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RESEARCH ARTICLE

Denial, acceptance and intervention in society regarding female workplace bullying - A mental health study on social media

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Abstract

Awareness surrounding the #MeToo movement prompts a crucial question: How does society perceive female harassment? Acknowledging the broad nature of this inquiry, we refined our focus to examine society's perception, specifically concerning workplace bullying of females. This paper dissects the topic of female workplace bullying, revealing distinct perspectives on denial, acceptance, and intervention held by mental health practitioners. Our study initially adopted a broad perspective, investigating society's outlook on workplace bullying, which we subsequently narrowed down to female workplace bullying. Our preliminary findings unveiled (1) Society's stance on this issue appeared divided between denial and acceptance, (2) Individuals affected by workplace bullying, particularly females, exhibited clear signs of negative psychological impact, and (3) Interestingly, discussions within society revolved around various intervention techniques aimed at mitigating these psychological effects. To delve deeper into the exploration of intervention techniques, we analyzed the most frequently mentioned hashtags. Consequently, these hashtags shed light on three primary characteristics associated with mental health practitioners: denial, acceptance, and intervention. Our research, employing a natural language processing (NLP) approach, identified these three characteristics as separate hashtags.

Keywords: workplace bullying, Female bullying, Natural language processing, Big data, Sentiment analysis, Social computing, Machine learning, Female bullying.

Introduction

Background and Context

The #MeToo movement garnered global scrutiny by shedding light on the pervasive issues of sexual harassment and abuse faced by females worldwide. This social media phenomenon ignited impassioned debates, with supporters rallying to confront these problems and opponents either denying their existence or claiming exaggeration.

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Warner *et al*. [2018] reported a stark gender disparity despite the fact that women constitute 50.8% of the population in the USA, earn nearly 50% of advanced degrees in fields like medicine and law, and hold 52% of professional and management positions. Nevertheless, they comprise only 19% of equity partners, 16% of medical school deans, 30% of college presidents, and 12.5% of Fortune 500 chief financial officers. This leads us to ask: What kinds of challenges do females encounter in their professional lives?

Researchers have probed the subject of bullying in the workplace much before the social media onset, revealing that both men and women experience it. Interestingly, the literature indicates that females can be targets of bullying from both genders. With the rise of social computing and the influential role of social media in reshaping perspectives (#MeToo being a prime example), the landscape of human interaction has transformed, as noted by authors in Parameswaran, M., & Whinston, A. B. [2007]. Abundant data from such platforms, combined with the era of big data, has piqued the interest of researchers across disciplines, who now mine this data for valuable insights.

Numerous studies, such as those by Monteith *et al*., [2015]; De *et al*., [2013]; Rajput *et al*., [2019], have employed Twitter user data in numerous fields such as medicine and more specifically mental health. Recognizing

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the significance of data collection, most social media platforms provide standard APIs, allowing researchers and corporations to access user-generated content. These platforms offer heuristic metrics like likes, dislikes, and more to gauge individuals' reactions to specific posts. However, the most valuable data is often found in unstructured text. This is where natural language processing (NLP) techniques come into play, as they extract and organize relevant text, providing contextual understanding and meaning.

NLP relies on existing corpora that represent a language Youyou *et al*., [2015]. These techniques have been applied in various disciplines, as exemplified by Demszky *et al*., [2019] in political science and Rajput, A., & Ahmed [2019] in the realm of mental health.

This raises a fundamental question: How dependable are the insights derived from such data? Youyou *et al*. [2015] demonstrated that profiles constructed from Facebook data could be more accurate than those provided by an individual's own friends and acquaintances. Previous work Rajput, A., & Rotenstreich, S. [2004] took steps to bridge and manage resources within a network. Paniagua and Korzynski [2007] argue that crowdsourcing is integral to social media platforms, which researchers have used for both active (users consciously provide feedback for a specific purpose) and passive crowdsourcing (users unknowingly contribute input for a task). Jordan *et al*., [2018] illustrates active crowdsourcing, where users affected in emergency situations provide feedback, while Twitter hashtags exemplify passive crowdsourcing. Our earlier studies Ahmed *et al*., [2020], Ahmed *et al*., [2020] utilized hashtags such as #depression and #unemployment to gather data and extract valuable insights.

However, a crucial question emerges: Do these insights solely mirror the sentiments of those who write the posts, or do they go further in uncovering interventions and possible reasons underlying feelings and emotions? This is a critical inquiry, particularly given that mental health professionals broadly center their approach on identifying and addressing three dimensions: denial, acceptance, and intervention.

Problem Statement

Given the above, we probe the following questions:

- What is the public perception regarding workplace bullying directed at females?
- Does this perception align with findings from traditional research?
- Are these perceptions consistent across various social media discussion groups?

Our current research leverages NLP approach to aggregate data from social media, specifically Twitter, in order to delineate the public's stance on female bullying in the workplace. Drawing from the data culled together, we have developed specific conjectures. Additionally, we have examined the most prevalent hashtags within these discussions. We have iterated this process to validate the hypotheses we derived from the characterization of diverse tweets. To ensure the robustness of our results, we have employed n-gram models (n = 1, 2, and 3) to minimize ambiguity and ensure consistency across the spectrum.

Our data collection focused on the hashtag #workplacebullying over a one-month period. The collected tweets were primarily in English, with out of vocabulary (OOV) words disregarded for the purposes of this study. In particular, our work aims to address the following research questions:

- RQ1: Does social media acknowledge the existence of workplace cyberbullying?
- RQ2: How does social media perceive female workplace cyberbullying?
- RQ3: What other societal issues emerge as a result of cyberbullying?

Literature Review

Traditional bullying/cyberbullying

The research conducted by Al-Garadi *et al*., [2016] underscored the emergence of cyberbullying as a significant national social and health concern. This study delved into Twitter data and introduced algorithms designed to identify instances of cyberbullying within social media. In a similar vein, Chatzakou *et al*., [2017] examined the prevalence of cyberbullying among young individuals and revealed that over half of the youth active on social media platforms are affected by this issue. Interestingly, the research also illuminated the fact that bullies often resort to deleting their accounts as a defensive measure.

Moving beyond the digital realm, Wang *et al*., [2009] concentrated on school bullying and explored its correlation with socio-demographic characteristics, parental support, and peer relationships. Employing a quantitative approach, the authors examined 6th and 10th grade students and discovered higher rates of bullying within school settings. Specifically, the results indicated that a significant percentage of students experienced bullying within the previous two months, with 20% encountering physical bullying, 53% subjected to verbal abuse, and 13% falling victim to electronic harassment. Importantly, this study emphasized the potential mitigating role of parental support in lessening the impact of bullying on adolescents.

