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Characterizing Female Workplace Bullying via Social Media

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Abstract: Motivated by the #Metoo movement, we explore in this paper people's perception of female bullying at workplace. We looked at #workplacebullying and found that 1) people were split between identifying the prevalence of workplace bullying against female and the view that such bullying simply does not exist and is a nuisance, 2) The tweets also showed the existence of psychological effects of cyberbullying, and 3) the tweets showed many intervention techniques that can minimize the effects of such bullying. We further explored the top three recurring hashtags mentioned under the #workplacebullying and found that the three top hashtags were #sexism, #feminism and #equality. Our results showed that the above hashtags represent the positive and negative approach to workplace bullying i.e. #feminism hashtag was mostly used by people who denied that workplace bullying against females exist while # sexism was mentioned as the prime cause by people who agree that such bullying exist. #equality overwhelmingly comprises of techniques to minimize workplace bullying against females.

Keywords: Social media, bullying, female,

1. Introduction

1.1. Motivation and Background

The #metoo movement brought attention to the world regarding the problems females face in terms of sexual harassment and abuse all over the globe. The social media storm saw people on both sides of the aisle where the debate raged between people supporting the movement to take a stand against such practices and people who either deny that such a problem exists or consider it greatly exaggerated. Warner et al. in [1] reported that despite women representing 50.8% of the US population, earning almost 50% of medical, law and specialized master's degree and holding 52 percent of management and professional positions, they only represent 19 percent of equity partners, 16 percent of medical school deans, 30 percent of college presidents and 12.5 percent of chief financial officers in Fortune 500. So the question we ask is: What kind of behavior females face in their professional lives?

Bullying at workplace has been a subject of traditional research before the advent of social media where the results show that both males and females have been subject to workplace bullying. Interestingly though, the literature indicated that females are subject to bullying by both males and females. Since the advent of social computing – using computers for social use – social media is increasingly playing a big role in changing perspectives and bringing issues to the front (#metoo is an example of this phenomenon). The authors in [2] make interesting point about change in people's interaction. The huge amount of data available from such platform and the rise of Big Data has researchers from various walks of life increasingly looking at such data to glean useful information. Work done by [3]–[5] show the use of using data from Twitter in the realm of mental health and medicine. Given the importance of collecting data, most of the social media providers provide standard APIs that allow researchers and corporations pull data from social media. Social media platforms provide certain heuristics such as likes, dislikes etc. that can gauge individuals' reaction to particular post. However, majority of valuable data is present in the form of unstructured text. Natural Language Processing (NLP) techniques are used to pull and put together relevant text gaining an insight in both the context and the relevant meaning. The NLP techniques depend on an existing corpus that can represent a language [8]. Such techniques have been used in various disciplines such as [6] in Political Science and [7] in mental health realm.

The question that comes to mind is: How reliable are insights gleaned from such data? Youyou et. al., in their work [8] showed that the profile gleaned from Facebook was more accurate than the one given by a person's actual friends and acquaintances. Paniagua and Korzynski in their work [9] contend that crowdsourcing is an integral part of the social media platform. Researchers have used the Twitter platform for both active (users are cognizant that their feedback is being used for a certain goal) and passive crowdsourcing (users are unaware that their input is being pulled together for a certain task).

Work done by [10] provides an example of active crowdsourcing where users affected in emergency areas provided feedback while hashtags used in Twitter are examples of passive crowdsourcing. Our earlier work [11], [12] has made use of various hashtags such as #depression and #unemployment to gather data and glean valuable insights. While the insights gained from such hashtags confirmed research that was done traditionally, the question we wanted to answer was: Do the insights only reflect sentiments of people who are writing or do they actually also portray interventions and possible reasons for the sentiments?

1.2. Problem Description

Based on the above, we ask the following questions: 1) How do people view female bullying at workplace? 2) Does it conform to what traditional research has found? 3) Are the results consistent across various discussion groups in social media? Our current work used NLP techniques to cull together data from the social media (specifically Twitter) to characterize public's opinion regarding female bullying at workplace. Based on the data we gathered, we formulated certain hypotheses. Furthermore, we looked at the hashtags that occur the most under such discussions and repeat the process to see whether the hypotheses we gleaned from characterizing various tweets can be proven. We employed the unigram, bigram and trigram model to eliminate any ambiguity and ensure that the results we deduce are consistent across the board.

