

# A Critical Discourse Analysis of Cyberbullying Language Based on Text-mining Techniques —A Case Study of Prince Harry and Meghan Markle

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With the development of AI, a large amount of cyberbullying language flooded into the Internet. Cyberbullying language damages the online environment and causes mental harm to the victims of online bullying. Many researchers, therefore, have paid much attention to the problem. This study collected online comments targeted at Prince Harry and Meghan Markle as a corpus and then analyzed text data based on Critical Discourse Analysis by using text-mining tools to explore the factors that contribute to the social ideological effects of the cyberbullying language. The research results show that cultural differences, prejudice, or social exclusion due to race or gender form cyberbullying on social media.

*Keywords:* cyberbullying language, critical discourse analysis, text-mining technology, non-traditional texts

## Introduction

With the rise of digital communication methods, the cyberspace environment is becoming complex. The Internet has changed how people communicate and provided a platform for people from around the world to express themselves. However, anonymity on the network has led to the rising phenomenon of cyberbullying, which leads to dire mental and emotional consequences and contributes to societal problems.

Belsey (2004) proposed that cyberbullying involves the use of information and communication technologies to support deliberate, repetitive, and hostile behavior by individuals or groups to harm others. Hinduja and Patchin (2006) pointed out that cyberbullying is mischief in which the sender does not make physical contact, but it still contains threats.

Many scholars have focused on the cyberbullying of teenagers. Some of them (Anggraini et al., 2018) aimed to prevent cyberbullying by dividing tweets on Twitter into two categories, bullying, and non-bullying. This can help young people to better identify violent language on the Internet and thus prevent them from receiving hurt. Other scholars (Kliem et al., 2020) focused on the definition of cyberbullying and its relationship with culture, family and environment (Balakrishnan, 2018). In general, research on cyberbullying has focused on the fields of communications, sociology, and psychology. Most research has studied the causes of cyberbullying. A small

number of research on cyberbullying derives from a linguistic perspective (Li, 2020), and even less from critical discourse analysis (Yuan & Liu, 2023).

Fairclough (1989) developed a three-dimensional framework for analyzing discourse. Van Dijk (1998) proposed a theory of ideology based on discourse analysis, which considered ideology as a culturally mediated system by which specific social groups influence human thought through language. Because CDA is a study that focuses on the relationship between discourse practice and power and ideology, researchers (Yuan & Liu, 2023) regard CDA as a tool to analyze the ideological factors that lead to online bullying, to probe the relationship between language use and unequal social interactions. However, traditional CDA research methods are often considered deficient in text selection and quantity (Stubbs, 1994). Some of the language-using patterns are likely to be unobserved in the text.

To address these problems, scholars started to use text-mining techniques. Mautner (1995) first introduced corpus techniques to the study of critical discourse analysis. Text-mining techniques can facilitate the abstraction of linguistic symbols above the word level and hence explore the relevant clues. They make language analysis more accurate and objective and deepen people's understanding of cyberbullying language, preventing and reducing its negative effects.

This study aims at analyzing and examining the linguistic features of cyberbullying language and their social implications from the perspective of critical discourse analysis. To fulfill the goal, researchers have set up a corpus of online bullying language targeting Harry and Meghan from Instagram, Facebook, Snapchat, and TikTok, and then used text-mining tools, such as topic modeling to explore the factors that contribute to the cyberbullying language ideologically. It is hoped that this article can deepen people's understanding of cyberbullying language, preventing and reducing its negative effects. At the same time, it can teach values to teenagers, promote people to make better use of the Internet, and create a more harmonious Internet environment.

## **Research Design**

### **Research Questions**

The study raised two research questions: (1) Are there some potential topics in cyberbullying language targeting Prince Harry and Meghan Markle? (2) What factors contribute to the social ideological effects of cyberbullying language targeting Prince Harry and Meghan Markle?

### **Data Collection**

The researcher built a corpus of 500 comments about Prince Harry and Meghan Markle on Twitter Instagram etc. To ensure a wide range of comments, the commenters were from different countries, ages, and genders.

Different from the standardization of textual systems, cyberbullying language toward Harry and Meghan is a kind of non-traditional text, which is hard to analyze through traditional critical discourse analysis approaches, so it is necessary to do text processing first and then extract critical features or attributes of an entity (the common topic) in text data.

