291, law violates the principles of secularism. This | **Muslim** | appeasement black law be abolished
[13362, 15] get guts, show it by making fun of | **Muslim** | religion, show it now
[13362, 24] religion, show it by making fun of | **Muslim** | religious leaders. Our Hindutva, our heritage
[22941, 17] Hindu gods for money. What were few | **Muslim** | producers and actors
[233451, 25] to uplift Muslim actors. They didn't allow | **Muslim** | actress because of Islam All Muslim
[243311, 5] @mrraisahab Chak De India's | **Muslim** | coach Kabir Khan originally a Hindu
[245411, 6] Put the sin of a | **Muslim** | youth on a boy named Hindu.

Also seen in the keyword-context-analysis (Tables 35 and 36) are words used in the same context with discrimination words in both countries, which include the words "pathetic", "chinks", "disingenuous", "hate group", "rants", "shitty", "race wars", "blacks", "browns", "targets", "beware", "anti-vaxxed", "unethical", "racist", "misogynistic", anti-lgbtqia", "kill all Asians", "fucking racist", "massacre", "drugs consumption", "trafficking", "murder", "anti-nationalism", "black law", "Identity". Such words, no matter the context they are used, are negatively connotated. They are unpleasant irrespecitve of who is their target.

3.1.5. Bullying/verbal abuse

Bullying is infused in cancel culture engagements to intimidate, harm, or belittle others. They can be used in the form of aggression to create a power imbalance against targeted individuals or groups. Expressions of bullying are indicated a speaker uses words like “clown”, “stupid”, “ugly fat”, “fat ass”, “worthless”, “dimwit”, “self-loather”, “shut up”, “liar”, “stupid”, “moron”, “triggered”, “gulag”, “cry bully”, etc. on others. Or when they use expressions like, “bla bla”, “virtue signaling”, “shut-the-fuck-up”, etc. In the analysis, the data returned positive results for bullying words in all the countries; South Korea, 28, India, 67, the Philippines 71, the USA 62, the UK 155, Nigeria, 129, South Africa 45, and Brazil, 47. Below in figure 29a and 29b are visualizations of top bullying/verbal abuse words used in the UK and Nigeria matching our dictionary, taken from a sample of ten thousand words.

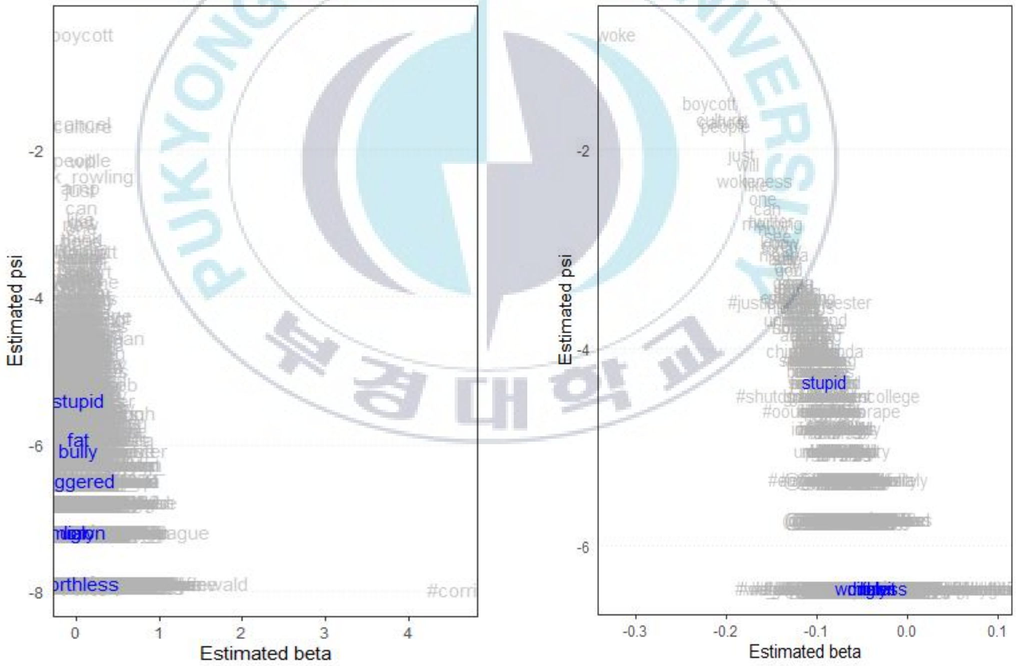


Figure 29a & 29b: Top bullying/verbal abuse words used in the UK and Nigeria data

Table 37 shows the result of keyword-in-context analysis conducted with bullying words taken from the UK data. The context includes where tweeters use bullying terms like “clown”, "triggered", "moron". "ugly", and "liar", etc. all in the context of cancel culture conversations.