We utilized the hashtag #workplacebullying and gathered data for one month to arrive at our results. We also gleaned the top three hashtags mentioned in the discussion and explored them to see whether the results we obtained are consistent. The gathered tweets were in English and for the sake of this work, we ignored the Out of Vocabulary (OOV) words. Specifically, we try to address the following questions in this work:

1. RQ1: Does social media recognize workplace cyberbullying?
2. RQ2: How does social media view female workplace cyberbullying?
3. RQ3: What other social issues are raised as a consequence of cyberbullying?

2. Literature Review

2.1. Traditional Bullying/Cyberbullying

This research conducted by [13] recognized that the cyberbullying has emerged both as a national social and health issue. The authors did a study on Twitter data and presented algorithms to detect cyberbullying in social media. [14] explored the cyberbullying among the youth and concluded that cyberbullying is affecting more than half of the youth on social media. The research further showed that bullies to delete their accounts. Research done by [15] focused on school bullying based on socio demographic characteristics, parental support and friends. The authors used a quantitative approach for children belonging to 6th and 10th grade. The results from this research showed greater prevalence rates of children bullied in the school. Specifically, the results showed that at least once in the previous 2 months a student was bullied. 20% of the students were physically bullied, 53% of the students were verbally bullied and 13% of the students were electronically bullied. This study showed that the parental support can minimize the bullying effects on the adolescents. The research conducted by [16] looked at the students belonging to the 9th to 12th grade, concluded that, a total of 15.8% of students were the victims of cyberbullying and 25.9% said that they were the victims of school bullying in the past 12 months. [17] explored the role of cognitive and the affective empathy using focus groups and found that adolescent's bystanders preferred providing indirect assistance to the cyber bullied people by addressing to adults over the direct intervention. The research reported that empathy training, teachers and parent's intervention can play a key role in the prevention and curtaining of cyberbullying both within and outside of the school environment. [18] in a study focused on high schoolers contended that participants involved in cyberbullying as bullies had greater levels of depression and problem alcohol use. [19] targeting influence of cyberbullying on mental health for both children and adults, found a weak correlation between cyberbullying and anxiety but very strong correlation between cyberbullying and depression.

[20] based the cyberbullying detection on specific words in the tweets – a technique that is similar to Bag of Words (BoW) approach specifically and focusing on the corpus (as an example, consider the work done by [7]). This approach is also reflected in the work done by [21] where the authors looked at tweets in Indonesia and discovered the terms and patterns used by bullies. [22] used text mining methods for English language and showed that “people”, “kids”, “students”, “schools”, and “stop” were most commonly used words – results that showed that many people were concerned with stopping the bullying behavior especially among the kids. [23] contended that adolescents tend to fall back on the trust between them and other individuals online and bullies tended to target the highly trusted relationship. [20] used an enhanced version of Bag of Words model (EBoW) on Twitter to detect bullying messages. Researchers in [24] studied negative behaviors of people on ask.fm – a famous website that led to many suicidal incidents as a result of cyberbullying. They used sentiment analysis techniques along with certain heuristics to categorize people into Highly Negative, Highly Positive, Positive Negative and Others buckets. [25] did a study on Twitter and ask.fm data sets and proposed a model that discovers both bullies and victims of cyberbullying in addition to new bullying vocabularies by implying seed dictionary of cyberbullying and social interactions. Results indicates that this method is able to detect new bullying vocabularies. [24] aimed to discover new approaches to detect cyberbullying occurring over images on Instagram by trying to find correlation between several features and cyberbullying. Results indicate that about half of instagram sessions included cyberbullying.

2.2. Workplace Bullying

[26] showed that young female lawyers were subjected to cyber bullying (mostly through WhatsApp) and amazingly many of these female lawyers were unaware of any existing legal framework on cyber bullying. The research done by [27] research showed that harassment and bullying have the direct negative important impact on job productivity along with higher rate of burnout. [28] in their study based on 158 trainee doctors found that 46.2% experienced one or more act of bullying that negatively affected job satisfaction and mental strain. The research done by [29] explored the effects of cyber bullying and in place work bullying and found that females were subject to more workplace bullying than cyber bullying while managerial professionals faced more cyber bullying. The study also concluded that both types of bullying are linked to bad workplace environment. [30] also showed that men were more subject to cyber bullying than females in Sweden.