Another study by Schneider *et al*., [2012] focused on 9th to 12th-grade students and found that 15.8% of them had experienced cyberbullying, while 25.9% reported being victims of school bullying within the preceding 12 months.

Shifting gears to explore the bystander perspective, Owusu, S., & Zhou, L [2015] delved into the role of cognitive and affective empathy through focus groups. Their findings indicated that adolescent bystanders often preferred indirect assistance, such as reporting to adults, over direct intervention when dealing with cyberbullying situations. They emphasized the potential efficacy of empathy training and interventions by teachers and parents in preventing and addressing cyberbullying both within and beyond the school environment.

In a study involving high school participants, Selkie *et al*., [2015] contended that those engaged in cyberbullying as perpetrators tended to exhibit higher levels of depression and alcohol use. Meanwhile, research targeting the impact of cyberbullying on mental health for both children and adults established a weak correlation with anxiety but a substantial correlation with depression Hamm *et al.*, [2015].

Another strand of research, exemplified by Zhao *et al.*, [2016], focused on cyberbullying detection based on specific keywords in tweets—a technique akin to the Bag of Words (BoW) approach, as exemplified in prior work like. This approach was also evident in Margono *et al.*, [2014], where researchers scrutinized tweets in Indonesia to identify terms and patterns used by cyberbullies.

In Tahamtan, I., & Huang, L. M [2019], text mining methods were applied to the English language, revealing that words like "people," "kids," "students," "schools," and "stop" were frequently used. This suggests a widespread concern about curtailing bullying behavior, particularly among children.

Exploring trust dynamics online, Mishra *et al.*,[2015] posited that adolescents often rely on trust in their online relationships, making highly trusted connections vulnerable to cyberbullying.

Researchers in Hosseinmardi *et al.*, [2015] investigated negative behaviors on ask.fm, a website linked to numerous cyberbullying-related incidents. They employed sentiment analysis and specific heuristics to categorize individuals into highly negative, highly positive, positive negative, and others categories.

Raisi, E., & Huang, B [2016] conducted a study utilizing Twitter and ask.fm datasets, proposing a model to identify both bullies and victims of cyberbullying, as well as new cyberbullying terminology. The results indicated the model's effectiveness in detecting new cyberbullying terms.

Furthermore, aimed to uncover novel approaches for detecting cyberbullying within images on Instagram by examining correlations between various features and cyberbullying incidents. Their findings indicated that approximately half of Instagram sessions included instances of cyberbullying.

Workplace bullying

In Aboujaoude *et al.*, [2015], research revealed that young female lawyers often encountered cyberbullying, primarily through platforms like WhatsApp. Astonishingly, many of these female lawyers were unaware of any legal framework addressing cyberbullying. The study conducted by Anjum *et al.*, [2018] demonstrated that harassment and bullying had a direct, detrimental impact on job productivity, contributing to higher burnout rates. In Farley *et al.*, [2015], a study involving 158 trainee doctors found that 46.2% had experienced one or more instances of bullying, negatively affecting job satisfaction and causing mental strain. Gardner *et al.*, [2016] investigated the effects of both cyberbullying and workplace bullying, uncovering that females were more frequently subjected to workplace bullying, while managerial professionals faced a higher incidence of cyberbullying. Furthermore, the study concluded that both forms of bullying were linked to an unhealthy workplace environment.

Contrastingly, Forssell *et al.*,[2016] found that in Sweden, men were more often targeted by cyberbullying than women. Crothers *et al.*, [2009] revealed in their research that women initiated 58% of bullying incidents, and in 90% of cases, the aggressors were also women. While men were reported to exhibit more aggressive sexual behavior, female bullies tended to engage in relational aggression, attacking their victims' social status and relationships. Similarly, Escartín *et al.*,[2011] highlighted gender-based differences in workplace bullying perception. Female employees were more affected by emotional bullying and professional discrediting, whereas male employees emphasized abusive work conditions. A study focused on Danish eldercare workers Rugulies *et al.*,[2012] established a strong correlation between female workers' experiences of bullying and the onset of major depression. Vartia, M., & Hyyti, J. [2002] uncovered that both males and females experienced workplace bullying, with females encountering sexual harassment to a greater extent. Female colleagues were identified as females' primary source of bullying, while coworkers and supervisors bullied males. An examination of the Austrian Armed Forces revealed that 6.5% of personnel experienced prolonged aggression and bullying, with support units acknowledging the competence of female members compared to combat units Koeszegi *et al.*, [2014]. Authors in Hinchberger [2009] addressed the violence experienced by female nursing students in developed countries like the US, UK, Canada, and Australia, and discussed practical approaches to prevent such occurrences. Research conducted in the Indian context Kishore [2015] substantiated the hypothesis that women were subject to severe workplace bullying. Harvey [2018] conducted a study in the UK, where, in addition to higher rates of bullying among females, 70% of female respondents reported being bullied by female managers. Lastly, the study in Rayner [1997] underscored the significance of workplace bullying and identified that more than half of the respondents, both males and females, had experienced bullying at work. The study also revealed a gender-based tendency, with males bullying other males and both males and females bullying females. A lower incidence of bullying by female managers was attributed to the relatively lower number of female managers in the workforce.

Workplace bullying and physical/mental health

In Verkuil *et al.*, [2015], the authors conducted a systematic review aiming to uncover a bidirectional relationship between bullying and mental health. Einarsen, S., & Nielsen, M. B [2015] delved into the enduring effects on mental health over an extended period, examining the mental well-being after a five-year span. Nielsen et al., [2014] also established a positive correlation between workplace bullying and mental health issues, including somatic symptoms. In Turney [2003], the author delves into the dynamics of various professions, the inherent power structures, and workplace bullying, offering diverse intervention techniques for mitigating bullying in the workplace. Furthermore, Kivimäki *et al.*, [2003] highlighted the impact of bullying on victims' mental health and shed light on the long-term risk of cardiovascular disease associated with such experiences. Lastly, Rajput, A., & Brahimi, T [2020] discussed how the adoption of Internet of Things (IoT) technologies contributes to gathering medical data for users.

Material and Methods

In line with standard research practices, we exclusively gathered data from publicly available sources to uphold privacy considerations, as recommended by Ahmed [2019], Chen, E. E., & Wojcik, S. P. [2016], and Ahmed, S. M., & Rajput, A. [2020]. Moreover, we refrain from disclosing any Twitter user handles and diligently remove duplicate tweets, ensuring the use of a pristine dataset.