## Research Tool

Taking efficiency, functionality, and convenience into account, this paper has chosen Python 3 as the programming tool, Scikit-learn (sklearn), and PyLDAvis as auxiliary tools. Scikit-learn is a popular and reliable software kit with a variety of algorithms and tools for ML visualization, pre-processing, model fitting, selection, and evaluation. PyLDAvis can visualize the LDA topic modeling and reveal the frequency of each topic term.

## Research Procedures

The first step is to build a corpus of 500 comments bullying Harry and Meghan on social media to form a corpus.

The second step is text collation. Because most comments are non-traditional text, the raw data has to be cleaned, organized, and structured before analysis. The researchers used EditPad Pro7 and made use of regular expressions to clean the corpus. To represent the words in topics more clearly, the researcher first removed the redundant symbols and then transformed the words into their prototypes. For example, change “studying” into “study”, “meeting” into “meet”, “better” and “best” into “good”.

The third step is to use Sklearn’s Latent Dirichlet Allocation (LDA) model to gain topic terms and themes. As Orpin (2005) points out, the main problem in combining corpus methods with CDA is how to find the entry point for research. The researchers set a special number based on the prior dataset to find the optimal topic numbers.

In the fourth step, the calculation of the Perplexity and score curve is performed. A model with higher log-likelihood and lower perplexity is considered to be good. According to the scoring rules of Perplexity, 10 topics have better scores. However, it is impossible to get 10 topics every time and some topics share the same keywords. Hence, this study found less than ten topics as shown in Figure 1.

```
: import matplotlib.pyplot as plt #困惑度, 折线变化折点意味适合划分的主题个数

: plexs = []
: scores = []
: n_max_topics = 16
: for i in range(1, n_max_topics):
:     print(i)
:     lda = LatentDirichletAllocation(n_components=i, max_iter=50,
:                                   learning_method='batch',
:                                   learning_offset=50, random_state=0)
:     lda.fit(tf)
:     plexs.append(lda.perplexity(tf))
:     scores.append(lda.score(tf))
```

Figure 1. Topics finding.

The fifth step is using PyLDAvis to visualize topics and topic items. The PyLDAvis offers the visualization of the topics-keywords distribution. Figure 2 shows that researchers used PyLDAvis to obtain accurate data figures and finally got a deep understanding of text data.

```
: import pyLDAvis #可视化
: import pyLDAvis.sklearn

: pyLDAvis.enable_notebook()
: pic = pyLDAvis.sklearn.prepare(lda, tf, tf_vectorizer)
: pyLDAvis.display(pic)
: pyLDAvis.save_html(pic, 'lda_pass'+str(n_topics)+' .html')
: pyLDAvis.display(pic)
```

Figure 2. PyLDAvis.

In the final step, the word frequencies of the corresponding topics were collated through Excel, and then the researcher built a network of relationships. The network mapping was completed through Cytoscape.

Results and Discussion

Research Results

In general, Perplexity represents the topic’s uncertainty, so researchers choose the ideal number of topics for LDA modeling by Perplexity. Theoretically, the bigger the number of topics is, the smaller the perplexity and the better the clustering effect is. However, in practice, the pursuit of the ideal modeling inevitably leads to too many topics and loses the significance of the research. Therefore, researchers usually choose the number of topics corresponding to the maximum change of the fold between adjacent inflection points. As shown in Figure 3, the number of topics can be theoretically determined as 3 or 4, so the present study extracted three topics.

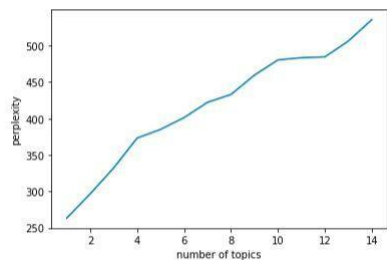


Figure 3. The number of topics.

After determining the number of topics, the study focused on the conceptual vocabularies represented by words, and the researcher used Python to remove stop-words from the corpus. Figure 4 demonstrates a visualization of the probability distribution of the words in each topic under the LDA algorithm.