Table 37: Keyword-in-context analysis with words, "clown", "triggered", "worthless", "liar", "ugly", and "moron" in tweets from the UK

[375102, 28]	means acting like a crap circus	**clown**	. PMQs unbearable. Perhaps opposition
[508103, 25]	I saw that covidiots are being	**triggered**	by a TV advert with Santa showing
[118610, 49]	viewers we will Boycott watching a	**Clown**	, ex hockey player and Rugby player no
[168312, 26]	Green giving shareholders a price for those	**worthless**	shares. We were lucky with
[215711, 18]	opposition MP agree to audibly call him a	**liar**	every time he speaks?
[420910, 5]	The beautiful game turned	**ugly**	today. If you have any interest in
[441310, 23]	not a unifying symbol. It is an	**ugly**	relic of an imperialist past. I boycott
[458413, 13]	this idiot completely, he is the biggest	**liar**	hidden in our country, khud
[508112, 11]	Why can't people boycott the show until the	**moron**	is sacked
[626210, 29]	culture, kneeling, dancing in streets,	**clown**	coloured police cars. Bring back
[642211, 19]	draining. It must be so tiring being	**triggered**	/ by everything
[658812, 7]	@afneil If she's delusional and a	**liar**	why do you pay such disgusting
[697710, 25]	btsportcricket is TERRIBLE. Boycott a complete	**moron**	!
[80573, 3]	folks Priti	**Ugly**	was in Israel at a dinner organized by
[83693, 4]	@roubaixcc This is	**triggered**	you appearing in this search: Its a
[90351, 17]	that they can already see a terrifying killer	**clown**	if they want to
[99042, 3]	What a	**Moron**	... Everyone who has an ounce
139953, 20]	in London! Why is RT giving this	**moron**	airtime. Complete shite. Glad I did

As seen in Table 37, words used in the same context as bullying words in the UK include; "crap circus", "covidiots", "triggered", "imperialist past", "idiot", "sacked", "delusional", "disgusting low life", "TERRIBLE", "terrifying killer". All these words have negative connotations for a person or groups they are used against.

3.1.6. Mockery/shaming/trolling/name-calling

Mockery, trolling, or name-calling are infused into cancel culture engagements to make fun of or ridicule other people. Words used in this context are emotionally hurtful to the targeted person, especially when the words are demeaning or dehumanizing. Expressions of mockery, shaming, trolling, and name−calling are indicated in the use of words like "magat", "qanon", "blue anon", "nonsense", "snowflakes", "faux-", "NPC", "talking head", "faggot", "remoaner", "karen", "mob", "rapist", "fat phobic", "moron", "stooge", "simp", "predator", "pedo", "pedophile", "teupemi", etc.

In the analysis, the data returned positive results for mockery words in all the countries. For South Korea it is 17, India, 52, the Philippines 14, the USA 67, the UK 150, Nigeria, 143, South Africa 65, and Brazil, 28. Below in Figure 30a and 30b are visualizations of top mockery, shaming, trolling, and name-calling words used in the USA and South Africa matching our dictionary, taken from a sample of ten thousand words.