Preprocessing and Processing Data

Our data preprocessing and processing procedure encompassed the following steps:

- We gathered tweets under the hashtag #workplace-bullying spanning one month.
- Employing the nltk toolkit, we parsed the text and removed stop-words
- We utilized the tf-idf algorithm as outlined in Rajput [2020] to generate keywords.
- N-gram keywords were generated (n = 1, 2 and 3).
- Next, we employed the sklearn library to tokenize and vectorize the tweets.
- In the context of our research, we considered the entire set of tweets as a single corpus.
- In addition to the keywords, we also generated the high recurring hashtags.

The APIs Used

The following Python APIs were extensively used:

- Twitter API: Utilizing the Twitter API necessitates registering with Twitter and setting up a Twitter development account.
- Pandas: Pandas library facilitated data preprocessing and processing phase.
- Natural Language Toolkit (NLTK): NLTK stands as one of the most potent Natural Language Processing (NLP) libraries, equipping users with fundamental tools such as tokenization, stemming, lemmatization, and more. Further details can be found in.
- Sklearn: Sklearn is a comprehensive Python library that supports extensive data analysis tasks including classification, regression, clustering, and more.

Algorithm

In our study, the algorithm employs a semi-depth-first search strategy, commencing with the hashtag #workplacebullying. We selected this hashtag due to its gender-neutral nature. Moreover, the algorithm effectively eliminates duplicate tweets and categorizes the hashtags mentioned within the #workplacebullying context.

Results and Discussions

To address the research inquiries, we conducted an analysis of the hashtag #workplacebullying, exploring the n-gram model for various values of unigrams, bigrams and trigrams. This model forms the foundation for our responses to RQ1 and RQ2. Additionally, we examined the three most frequently mentioned hashtags within the results, which serve as the groundwork for our response to RQ3.

#Workplace Bullying

We conducted an analysis of #workplacebullying spanning one month. In Table 1, the reader will find a list of the top ten relevant words.

The list in Figure 1 was compiled by examining the tf-idf scores, with a particular emphasis on the idf score, as it signifies the frequency of terms across a multitude of tweets in the corpus. In the unigram model, it became apparent that the discussion predominantly revolved around unspecified psychological effects and the imperative need to terminate such behavior.

Table 1: Algorithm

1	For each tweet t in #workplacebullying		
2		Add to corpus c if unique	
3		Tokenize	
4		Extract_lemma remove_top_words	
5		If hashtag	
6			if unique add to hashtag_list
7			else increment hashtag_counter
8		For n = 1..3	
9			Extract n_gram
10			Extract top 50
11		Extract top 3 hashtags	
12		Repeat steps 3-10	

Table 2: n-gram model - #workplacebullying hashtag

Unigram	*Bigram*	*Trigram*
Accusations	Accusations work	Accusations work nowyouknow
Endworkplaceabuse	Endworkplaceabuse workplacebullying	
False	False accusations	False accusations work
Anger	Anger end	
Shameful	Shameful workplacebullying	End shameful workplacebullying
Abuse	Workplace abuse	
Psychologicallyharassed	Workplacebullying psychologicallyharassed	People workplacebullying psychologicallyharassed
Understanding	Bullying understanding	Bullying understanding bullying
-	Overcome workplace	Overcome workplace bullying
-	Bullying solutions	Workplace bullying solutions