[31] discovered in their work that women initiated 58% of bullying incidents and 90% of the time other women. While men were said to be more aggressive in terms of sexual behavior, women bullies focused on relational aggression – attacking the victims' social status and relationships. Similarly, the work done by [32] showed the difference between gender-based view of workplace bullying where female employees were bothered more by emotional bullying and professional discredit while the males focused more on abusive work conditions. The study aimed at Danish eldercare [33] workers showed a high correlation of female workers' bullying and the onslaught of major depression. The work done by [34] showed that a) both males and females faced bullying at work, 2) females were subjected to sexual harassment much more and 3) females were subjected to bullying more by their male colleagues while males were bullied by both coworkers and supervisors. [35] did a study on Austrian Armed forces and found that 6.5% suffer from long-term aggression and bullying. They also showed that the support units were cognizant of females' abilities to perform their duties competently compared to the combat units. Authors in [36] discussed the violence suffered by graduate and undergraduate female nursing students in developed countries - such as US, UK, Canada and Australia - and discussed practical approaches to prevent such phenomenon. [37] studied the environment in India and proved the hypothesis that women are subject to severe bullying. The study done by [38] showed in UK that in addition to the fact that females faced more bullying, interestingly 70% of the female respondents reported being bullied by female managers. The study in [39] established the role of workplace bullying and showed that 1) more than half the respondents including males and females faced bullying at work, 2) males were bullied by males while females were bullied by both males and females and 3) lower bullying by female managers could be attributed to lower number of female managers.

2.3. Workplace Bullying and Physical/Mental Health

Authors in [40] did a systematic review to find a bi-directional correlation between bullying and mental health. [41] showed that the lingering effects on mental health on a long term basis where the authors studied the mental health status after five years. [42] also showed a positive correlation between workplace bullying and both mental health as well as somatic symptoms. The author in [43] discussed the role of various professions, the inherent power structure and the workplace bullying and offers different intervention techniques to be used at workplace to minimize bullying. Furthermore, [44] shows that bullying not only affects the mental health of victims but also puts them at risk for cardiovascular disease in the long term. Lastly, authors in [45] discussed how choice of IOT is also helping gather medical data for users

3. Experimental Setup

As is the case in such research, we only collected the data from public sources to ensure that we address the privacy concerns of using such data [46], [47] and [48]. Furthermore, we do not publish

any user handle on twitter but make sure that we eliminate duplicate tweets to ensure that we are working from a clean set of data.

3.1. Preprocessing and Processing Data

We followed the following process for preprocessing and processing of data:

1. Collected a months' tweets under the hashtag #workplacebullying
2. Used the nltk toolkit to parse the texts and get rid of the stop-words (recurring words such as articles that need to be filtered out)
3. We use the tf-idf algorithm [49] to generate the keywords
4. Generated the unigram, bigram and trigram keywords
5. Once we have finalized the preprocessing part, we used the sklearn library to tokenize and vectorize the tweets.
6. For the sake of our work, we treated the entire set of tweets as one corpus.
7. In addition to collecting the n-gram keywords, we also collected all the hashtags that are mentioned in the tweets and the number of times they were used.
8. Implemented the above on a standard Dell running Ubuntu Linux and Python3 program with a 16G RAM

3.1.1. The APIs used

For this work, we used the python programming to gather and analyze the data. We used the following open-source APIs available for python programming language.

1. Twitter API: This requires registering with Twitter and creating a twitter development account. The twitter library can be installed for Python that provides all the requisite APIs
2. Pandas: This is an open-source python library which allows data cleaning, preparation and fast analysis. The data can be easily imported into Excel.
3. NLTK: This is one of the most powerful NLP libraries that provides the basic tools such as tokenization, stemming, lemmatization etc. Interested readers can refer to [49] for pertinent details.
4. Sklearn: This library helps in big data analysis such as classification, regression, clustering etc.