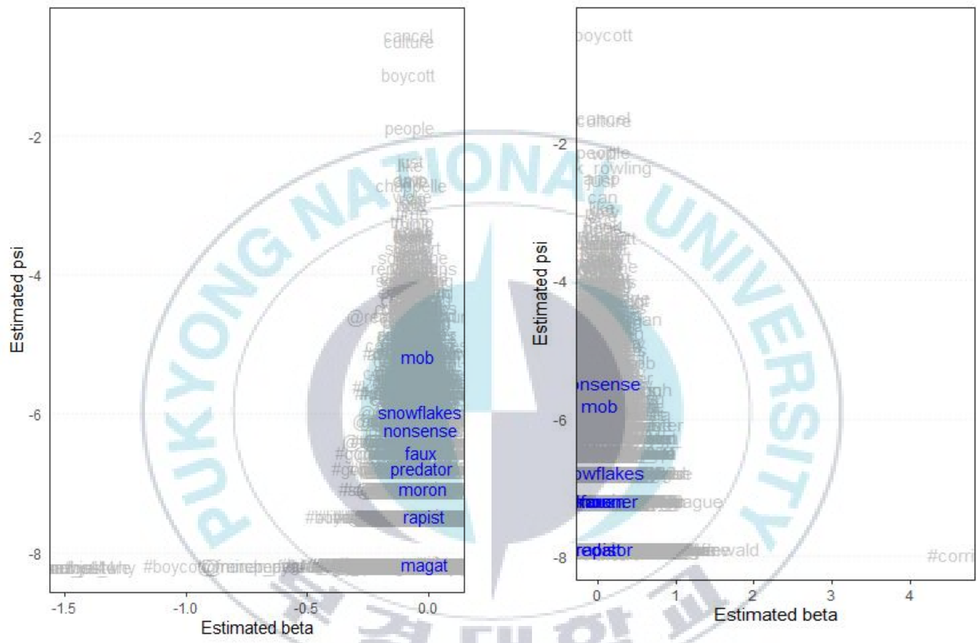


Figure 30a & 30b: Top Mockery/shaming/trolling/name-calling words used in the USA and South Africa data

Further, Tables 38 and 39 below show the result of keyword-in-context analysis conducted with mockery, trolling and name-calling words taken from the Nigeria and South Korea data. These include where tweeters use mockery or slur terms like “mob”, “rapist”, “faux” and “nonsense” in cancel culture conversations.

Table 38: Keyword-in-context analysis with words, “faux”, “mob”, “nonsense”, and “rapist” in tweets from Nigeria.

[142107, 23]	NG. Calling out, Cancel culture,	**faux**	outrage, political correctness, moral grandstanding,
[147108, 4]	Extremists views The	**mob**	Cancel culture I hate all of

[176107, 14]	but the audience just want gist,	**faux**	rage and cancel culture... Dare
[271104, 6]	@je_mc2 Cancel Culture and Mad	**Mob**	Movements
[275107, 17]	Cancel culture nothing but online	**mob**	justice. It doesn't really seek to correct
[392105, 41]	in those years. This cancel culture	**nonsense**	needs to die. That is not how
[465105, 6]	@NigBarAssoc I am% against	**mob**	action... cancel culture is mob
[465105, 14]	mob action... cancel culture is	**mob**	action. It is against free speech&
[486104, 36]	is called names like" enablers,	**rapist**	apologists..." But we must
[87216, 10]	interesting. so cancel culture is just a	**nonsense**	excuse for sick vendettas. got it
[91117, 5]	You people and your	**nonsense**	cancel culture rubbish.
[92216, 41]	in those years. This cancel culture	**nonsense**	needs to die. That is not how
[99516, 6]	@NigBarAssoc I am% against	**mob**	action... cancel culture is mob
[99516, 14]	mob action... cancel culture is	**mob**	action. It is against free speech&

Table 39: Keyword-in-context analysis with words, "rapis", "nonsense", and "predator" in tweets from South Korea

[476, 15]	ambassador has returned. Probably her	**rapist**	father is now well hidden. Shameles
[683, 12]	illiterate@rkelly is, he is still a	**rapist**	, pedophile& amp; predator. He
[683, 18]	still a rapist, pedophile& amp;	**predator**	. He may not know how count,
[1041, 29]	gov'nor Ahn Hee-jung alleged serial	**rapist**	apologizes to nation
[1575, 22]	my face again to spurt believe women	**nonsense**	. I'm gonna smack the maga's ass.
[1734, 15]	ambassador has returned. Probably her	**rapist**	father is now well hidden.
[1941, 12]	llliterate@rkelly is, he is still a	**rapist**	, pedophile& amp; predator. He
[1941, 18]	still a rapist, pedophile& amp;	**predator**	. He may not know how count,
[3011, 7]	@sangchutg with a patient with	**nonsense**	adulterous desire Victims
[3468, 40]	conference? Evidence is also.. mostly	**nonsense**	.. Mayor... Why did
[7278, 12]	% female quota is in favor It seems	**nonsense**	to associate it with#MeToo." It's
12934, 14]	affair from the beginning. Me Too is	**nonsense**	." Mr. Min Joo-won" Kim

Also, as seen in Tables 38 and 39, these mockery and trolling words are used in the same context as words like "outrage", "political correctness", "moral grandstanding", "extremists views", "I hate all of them", "rage", "mad", "needs to die", "enablers", "apologists", "sick vendettas", "rubbish", "pedophile", "predator", "maga", "ass", "adulterous desire", "victims", etc. All these words are negatively connotated no matter the context of communication.