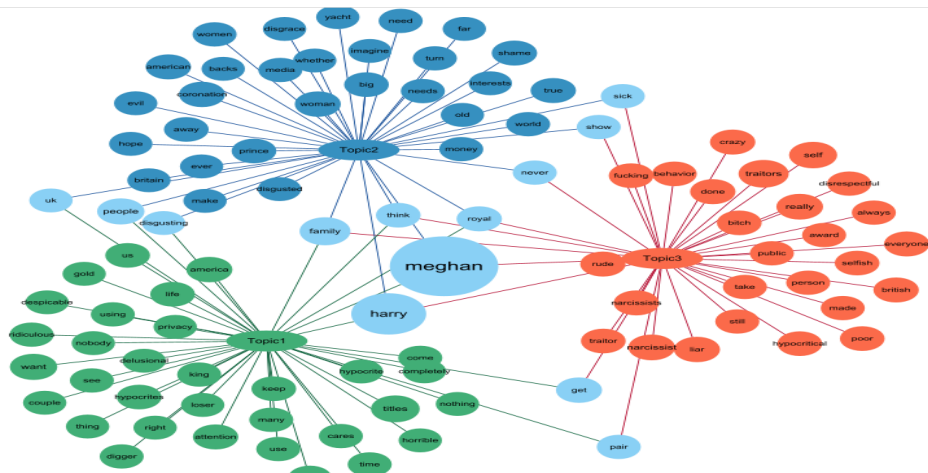


Figure 4. Topics visualization.

All the bubbles are radially linked to their corresponding topic. The size of the bubble indicates the probability of the word appearing in each topic. Different colors of the bubbles (blue, orange, green) represent parallel topics, and the middle bubbles (light blue) represent the identical words shared by the three topics.

Table 1  
*Topic Word List*

Topic ID	The most important key words
Topic 1	America Titles come ridiculous right horrible hypocrites privacy classless despicable Loser use life delusional attention
Topic 2	Britain American Coronation disgrace yacht shame woman disgusted money world evil away turn old hope
Topic 3	British bitch narcissist disrespectful behavior traitors hypocritical poor crazy selfish rude public liar fucking award

To gain a more intuitive understanding of the cyberbullying language discourse, the researcher manually removed the most weighted keywords “Harry” and “Meghan” from the keyword list. In Table 1, the first column shows the topics and the second column covers the keywords under each topic. Since the topic modeling tool LDA automatically generates three topic categories as in Figure 4, we can answer the first question “Are there some potential topics in cyberbullying languages targeting Harry and Meghan?” Following the keywords listed, three topics are included: (1) American comments on Harry’s moving to the US; (2) the coronation of Prince Charles; (3) British people’s comments on Harry and Meghan’s activities.

Next, the high-frequency words in Table 1 have a strong connection with question 2 “What factors contribute ideologically to the cyberbullying language targeting Harry and Meghan?” We can see that there are many negative words in Figure 3, such as, ridiculous, horrible, disrespectful, disgusted, disgrace, and despicable. These negative words implied netizens’ attack on Megan and Harry. They indicated that the couple has lost support in the US and Britain. People had a negative opinion of them. The reasons leading to the phenomena might be the answers to question 2.

### Discussion on the Findings

According to the three-dimensional model put forward by Fairclough (1989), discourse can be regarded as a three-dimensional concept. The first is discourse as text, both in spoken or written form. The second is discourse as a discursive practice, including discourse generation and interpretation. The third is discourse as social practice, indicating the ideological effects that discourse has. The nature of discourse requires that discourse analysis should also be three-dimensional, including a linguistic description of discourse, an explanation of the relationship between discourse and its production, and an interpretation of the relationship between discourse and social process.

The first dimension is text in which the discourse characteristics of texts are mainly studied based on linguistics. Therefore, the high-frequency words are the focus of the research. Most words are emotional words that are used to convey specific and complex feelings. They are a semantic category that includes positive and negative emotions. As for the linguistic description of the present data text, we find most cyberbullying language consists of negative emotional adjectives, and less neutral nouns and adjectives. It means bullies online only focus on expressing their feelings instead of stating their views.