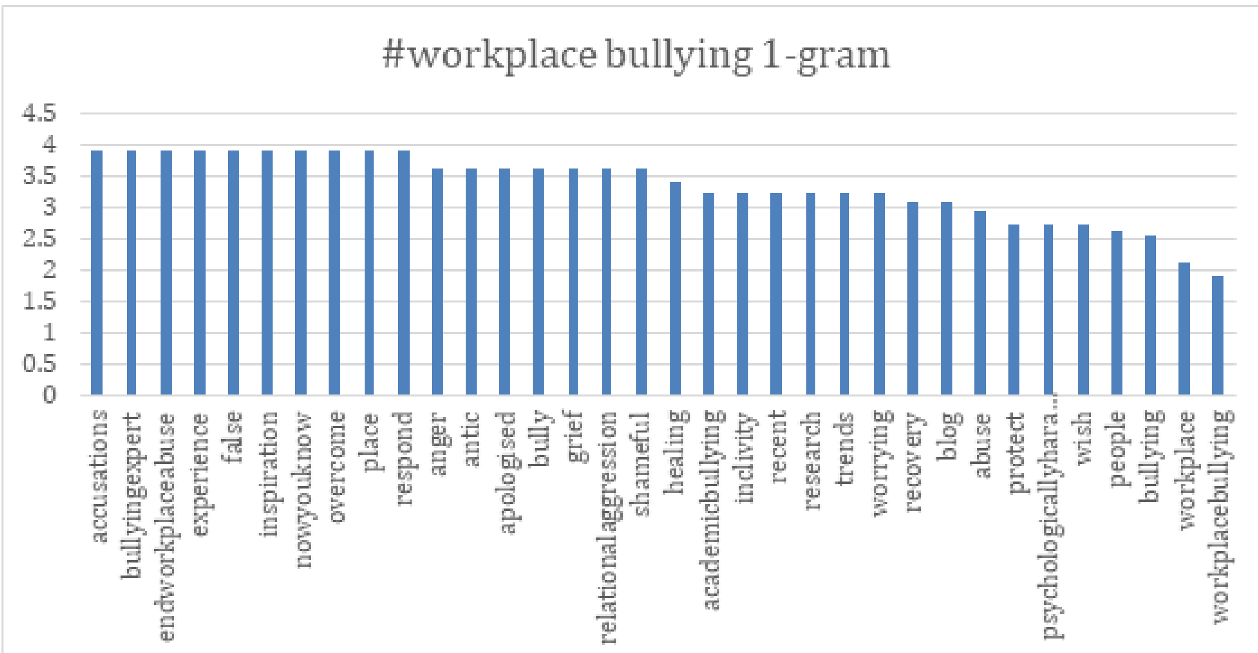


Figure 1: #workplace bullying 1-gram

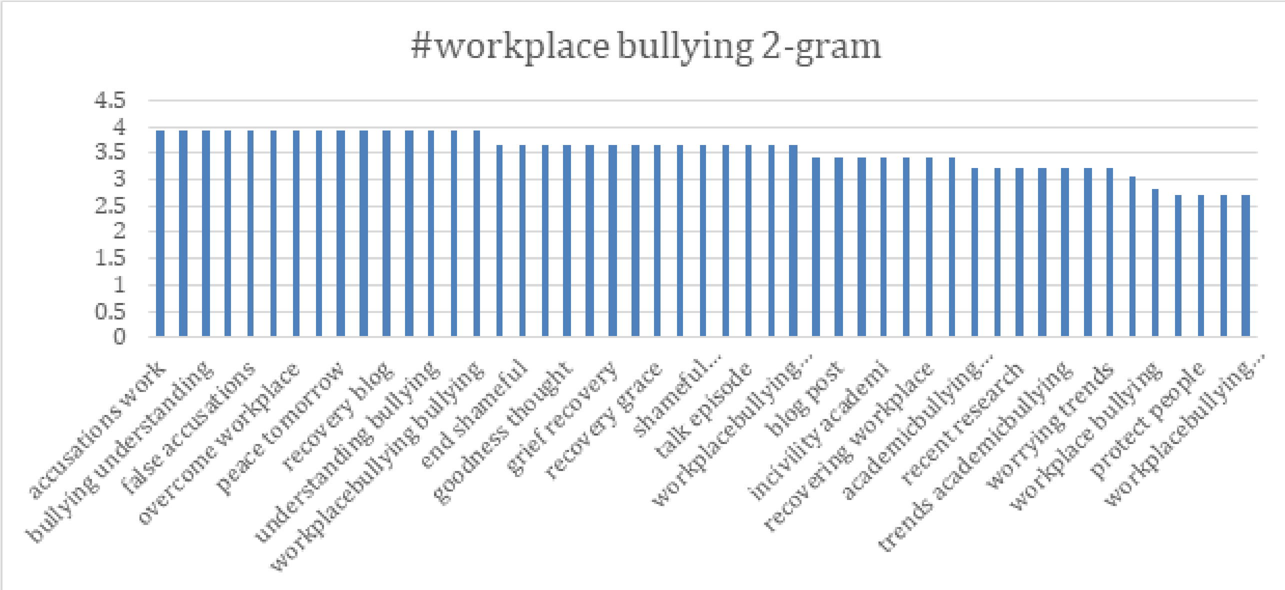
It's important to note that the intervention aimed at addressing the common misconception that workplace bullying doesn't exist, challenging the notion often held due to the limitations of traditional research. In summary, the findings from the bigram and trigram models provide responses to RQ1 and RQ2 (Figures 2 and 3). From a characterization standpoint, we observed an almost equal distribution of keywords suggesting the tangible existence of workplace bullying and those indicating a belief that workplace bullying consists primarily of unfounded allegations. This duality is depicted in the Table 1.

The tweets provided evidence of the presence of psychological consequences resulting from cyberbullying. Numerous tweets also highlighted potential intervention strategies, including a) the importance of comprehending the nature of bullying and b) potential solutions (not explicitly identified). The subsequent table corroborates these findings.

We additionally gathered the top three hashtags mentioned within the #workplacebullying hashtag, namely #feminism, #equality, and #sexism. It's worth noting the following:

- #sexism may be mentioned as a potential factor contributing to workplace bullying.
- #equality likely represents the desired goal of eradicating bullying.
- #feminism could potentially be listed by individuals who assert that workplace bullying is nonexistent.

Considering these potential factors, we replicated the experiments conducted on #workplacebullying.



Figrue 2: #Workplace bullying 2-gram

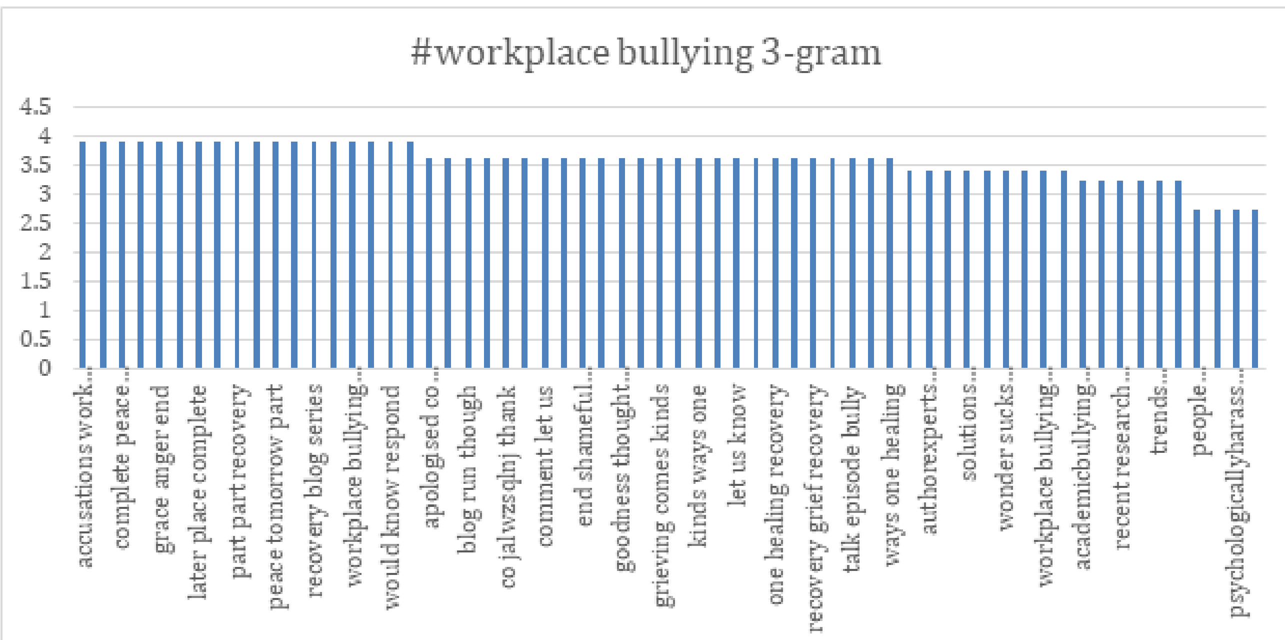


Figure 3: #Workplace bullying 3-gram

#Equality

Examining the #equality hashtag, we identified the following keywords for the unigram, bigram, and trigram models, as outlined in Table 2.

Specifically, the following Figure 4 shows us the 1-gram model

Based on the findings presented in Figure 4, we draw the following conclusions:

- The noteworthy mention of the word "Japan" is particularly interesting, as Japan recently has taken concrete steps to eliminate bullying in the workplace. Research suggests that both males and females experience workplace bullying.
- A substantial portion of gathered data revolved around possible solutions to the problem of workplace bullying, including the pursuit of safe environments and seeking justice.
- The presence of the word "children" did not provide clear context.

Turning to the 2-gram model, as depicted in Figure 5, brought additional clarity to the situation.