3.1.7. Defamation/blackmail

Defamation and blackmail are infused into cancel culture engagements when words are used to issue threats, coerce actions, manipulate, or control someone or a group of people often to cause them to pursue or desist from certain course of action. They may be used to make someone afraid for their reputation or their life. Expressions of defamation and blackmail are indicated in a tweet by the use of negative labels like “traitor”, “uncle Tom”, “race traitor”, “race hustler”, “shill”, “betrayer”, “enabler”, “stooge”, or use of accusation expressions like “hidden agenda”, “fake-”, “quack”, “baiter”, etc.

The keyword-in-context analysis result returned positive outcomes for defamation and blackmail words in the countries of India 215, USA 8, UK 26, and Nigeria 3. The dictionary does not match any words with South Korean, the Philippines, South Africa, and Brazil data. Below in figure 31a and 31b are visualizations of top defamation and blackmail words used in India and the UK matching our dictionary, taken from a sample of ten thousand words..

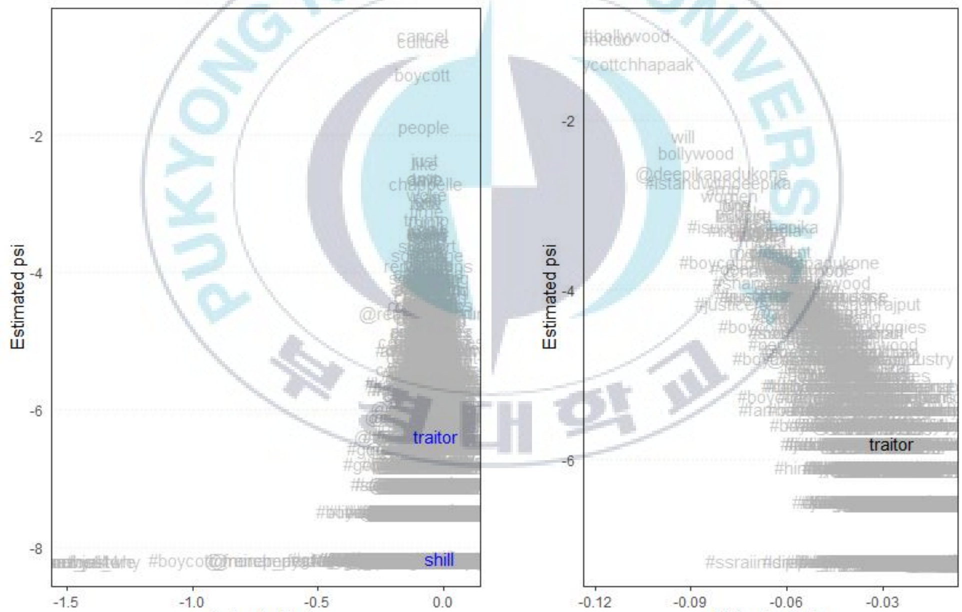


Figure 31a & 31b: Top Defamation/blackmail words used in India and the UK data

Further, Table 40 is an example of keyword-in-context analysis conducted with defamation and blackmail words with data taken from the USA. The terms used for the analysis include “traitor”, “shill”, “stooge”, and “enabler”, all used in the context of cancel culture conversation.