4. Results and Discussion

As a reminder, we will restate the research questions we posed as goals of this study:

1. RQ1: Does social media recognize workplace cyberbullying?
2. RQ2: How does social media view female workplace cyberbullying?
3. RQ3: What other social issues are raised as a consequence of cyberbullying?

To answer the questions, we did an analysis of the hashtag #workplace bullying and looked at the n-gram model for n= 1, 2 and 3. The n-gram model gives us the basis to answer RQ1 and RQ2. Furthermore, we looked at the top three hashtags that were mentioned in the results. These hashtags gives us the basis to answer RQ3.

4.1. #workplacebullying

We analyzed the #workplacebullying for the month of April. Following are the top ten words that were mentioned (Table 1 below).

Table 1. 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

The unigram model indicated only the psychological effects (without specifying) and the need to put an end to such behavior. Note that the intervention regarding lack of understanding of bullying goes back to address the prevalent view that workplace bullying does not exist which given the traditional research is not a true notion. In summary, the bigram and trigram model reflected the following as answers to RQ1 and RQ2:

From a characterization perspective, we had almost equal number of keywords that indicated the obvious existence of workplace bullying and the impression that workplace bullying is not an actual phenomenon but rather comprised of false accusations.

The tweets showed the existence of psychological effects of cyberbullying.

A huge number of tweets reflected the possible intervention techniques such as a) need to understand what bullying is and b) possible solutions (not specified/detected).

We also collected the top three hashtags mentioned under the hashtag #workplacebullying which were #feminism, #equality and #sexism. Note the following:

1. #sexism is potentially mentioned as a reason for workplace bullying
2. #equality potentially reflects the desired outcome of getting rid of #bullying
3. #feminism is possibly listed as a reason by people who believe that workplace bullying does not exist.

Given the above possible reasons, we repeated the experiments done on #workplacebullying.

4.2. #equality

Looking at the #equality hashtag, we found the following keywords for the unigram, bigram and trigram model. (Table 2).

Table 2. 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 Media	Justice Equality Equality Media	- Equality Treated Media
Verbally	Verbally Physically	Verbally Physically Harassed
Human House	Human Rights Left House	Human Rights Equality Time Left House
Sexism Boys	Teaching Sexism Sexism Boys	Book Teaching Sexism Sexism Boys Nice
Search	Search Safe	Search Safe Harbor
Truth	Truth Gets	Truth Gets Away

Looking at the results above, we conclude the following:

1. The word Japan was mentioned significantly. Interestingly, Japan has recently put a roadmap to end workplace bullying in place. Research indicated that both males and females were subject to workplace bullying
2. Majority of the tweets discussed potential solutions to workplace bullying such as searching for safe harbor and seeking justice.
3. The status quo of being physically and verbally abused is potentially prevalent in Japanese culture and that the truth might get away.
4. Even though the potential workplace bullying equally applied to males and females in Japanese culture, concerns regarding females were discussed in more detail as females face unique challenges due to being working mothers in such culture (indicated by the term "Time Left Home") and the fact they are working with males on the frontlines in top professions indicated by the term "Doctors Engineers Frontline". This was also evident in terms of support for working moms as "Shine working moms".
5. Lastly, we also saw the term "Sexism" used quite often but interestingly in a positive way indicating that potentially the dominant male culture look at teaching sexism in a positive way.

The hashtag #equality, included other hashtags such as well, such as #girlsmatter #humanrights #environmnet #sexism #womenleaders which further asserts the fact that workplace bullying for females is being discussed in this hashtag.

4.3. #feminism

The hashtag #feminism generated the following results (Table 3).

Table 3. n-gram model - #feminism hashtag

Unigram	Bigram	Trigram
feminismcoronavirus	-	-
feminismcancer	-	-
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 hood	women come hood feminism	women come forward hood feminism notes
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The #feminism keywords has a mostly negative connotations confirming our assumption from the keywords gleaned from #workplacebullying as many people considered it equivalent to corona virus and cancer as can be seen above. The keywords “sexism boys nice” was interestingly also present in the #equality. Also many people considered feminism as fake.