Please note the following:

- The frequent mention of workplace bullying during the tweet collection period is likely attributed to Japan

Table 3: n-gram model - #equality hashtag

Unigram	*Bigram*	*Trigram*
Japan	Japan government	Japan Government Says
Working	Shine Working	Shine Working Mom
Understand	Please Understand	Please Understand Meaning
Doctors	Doctors Engineers	Doctors Engineers Frontline
Justice	Justice Equality	-
Media	Equality Media	Equality Treated Media
Verbally	Verbally Physically	Verbally Physically Harassed
Human	Human Rights	Human Rights Equality
House	Left House	Time Left House
Sexism	Teaching Sexism	Book Teaching Sexism
Boys	Sexism Boys	Sexism Boys Nice
Search	Search Safe	Search Safe Harbor
Truth	Truth Gets	Truth Gets Away

passing a law against it during that time.

- The emphasis on equality for both males and females suggests that many males also reported experiencing this phenomenon. This observation aligns with the findings from the traditional research discussed in the literature review section.
- The concept of females being underrepresented in fields like medicine and engineering also emerged from the data.

Transitioning to the 3-gram model provided further clarity to the situation (Figure 6).

Note the following:

- The prevailing acceptance of physical and verbal abuse within Japanese culture suggests that the truth might often go unacknowledged.
- While potential workplace bullying appeared to affect both males and females equally in Japanese culture,