Table 40: Keyword-in-context analysis with words, "traitor", "shill", and "stooge" in tweets from the USA

[348210, 45] morally" You cancel culture cuck comedian | **traitor** | !"
[600110, 14on I'm watching. IDGAF who celebrities | **shill** |. You cancel culture fucks are douchebags
[6444, 39] SUCKER KISSING THEIR ASSES YOU | **TRAITOR** | SON OF A BITCH I AM PRAYING
[20219, 3] @DineshDSouza Seditious | **traitor** | and felon and cancel culture warrior says
[20790, 18] Cancel Culture. I don't think he's a | **traitor** | , though.
[229191, 18] garbage? Cancel culture at the ready you | **traitor** |
[233532, 3] Resign seditionist | **traitor** | tot! Celebrating Nazi cancel culture! The
[23460, 17] fair elections. GOP: Shut up, | **traitor** | ! Marjorie Taylor Greene: I believe in
[239792, 27] .....@HawleyMO is a | **traitor** | , a fraud, a racist
[248962, 8] Cancel culture much? You are a | **traitor** | to this country and should be thrown out
[31061, 24] to do is ban together and get that | **stooge** | @SenTedCruz outta office [32223, 41] victims of cancel culture. You're a | **traitor** | ! You're the incarnation of evil.
[32251, 4] @LAGOP Republican fascist | **traitor** | cancel culture at it again.
[32347, 24] the UCMJ REGARDING OPSEC you will find a | **traitor** | definition for
[33437, 38] Hey@Jim_Jordan you are a child abuser | **enabler** | and that's a fact. Your little speech
[34357, 4] Impeachment of a | **traitor** | , Trump, is the only right thing

Also, seen in the keyword-context-analysis (Table 40) are words used in the same context with the selected keywords, like "fucks", "douchebags", "SON OF A BITCH", "Seditious traitor", "felon", "garbage", "seditionist", "Nazi", "fraud", "incarnation of evil", "fascist", "child abuser", etc. These words are very negatively connotated in all communicative contexts.

Chapter V. Summary and Conclusions

1. Summary

1.1 On the similarity of cancel culture conversations

The first analysis conducted in this study was to evaluate the similarity/diversity of themes in cancel culture as a way to determine if the motivation for it is about single or multiple issues. I argued that beyond the idea of wokeness, the cancel culture conversations might have tilted into diverse concerns that are not popular in the existing literature.

I created three categories for the extent of the similarity; highly similar, averagely similar, and lowly similar, depending on the result of the cosine similarity between two pairs of countries represented in the data. A similarity scores higher than 0.7 is considered high similarity. It indicates that the content words in the data from both countries are similar above seventy percent, and invariably indicates that the conversations between tweeters in both countries speak to the set of issues, hence using a lot of similar words which define the set of ideas.

The similarity scores between 0.3 and 6.9 are considered average similarity, which means that the content words in the texts being paired are loosely related. The variation indicates here indicates that while a good number of the content words are shared in common, many words are also different. In essence, while the discussion is about, the themes in the difficult are variegated. The tweeters possibly speak to different sets of issues.

Meanwhile, cosine similarity scores below 0.3 are considered low similarity. This indicates that the test documents of the paired countries are quite dissimilar. It is possible on this score to argue that the cancel culture conversations evolve over unrelated themes. Based on this, it is possible to argue that different sets of motivations are behind involvement in cancel culture.

The result of the analysis indicates that cancel culture may have local variations since among the countries, the similarity scores vary, but to different extents. It is high when the countries of the Philippines, the USA, Nigeria, South Africa, and Brazil are paired against each other. It is average when the UK is paired with the Philippines, USA, and Nigeria. It is low when South Korea or India is paired against all the other countries, also the UK is paired and Brazil, and also when South Africa is paired with the UK, and, when Brazil is paired with India and the UK.

In essence, it is arguable that cancel culture conversations in the Philippines, the USA, Nigeria, South Africa, and Brazil share similar themes of discourse, hence similar topics and motives, and hence the choice of similar words in the conversations. The UK differs to some extent, being averagely similar to these other countries. South Korea and India are the most isolated countries; they seem to involve in cancel culture but with entirely different sets of motivations as the languages of their cancel culture discourse are way different from each other and the rest.

The result, hence, suggests not of one cancel culture. Rather probably many types of cancel culture driven by different kinds of themes and motives. To explicate some of these was the focus of the second research question.