Moreover, the #feminism hashtag contained other hashtags such as #sexism, #feminist, #women, #genderbias and #stopsexualharassment.

4.4. #sexism

Looking at the #sexism hashtags, we arrived at the following results (Table 4).

Table 4. 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	Teaching sexism boys
Sexism	Sexism boys	Sexism boys nice
Like	Liberal women	Like liberal women

Strictly looking at the unigram, bigram and trigram model, we see that the tweets indicated the prevalent issues against females in workplace. Interestingly, the hashtag pointed out the prevalence of misogyny in the field of science. Overall, the hashtag characterizes the status quo when it comes to workplace bullying against females.

The hashtags we found mentioned overwhelmingly under the #sexism tag were #racism, #feminist and #women.

5. Conclusions

In this paper, we explored how cyberbullying against females at work is viewed in social media. We started with looking at #workplace bullying and found that 1) people were split between identifying the prevalence of workplace bullying against female and the view that such bullying simply does not exist and is a nuisance, 2) The tweets also showed the existence of psychological effects of bullying in the workplace, and 3) the tweets showed many intervention techniques that can minimize the effects of such bullying. We explored the top three hashtags that came up under the #workplacebullying and found that the three top hashtags were #sexism, #feminism and #equality. This led us to the conjecture that the three top hashtags go back to the three results we obtained under the #workplacebullying namely 1) cause of bullying against females (#sexism), 2) denial of bullying existence (#feminism) and possible intervention techniques (#equality). Our results confirmed the above and found overwhelming negative connotation to #feminism while the opposite was true for #equality.

We believe that the results from this study are significant enough to explore this further. Specifically, we want to explore the concept of wisdom of crowd and see if it applies to social media to give further credence to this work. Furthermore, it will be interesting to compare the results of this study to tweets written in another language.

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References

- [1] J. Warner, N. Ellman, and D. Boesch, “<https://www.americanprogress.org/issues/women/reports/2018/11/20/461273/womens-leadership-gap-2/>,” *The Women’s Leadership Gap*. .
- [2] M. Parameswaran and A. B. Whinston, “Social computing: An overview,” *Communications of the association for Information Systems*, vol. 19, no. 1, p. 37, 2007.
- [3] S. Monteith, T. Glenn, J. Geddes, and M. Bauer, “Big data are coming to psychiatry: a general introduction,” *International journal of bipolar disorders*, vol. 3, no. 1, p. 21, 2015.
- [4] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz, “Predicting depression via social media.,” 2013.
- [5] A. E. Rajput and S. M. Ahmed, “Big data and social/medical sciences: state of the art and future trends,” *arXiv preprint arXiv:1902.00705*, 2019.
- [6] D. Demszky *et al.*, “Analyzing polarization in social media: Method and application to tweets on 21 mass shootings,” *arXiv preprint arXiv:1904.01596*, 2019.
- [7] A. Rajput and S. Ahmed, “Making a case for social media corpus for detecting depression,” *arXiv preprint arXiv:1902.00702*, 2019.
- [8] W. Youyou, M. Kosinski, and D. Stillwell, “Computer-based personality judgments are more accurate than those made by humans,” *Proceedings of the National Academy of Sciences*, vol. 112, no. 4, pp. 1036–1040, 2015.
- [9] J. Paniagua and P. Korzynski, *Social media crowdsourcing*. 2017.
- [10] S. E. Jordan, S. E. Hovet, I. C.-H. Fung, H. Liang, K.-W. Fu, and Z. T. H. Tse, “Using Twitter for public health surveillance from monitoring and prediction to public response,” *Data*, vol. 4, no. 1, p. 6, 2019.
- [11] S. Ahmed, A. E. Rajput, A. Sarirete, A. Aljaberi, O. Alghanem, and A. Alsheraigi, “Studying Unemployment Effects on Mental Health: Social Media versus Traditional Approach,” Aug. 2020, doi: 10.20944/preprints202008.0355.v1.
- [12] S. Ahmed, A. Rajput, A. Sarirete, and T. Chaudhery, “Social Media Platform: Measuring Readability and Socio-Economic Status,” 2020, doi: 10.13140/RG.2.2.19861.96484/1.
- [13] M. A. Al-garadi, K. D. Varathan, and S. D. Ravana, “Cybercrime detection in online communications: The experimental case of cyberbullying detection in the Twitter network,” *Computers in Human Behavior*, vol. 63, pp. 433–443, 2016.