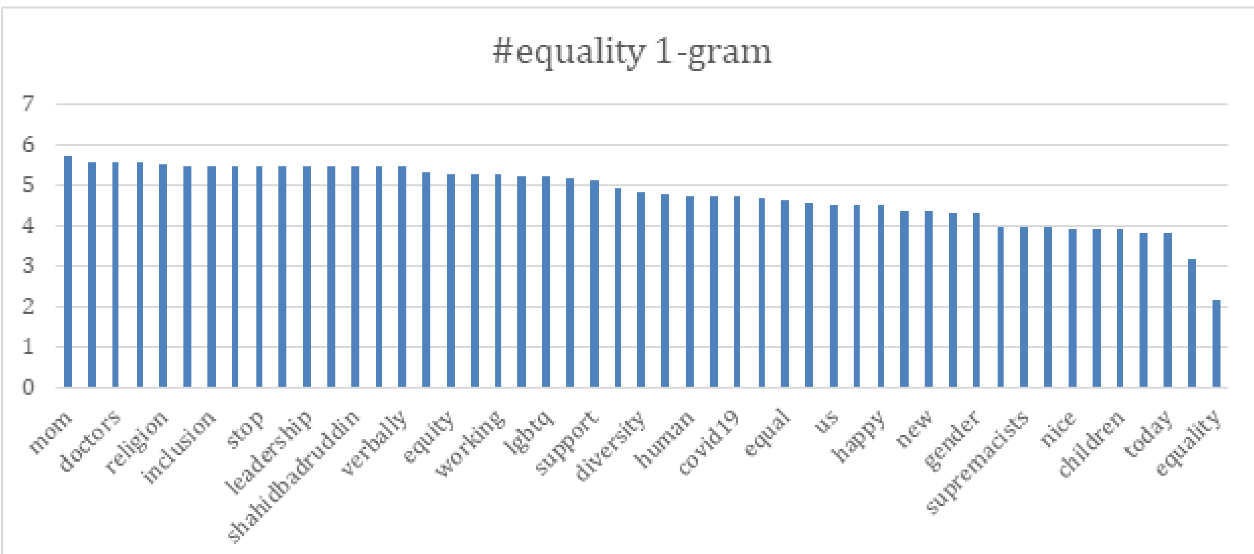


Figure 4: #Equality 1-gram

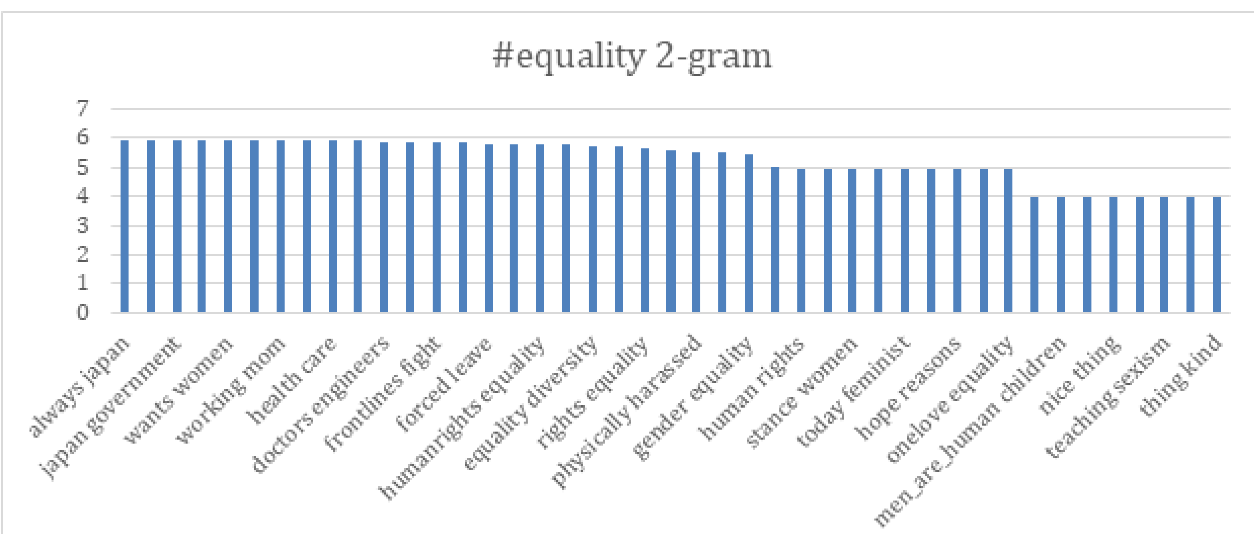


Figure 5: #Equality 2-gram

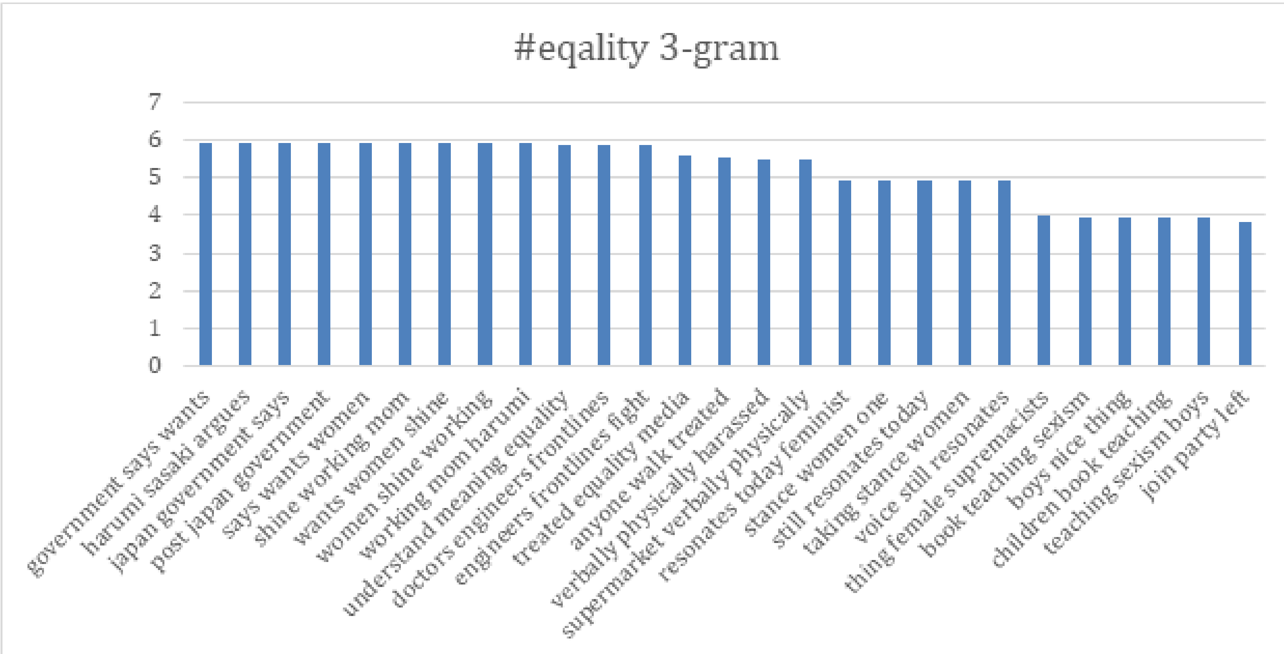


Figure 6: #Eqality 3-gram

more detailed discussions revolved around concerns specific to females. These concerns included the challenges faced by working mothers that included leaving their children at home and working with males in traditionally male dominated professions ("Time Left Home," ,"Doctors Engineers Frontline.") "Shine working moms" indicated the show of support for what these mothers face.

- Notably, the term "Sexism" was frequently used in a positive context as it appears that majority of males probably do not assign a negative connotation to this term.

The hashtag #equality was accompanied by other hashtags such as #girlsmatter, #humanrights, #environment, #sexism, and #womenleaders. This further reinforces the idea that discussions surrounding workplace bullying for females are prevalent within this hashtag.

#Feminism

The results from probing of this hashtag are tabulated in Table 3.

Table 4: n-gram model - #feminism hashtag

Unigram	*Bigram*	*Trigram*
feminismiscoronavirus	-	-
feminismiscancer	-	-
women	women compared	women compared men
fake	fake feminism	fake feminism loaded
compared	compared men	compared men died
feminism	feminism said	feminism said equality
sexism	sexism boys	sexism boys nice
women	women come	women come forward
hood	hood feminism	hood feminism notes

The keywords associated with #feminism predominantly carry negative connotations, affirming our initial assumption based on the keywords gathered from #workplacebullying. Many individuals appear to equate feminism with highly negative concepts, akin to terms like "coronavirus" and "cancer," as demonstrated earlier. Additionally, within the context of #equality, the keywords "sexism boys nice" were discussed. Furthermore, a significant number of individuals perceive feminism as inauthentic.

The subsequent Table 4 displays the results for the 1-gram model (Figure 7).

The findings in Figure 7 suggest that the term 'feminism' is associated with negative connotations for the majority, with many considering it either insincere or detrimental to society. Additionally, numerous individuals extended the discussion to encompass issues related to race and reverse discrimination under the same umbrella. A closer examination of the 2-gram model reinforced these observations, as illustrated in the Table 4 and Figure 8.

The 3-gram model displayed below primarily suggests that a particular segment of society holds the belief that reverse discrimination exists against males and specific racial groups (Figure 9).

Furthermore, within the #feminism hashtag, there were additional hashtags including #sexism, #feminist, #women, #genderbias, and #stopsexualharassment.

#Sexism

This hashtag generated the following results as shown in Table 5.

By exclusively examining the unigram, bigram, and trigram models, it becomes evident that the tweets highlight