1.2 On the motivation for cancel culture involvement

The second analysis conducted here was to evaluate the motivations behind cancel culture based on the themes of the people's conversation. I created categories of likely motivations following topic modeling. Then I used dictionary analysis to evaluate the data to match words related to each topic. The result indicates that various motivations are behind what can be called cancel culture these days. There are those who involve in the conversations because of woke ideology. There are those who use cancel culture to advance a political ideology. There are those involved in it to advance nationalistic sentiment, there are those whose causes are related to Cultural/Moral/Ethical values. There are those whose concerns are just in pursuit of normative/traditional forms of activism that are not linked to cancel culture, and finally, there are those whose cause is to advance the discourse of free speech.

Wokeness as a motivating factor for involvement in cancel culture conversations is strong in all countries in our data; South Korea, the Philippines, India, the USA, the UK, Nigeria, South Africa, and Brazil. However, it is not that everyone is for it; there are those who like and advance it, and there are also those who oppose it as the analysis of keywords-in-context suggests. Conversations around woke ideology invoke the use of words like #metoo, #blacklivesmatter, historical racism, sexual violence, toxic masculinity, etc. The hashtags associated with these kinds of tweets include #cancelculture, #metoo, #takeaknee, #woke, etc.

Also, politics as a motivating factor for involvement in cancel culture cuts across all the countries represented in the data. People raise campaigns against politicians, celebrities, or businesses who support politicians they oppose. In this context, therefore, cancel culture serves as a tool for advancing political interest. Many hashtags like #gop, #dnc, #trump, #boycottwhitehouse, etc. trend in the context of cancel culture in the USA. In South Korea, #party and #democratic are hashtags that trend in the context of cancel culture conversations. In Brazil #forasarah and #forabolsonaro, and in Nigeria #boycottelection and #apc are political hashtags that trend in the context of cancel culture.

Meanwhile, cancel culture used to advance conversations on nationalism is popular in South Korea, India, the USA, the UK, and Nigeria. In South Korea, it pivots on the historical issue with neighbors Japan for which campaigners fight to cancel Japan. In the Philippines, nationalism-driven cancel culture conversations focus on their relationship with another East Asia neighbor, South Korea. Many Philippine netizens consider South Koreans as being racist toward Filipinos. How and when this opinion was formed is beyond the scope of this study since the information did not show up in the analysis. However, a significant number of cancel culture activists in the Philippines would rather have South Korea canceled. In India cancel culture is used in advancing Hindu nationalism. This is used especially by those who want to cancel non-Hindu especially Muslims whom they believe dominate some key sectors of the economy like the Bollywood industry. These kinds of tweets launder Hindu religions and want anyone canceled who is alleged to have offended Hindu systems of belief and life. In the USA, the cancel culture campaign has been directed against China and Russia for economic and political reasons. These intermittent campaigns target personalities, businesses, and brands doing business in China. In the UK, cancel culture conversations have revolved around Brexit. People are sporadically canceled for opinions about Brexit. In Nigeria, meanwhile, South Africa and their citizens are targeted for canceling. The keyword-in-context analysis was a result of alleged homophobic attacks on Nigerians in South Africa. Such campaigns have targeted South African brands doing business in Nigeria. These names float up in word cloud analysis. Some cancel culture hashtags associated with nationalism "#cancelKoreans", "#canceljapan" "#uniqlo", "#hindu" "#boycottbollywood", "#cancelsa", "#xenophobia", etc.

Meanwhile, cultural/Moral values are strongly held as a motivating factor for cancel culture in the countries of India, the Philippines, the USA, Nigeria, South Africa, and Brazil. People and businesses are canceled for alleged cultural misconduct against gods (India), mistreating workers/domestic staff (Philippines), offending Judeo/Christian values (USA), insulting Christianity or Islam (Nigeria), and misrepresentation of cultural practice in a movie (South Africa). In all these and many more, the concerns for these conversations are about violation of cultural, moral, or ethical norms or values that people in each context consider important to them, and for which enormous raucous are made online to cancel a person or brand. Hashtags associated with these kinds of campaigns include #gods

Normative activism is much more popular in South Korea and India.

In these places cancel culture has been framed into traditional forms of activism that have been in existence prior to cancel culture itself. In the UK, BDS campaigns over the Israeli versus Palestinian conflict have become the subject of cancel culture discourse, as well as global warming and animal rights protests. In South Korea, feminist groups have repurposed their activism and exist alongside cancel culture.