- [14] D. Chatzakou, N. Kourtellis, J. Blackburn, E. De Cristofaro, G. Stringhini, and A. Vakali, "Mean birds: Detecting aggression and bullying on twitter," in *Proceedings of the 2017 ACM on web science conference*, 2017, pp. 13–22.
- [15] J. Wang, R. J. Iannotti, and T. R. Nansel, "School bullying among adolescents in the United States: Physical, verbal, relational, and cyber," *Journal of Adolescent health*, vol. 45, no. 4, pp. 368–375, 2009.
- [16] S. K. Schneider, L. O'donnell, A. Stueve, and R. W. Coulter, "Cyberbullying, school bullying, and psychological distress: A regional census of high school students," *American journal of public health*, vol. 102, no. 1, pp. 171–177, 2012.
- [17] S. Owusu and L. Zhou, "Positive bystanding behavior in cyberbullying: The impact of empathy on adolescents' cyber bullied support behavior," in *2015 IEEE International Conference on Intelligence and Security Informatics (ISI)*, 2015, pp. 163–165.
- [18] E. M. Selkie, R. Kota, Y.-F. Chan, and M. Moreno, "Cyberbullying, depression, and problem alcohol use in female college students: A multisite study," *Cyberpsychology, Behavior, and Social Networking*, vol. 18, no. 2, pp. 79–86, 2015.
- [19] M. P. Hamm *et al.*, "Prevalence and effect of cyberbullying on children and young people: A scoping review of social media studies," *JAMA pediatrics*, vol. 169, no. 8, pp. 770–777, 2015.
- [20] R. Zhao, A. Zhou, and K. Mao, "Automatic detection of cyberbullying on social networks based on bullying features," in *Proceedings of the 17th international conference on distributed computing and networking*, 2016, pp. 1–6.
- [21] H. Margono, X. Yi, and G. K. Raikundalia, "Mining Indonesian cyber bullying patterns in social networks," in *Proceedings of the Thirty-Seventh Australasian Computer Science Conference-Volume 147*, 2014, pp. 115–124.
- [22] I. Tahamtan and L.-M. Huang, "# Cyberbullying in the digital age: Exploring people's opinions with text mining," *Proceedings of the Association for Information Science and Technology*, vol. 56, no. 1, pp. 672–673, 2019.
- [23] M. K. Mishra, S. Kumar, A. Vaish, and S. Prakash, "Quantifying degree of cyber bullying using level of information shared and associated trust," in *2015 Annual IEEE India Conference (INDICON)*, 2015, pp. 1–6.
- [24] H. Hosseinmardi, S. A. Mattson, R. I. Rafiq, R. Han, Q. Lv, and S. Mishra, "Detection of cyberbullying incidents on the instagram social network," *arXiv preprint arXiv:1503.03909*, 2015.
- [25] E. Raisi and B. Huang, "Cyberbullying identification using participant-vocabulary consistency," *arXiv preprint arXiv:1606.08084*, 2016.
- [26] E. Aboujaoude, M. W. Savage, V. Starcevic, and W. O. Salame, "Cyberbullying: Review of an old problem gone viral," *Journal of adolescent health*, vol. 57, no. 1, pp. 10–18, 2015.
- [27] A. Anjum, X. Ming, A. F. Siddiqi, and S. F. Rasool, "An empirical study analyzing job productivity in toxic workplace environments," *International journal of environmental research and public health*, vol. 15, no. 5, p. 1035, 2018.
- [28] S. Farley, I. Coyne, C. Sprigg, C. Axtell, and G. Subramanian, "Exploring the impact of workplace cyberbullying on trainee doctors," *Medical education*, vol. 49, no. 4, pp. 436–443, 2015.
- [29] D. Gardner *et al.*, "Predictors of workplace bullying and cyber-bullying in New Zealand," *International journal of environmental research and public health*, vol. 13, no. 5, p. 448, 2016.