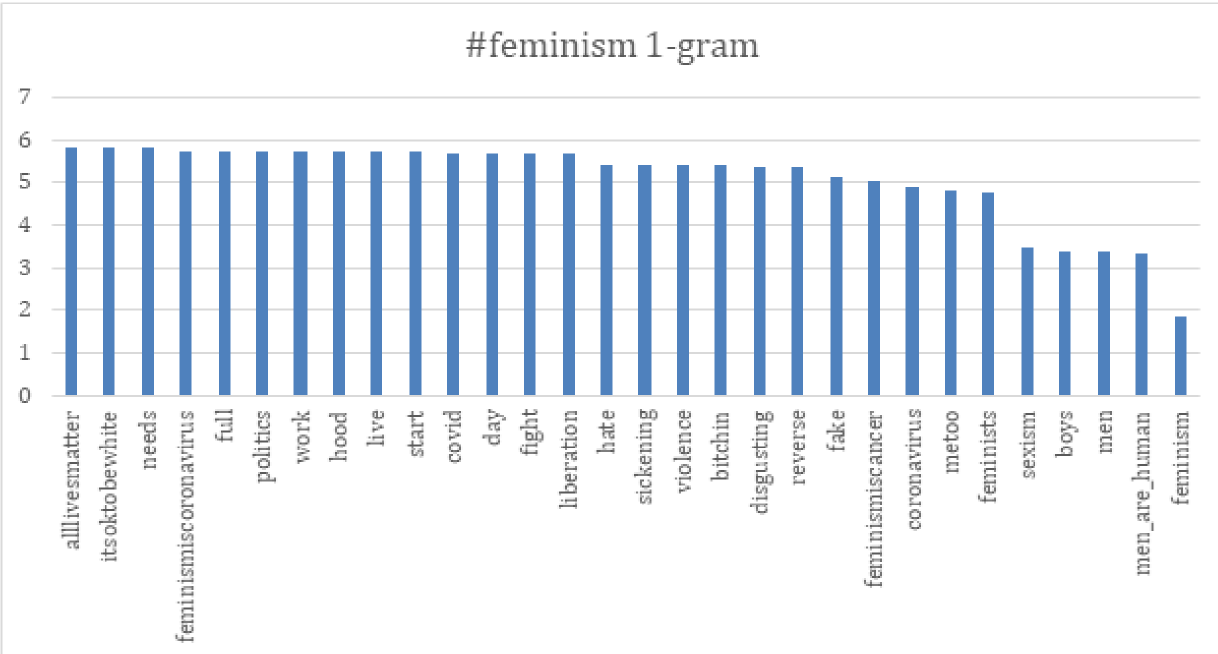


Figure 7: #Feminism 1-gram

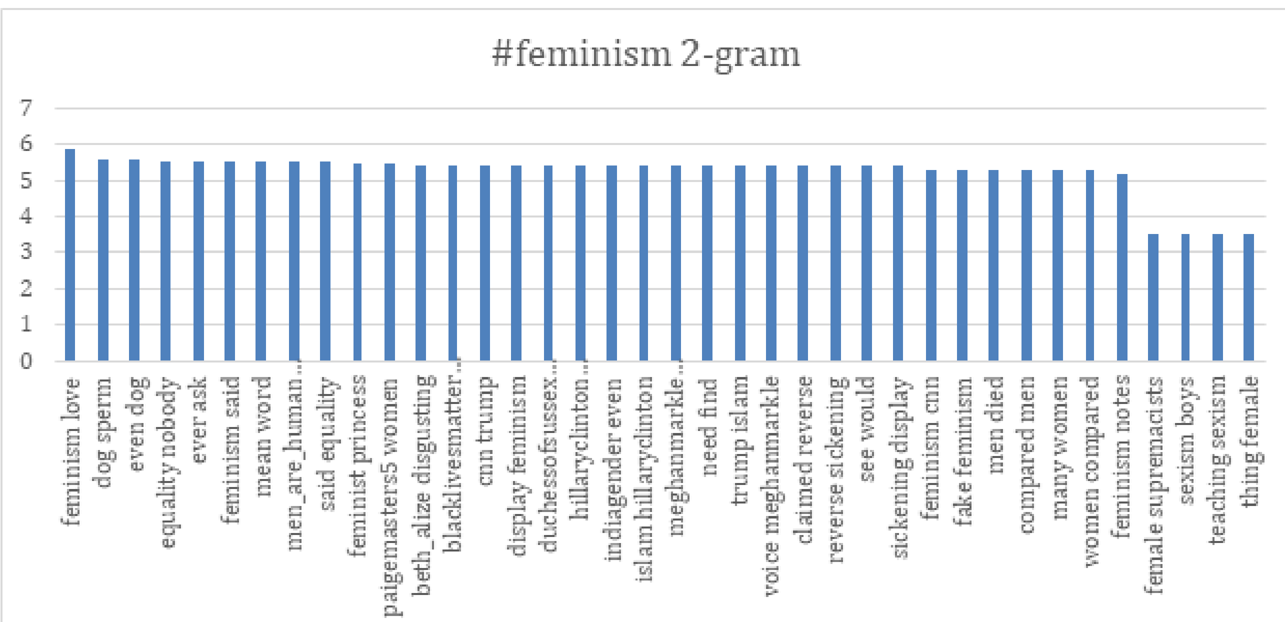


Figure 8: #Feminism 2-gram

Table 5: n-gram model - #sexism hashtag

Unigram	Bigram	Trigram
Sexism	Sexism misogyny	Science stands racism
Inequality	Sexism inequality	Sexism inequality likely
Racism	Racism sexism	Experiences racism sexism
Talk	Talk sexism	Talk sexism co
Abusive	Deciding abusive	Weigh deciding abusive
Teaching	Teaching sexism Sexism boys	Teaching sexism boys Sexism boys nice
Like	Liberal women	Like liberal women

the prevalent challenges faced by females in the workplace. Interestingly, the hashtag sheds light on the pervasive issue of misogyny within the realm of science. In essence, the hashtag serves as a portrayal of the current state of workplace bullying against females.

More specifically, the 1-gram model presented in Figure 10 underscores that the prevailing male-centric culture perpetuates harassment and gender discrimination against women.

The 2-gram model advanced the previously mentioned concept, delving deeper into the discrimination experienced