Meanwhile, in the USA, there are those who involve in cancel culture as a way to advance free speech. As ironic as this sounds, our analysis indicates that such activists advocate for canceling persons, businesses, and brands that breach the idea of free speech. They will cancel/boycott any business if the owner "caves" to demands to censor a person accused of breaking the social justice code. In essence, in defense of freedom of speech/expression, those people are willing to cancel or boycott a social media platform like Facebook, Twitter, or YouTube, read mainstream newspapers like New York Times and Washington Post, or watch CNN.

1.3 On the implication of cancel culture types of conversation

The third analysis I conducted on the study was to explicate evidence from the data of the implications of some unpleasant kinds of cancel culture communication. I focused on the negative implications because, as I noted, they are often overlooked in cancel culture discourse. The categories I drew for the implication include; hatred, polarization, stereotyping, discrimination/prejudice, bullying, mockery/trolling/name-calling, and blackmail.

We explicated examples from the study data of the use of such offensive language to express hostility towards individuals or groups because of disagreements in the context of cancel culture. Some words are used to convey hatred, some are intended to demean, insult, or dehumanize the target. These words, therefore, contribute to a culture of discrimination, intolerance, and divisiveness in the online environment.

In the cancel culture context, hateful words/phrases we have exemplified in our data include but are not limited to “bigot”, “idiot”, “hypocrite”, “go fuck yourself”, “go die”, “nazi”, “collaborator”, “mentally ill”, “propagandist”, “snowflakes”, “fascist”, “leftist”, “rightist”, “grifter”, “faggot”, “extremist”, “ideologues”, “bigot”, “scammers”, “homophobes”, “racist”, “hitler”, “snowflakes”, “nazi”, “pro-”, “anti-”, “Muslim”, “jew”, “Whiteman”, “far-”, “clowns”, "stupid", "ugly", "fat", “fat ass”, "worthless", “dimwit”, “self-loathing”, “magat”, “qanon”, “snowflakes”, “NPC”, “talking head”, “remoaner”, “karen”, “mob”, “rapist”, “ashamed of”, “hidden agenda’, “traitor”, “race hustler”, etc.

Many of these ones are negatively connotated in whatever context they are used. The consequences of using them are many. They can cause emotional distress, anxiety, depression, and low self-esteem in the individuals targeted. They contribute to a hostile online environment that negatively impacts people who use social media. They can also lead deepen existing divisions within the society.

Also, these kinds of communication create an "us versus them" mentality, it is likely to promote hostility and hinder constructive dialogue and understanding, as well as spread of negativity, affecting a wider audience who get engaged in a cycle of hostility and animosity, among other things.

Importantly, the primary goal of cancel culture is lost. As this study has shown, the motivation for cancel culture can vary depending on the perspective of those participating in it. However, the main aim over time has been about challenging power imbalance, by amplifying the voices of the marginalized and weak. But if so much negativity arises in the course of it, then the primary aim is lost, and sooner it may be difficult to use it to achieve such goals.

2. Conclusions

The study finds that the language used in cancel culture exchanges is quite closely related in many of the countries where the study was gotten. High similarity shows they speak to similar themes and motivations for involvement in that kind of discourse. But there are also countries where similarity is about average. In these contexts, cancel culture discourse is anchored on more divergent themes and motivations, hence words used in describing these realities vary to some extent. Then there are countries with low similarity. Here the cancel culture discourse is mostly about unrelated issues, which are at best context-dependent.

The study also finds various motivations for cancel culture. Wokeness ideology is still a central issue in cancel culture discourse. In all the countries where the data for this study were obtained, wokeness is relevant in cancel culture discourse. Words and hashtags associated with the woke movement like #metoo are popular in all countries. However, wokeness related to racism and gender equality is popular in the USA, South Africa, and Brazil, somewhat in the Philippines and the UK, but not in South Korea and Nigeria. Rather in South Korea and Nigeria, the wokeness conversations revolve around the sexual exploitation of women.

Meanwhile, politics as a motivation for cancel culture is also popular. Cancel culture becomes associated with hashtags whose goal is to gain political power. Also, nationalism is a strong motivating factor for many advocating canceling some brands. This is true in South Korea, the Philippines, India, the USA, and even Nigeria. Also, concerns for cultural, moral, and ethical values have formed the basis for which people involve in cancel culture arguments. Normative and traditional forms of activism that predated woke movement are gradually getting nestled into the goals of cancel culture. And finally, even free speech rights advocates are involved in canceling businesses and brands, ironically in their quest to defend speech rights.