- [30] R. Forssell, "Exploring cyberbullying and face-to-face bullying in working life—Prevalence, targets and expressions," *Computers in Human Behavior*, vol. 58, pp. 454–460, 2016.
- [31] L. M. Crothers, J. Lipinski, and M. C. Minutolo, "Cliques, rumors, and gossip by the water cooler: Female bullying in the workplace," *The Psychologist-Manager Journal*, vol. 12, no. 2, pp. 97–110, 2009.
- [32] J. Escartín, D. Salin, and Á. Rodríguez-Carballeira, "Conceptualizations of workplace bullying," *Journal of Personnel Psychology*, 2011.
- [33] R. Rugulies *et al.*, "Bullying at work and onset of a major depressive episode among Danish female eldercare workers," *Scandinavian journal of work, environment & health*, pp. 218–227, 2012.
- [34] M. Vartia and J. Hyyti, "Gender differences in workplace bullying among prison officers," *European Journal of work and organizational psychology*, vol. 11, no. 1, pp. 113–126, 2002.
- [35] S. T. Koeszegi, E. Zedlacher, and R. Hudribusch, "The war against the female soldier? The effects of masculine culture on workplace aggression," *Armed Forces & Society*, vol. 40, no. 2, pp. 226–251, 2014.
- [36] P. A. Hinchberger, "Violence against female student nurses in the workplace," in *Nursing forum*, 2009, vol. 44, no. 1, pp. 37–46.
- [37] B. Kishore, "Bullying of female employees at workplace," *Review of HRM*, vol. 4, no. 1, p. 19, 2015.
- [38] C. Harvey, "When queen bees attack women stop advancing: recognising and addressing female bullying in the workplace," *Development and Learning in Organizations: An International Journal*, 2018.
- [39] C. Rayner, "The incidence of workplace bullying," *Journal of Community & Applied Social Psychology*, vol. 7, no. 3, pp. 199–208, 1997.
- [40] B. Verkuil, S. Atasayi, and M. L. Molendijk, "Workplace bullying and mental health: a meta-analysis on cross-sectional and longitudinal data," *PloS one*, vol. 10, no. 8, p. e0135225, 2015.
- [41] S. Einarsen and M. B. Nielsen, "Workplace bullying as an antecedent of mental health problems: a five-year prospective and representative study," *International archives of occupational and environmental health*, vol. 88, no. 2, pp. 131–142, 2015.
- [42] M. B. Nielsen, N. Magerøy, J. Gjerstad, and S. Einarsen, *Workplace bullying and subsequent health problems*. 2014.
- [43] L. Turney, "Mental health and workplace bullying: The role of power, professions and 'on the job' training," *Australian E-journal for the Advancement of Mental Health*, vol. 2, no. 2, pp. 99–107, 2003.
- [44] M. Kivimäki, M. Virtanen, M. Vartia, M. Elovainio, J. Vahtera, and L. Keltikangas-Järvinen, "Workplace bullying and the risk of cardiovascular disease and depression," *Occupational and environmental medicine*, vol. 60, no. 10, pp. 779–783, 2003.
- [45] A. Rajput and T. Brahimi, "Chapter 15 - Characterizing internet of medical things/personal area networks landscape," in *Innovation in Health Informatics*, M. D. Lytras and A. Sarirete, Eds. Academic Press, 2020, pp. 353–371.
- [46] S. Ahmed, "BYOD, Personal Area Networks (PANs) and IOT: Threats to Patients Privacy," in *Research & Innovation Forum 2019*, Cham, 2019, pp. 403–410.
- [47] E. E. Chen and S. P. Wojcik, "A practical guide to big data research in psychology.," *Psychological methods*, vol. 21, no. 4, p. 458, 2016.

- [48] S. M. Ahmed and A. Rajput, "Chapter 16 - Threats to patients' privacy in smart healthcare environment," in *Innovation in Health Informatics*, M. D. Lytras and A. Sarirete, Eds. Academic Press, 2020, pp. 375–393.
- [49] A. Rajput, "Natural Language Processing, Sentiment Analysis, and Clinical Analytics," in *Innovation in Health Informatics*, Elsevier, 2020, pp. 79–97.