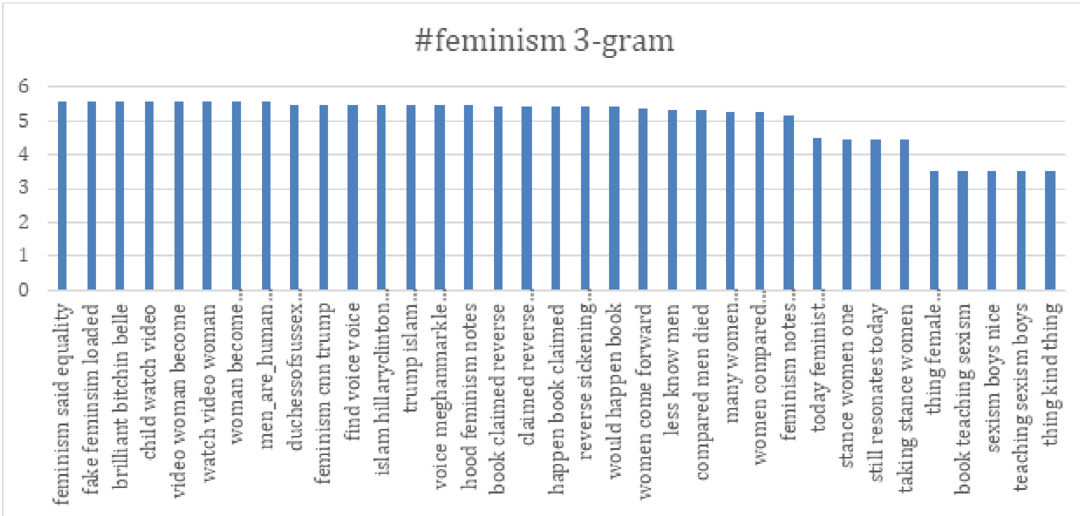


Figure 9: #Feminism 3-gram

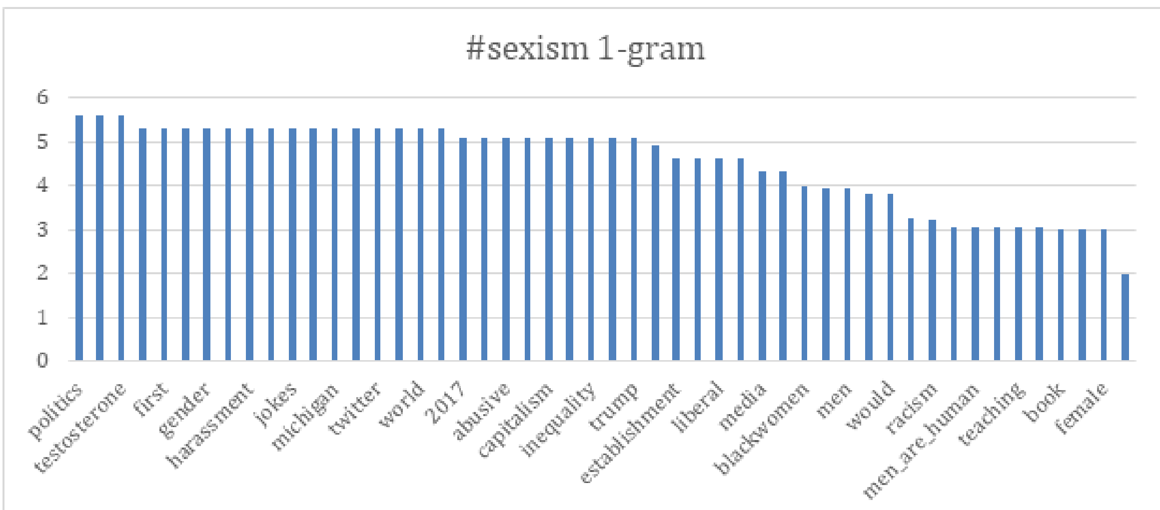


Figure 10: #Sexism 1-gram

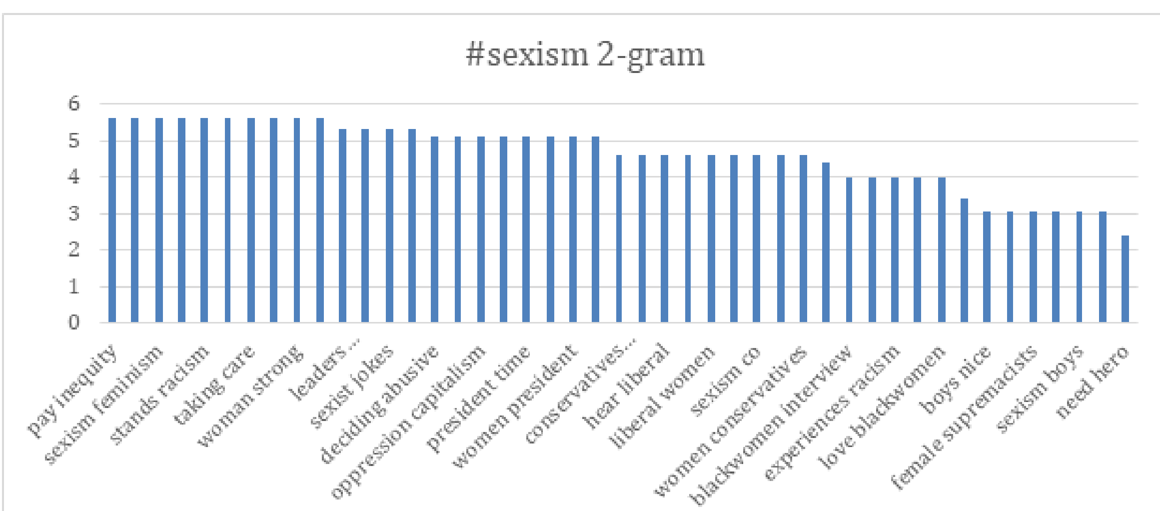


Figure 11: #Sexism 2-gram

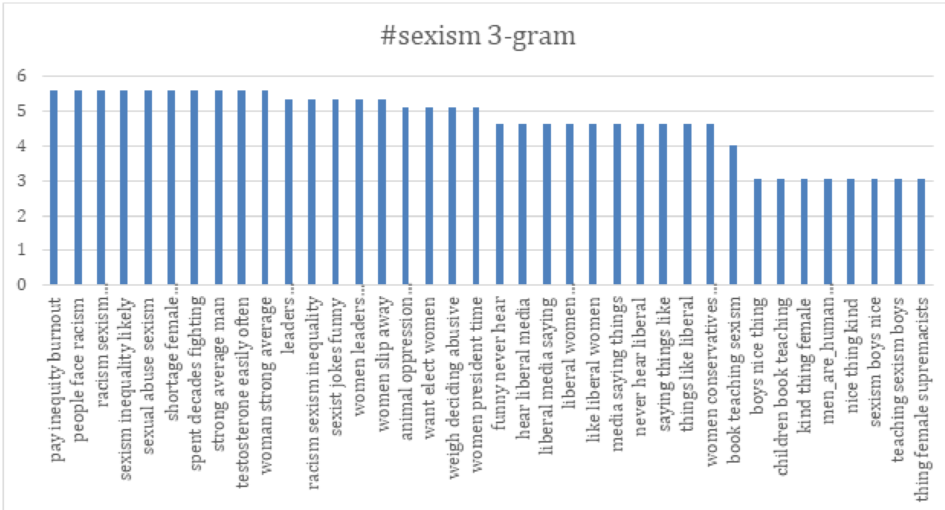


Figure 12: #Sexism 3-gram

by females while highlighting the capabilities of females in comparison to males (Figure 11).

Lastly, the 3-gram model introduced the concept of sexual abuse alongside emphasizing the positive impact of a robust female presence in society (Figure 12).

The hashtags predominantly discovered here were 1) #racism, 2) #feminist, and 3) #women.

Summary

From the information presented, we draw the following conclusions:

- #Workplacebullying predominantly highlighted females as victims of bullying.
- The leading hashtags under #workplacebullying included #equality, #feminism, and #sexism.
- Within #feminism, there was a prevailing sentiment that the notion of females being victims of bullying is unfounded.
- #Sexism underscored that females experience various forms of bullying, encompassing physical and verbal abuse.
- The #equality hashtag offered potential solutions for addressing the issue of bullying experienced by females.

Conclusion

This paper delved into the perception of cyberbullying against women in the workplace as portrayed on social media. Our investigation commenced by examining the hashtag #workplacebullying and unveiled several key insights:

- There was a noticeable divergence in opinions, with some acknowledging the prevalence of workplace bullying against women while others dismissed it as non-existent or merely a nuisance.
- Tweets also shed light on the psychological toll of workplace bullying, underlining its tangible impact.
- A multitude of tweets offered potential intervention strategies to mitigate the negative outcomes associated with bullying

Supplemental investigation into the three highest frequently hashtags being mentioned with #workplacebullying (#sexism, #feminism, and #equality) revealed an intriguing correlation:

- #Sexism appeared to be linked to the root causes of bullying against women.
- #Feminism, conversely, was met with predominantly negative sentiments, potentially reflecting denial or resistance toward acknowledging the issue.
- #Equality was associated with positive sentiments, suggesting a receptiveness to intervention techniques.

These findings underscore the significance of our study and warrant deeper exploration. Further probing of the "crowd wisdom" concept in Twitter data for example will bolster the validity of our research. Furthermore, comparing our results with tweets in other languages could provide valuable cross-cultural insights into this phenomenon.

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