Finally, the types are different within the data words indicating negative implicature for cancel culture. Words directly conveying hatred, and toxicity, negative stereotypes about other people, the polarization of discourse and partisanship, discrimination, bullying, and even mockery and blackmail are well used in the context of cancel culture conversations. In essence, cancel culture as it is presently being propagated across varying countries is no longer entirely a force for good on the platforms. There needs to be some kind of stocktaking and redirection of attention to refocus it to noble goals of serving as agency for justice and fairness.

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국문초록

이 연구에서는 자연어 처리 방법을 통해 거부 문화의 행동주의 동기를 나타내는 언어 사용과 소셜미디어 플랫폼에서의 소통에 미치는 영향을 8개국의 트위터 이용자의 텍스트 데이터를 조사하여 규명한다. 거부 문화는 사람들에게 접근하고 조직하기 위해 소셜미디어를 활용하는 행동주의의 일종이다. 최근 몇 년간 '#거부_(Cancel)'와 '#보이콧'와 같은 해시태그는 거부 문화를 발전시키는 데 사용되며, 큰 인기를 끌었다. 이러한 행동주의는 많은 미디어 담론과 학술 연구, 특히 이론적 가정을 이끌어내고 있다. 선행연구들은 거부 문화의 의미와 그 이면에 있는 동기를 탐구하며, 거부 문화는 2017/18년경 미국에서 시작된 이후에 전 세계적으로 확산된 '깨어났어 운동'(woke movement)을 통해 주도된 사회 정의에 관한 우려와 관련이 있다고 결론을 내리고 있다. 거부 문화는 전 세계에 걸쳐 눈에 띄는 지속적인 현상이고, 따라서 더 공정한 사회를 이룩하자는 목표를 행동주의가 여전히 추구하고 있는지를 질문하는 것이 이제는 필요해졌다. 그래서 이 연구는 더 공정한 사회를 이룩하자는 것을 목적으로 하는 행동주의의 한 형태로서의 거부 문화가 어떤 유사성을 지니고 있는지, 그리고 이러한 행동주의의 동기 부여 요인과 이러한 종류의 소통이 소셜 미디어를 통해 대화적 교류에 참여한 사람들에게 미치는 (부정적) 영향을 조사하려 한다. 이 연구는 깨어났어/사회적 정의 외에도 다양한 동기가 다양한 맥락에서 거부 문화를 주도하고 있으며, 그것들의 일부는 훌륭한 것들이지만 다른 일부는 명백히 저급한 것이라고 주장한다. 이 연구는 트위터를 통해 거부 문화 데이터를 분석하고 그 대화들을 살펴봄으로써 그 이면에 있는 두드러진 동기를 강조하고자 했다. 이러한 동기는 거부 문화 대화에 사용되는 단어와 문구 속에 잘 드러나 있다. 자연어 처리의 다양한 기능을 활용하여 텍스트 데이터를 조사하여 이용자들의 동기를 설명하고 그것이 사회에 미치는 영

향을 강조할 것이다. 분석을 위해 사용한 데이터는 2018년부터 2022년 사이에 작성된 트위터의 이용자 생성 댓글과 그 맥락을 나타내는 거부 문화 해시태그를 통해 수집했다. 연구 대상 국가는 한국, 인도, 필리핀, 미국, 영국, 나이지리아, 남아프리카공화국, 브라질을 선정했다. 이 국가들에선 트위터와 주류 미디어의 담론을 통해서 거부 문화가 유행하는 다양한 맥락들이 나타났었다. 이 연구는 분석 방법으로써 텍스트 마이닝과 자연어 처리(NLP) 방법이 사용하였고, 이로써 연구 목적과 관련된 명제를 분석했다. 분석은 R과 VOS뷰어 소프트웨어로 구현했으며, 텍스트 유사도 분석, 단어 네트워크 분석, 사전 분석, 문맥 내 키워드 및 기타 텍스트 빈도 통계를 수행하였다. 이러한 분석은 거부 문화 뒤에 숨어 있지만 종종 인식되지 않는 다양한 동기를 밝히는 데 도움이 됐으며, 분석 결과 그러한 동기 중 일부는 사회에 부정적인 영향을 미칠 수 있었다.