Discourse practice refers to the process of producing discourse in a certain context. Intertextuality is the interaction between texts. According to CDA, cyberbullying language can be seen as a form of discursive

behavior that includes a variety of assaults, such as mocking, despising, insulting, swearing, slandering, morally condemning, threatening, and violating privacy. As for the relationship between discourse and its production, the online bullying implication is mainly realized by summarizing previous microblogs to provide reliable evidence for subsequent violence. Cyberbullying language is closely linked to the activities involving Harry and Meghan. For example, as in topic 2, we find the keywords “coronation”, “disgrace”, “shame”, and “disgusted” at the same time. This implies that when official media leaked news of the coronation of Prince Charles, the cyberbullying language about Prince Harry and Meghan Markle appeared, attacking, and humiliating the couple.

In terms of social practice, cyberbullying language is a social behavior. It reflects people’s social cognition. For example, netizens use “narcissist”, “bitch”, and “evil” to describe Harry and Megan, reflecting people’s aversion to the pair. Concurrently these words also express some negative ideologies in society. First, these high-frequency words are filled with female discrimination and personal insults, which indicates that people from both Britain and America have more nasty comments about Meghan than Harry. Gender prejudice exists not only in reality but also in cyberspace.

Netizen’s languages vary too. As in topic 1 and topic 2, Americans are concerned with affirmative action while people from Britain are mindful of royal honor. Because of their various focuses, the British and Americans choose different words for bullying Harry and Meghan. After analyzing these high-frequency words in detail, we can find more specific social ideologies.

What factors contribute to the social ideological effects that the cyberbullying language has? The first factor is cultural differences and prejudice. Since Meghan is an American citizen and Harry is a British citizen, bullies on the Internet mainly come from the two countries. High-frequency words in topic 1, such as, “come”, “America”, “title”, “right”, “couple”, “ridiculous”, “despicable”, “and “privacy” are concerned with American rights. They express the attitudes of the American people toward Harry’s naturalization as a citizen of the United States. They also imply cultural differences. The United States is a country where civil rights are paramount. American people are extraordinarily sensitive about privacy and human rights. American netizens believe that if Harry were to apply for US citizenship, it would not only be an insult to the US Constitution but also a major challenge to the equality of all people in the US. Currently, Prince Harry has left the royal family and it is said that Harry may join the American nationality because Meghan is an American citizen. However, words calculated under the topic modeling show that the American people do not welcome Harry, and even consider the event as ridiculous.

The second reason is social exclusion due to racial discrimination. Just as the words “bitch”, “narcissist” and “fucking” show, Meghan is the target of most cyberbullying language. Before this couple got married, the British people had a strong opinion of Megan, just because she had black ancestry. Meghan’s mother is an African American and Meghan is a mixed woman. Although she has an African ethnic background, Meghan looks much like a tanned woman. She, however, is too black for British Internet users.

Meghan once said it was only after she came to Britain that she “started to understand what it was like to be treated like a black woman”. Over the years, there have been many incidents of racism in the UK, and structural racism is deeply rooted in British society. More than a quarter of Britain’s ethnic minorities have experienced racial stigmatization, and it is even worse for people of African descent. After the 2008 international financial crisis, the UK implemented economic tightening policies for a long time. The policy exacerbated racial

discrimination and violated their fundamental rights. The British media has pointed out that discrimination and marginalization of ethnic minorities not only in education but also in employment, justice, and many other areas have “normalized”. Due to these facts, it is not surprising at all that Meghan gets more disapproval from British netizens.

## Conclusion

With the development of AI, the number and variety of information resources increase, so how to quickly and accurately explore non-traditional texts, such as microblogs, tweets, and comments to extract the effective information we need is the main topic of critical discourse analysis in the era of big data.

To help people understand the harm of cyberbullying language and its influence on society, this study analyzed the cyberbullying language directed at Prince Harry and Meghan Markle. With the help of text-mining tools in corpus-driven CDA analysis, the researcher revealed the potential topics of the text and discussed the factors that lead to the social ideological effects of cyberbullying language.

It is hoped that this study can enhance people’s ability to identify, prevent, and address negative influences brought by cyberbullying language. We should create an open and peaceful Internet platform for everyone so that we will have more chances to gain positive information online.

## References

- Angraini, I. et al. (2018). Cyberbullying detection modelling at twitter social networking. *JUITA: Jurnal Informatika*, 6(2), 113-118.
- Balakrishnan, V. (2018). Self-esteem, empathy and their impacts on cyberbullying among young adults. *Telematics and Informatics*, 35(07), 2028-2037.
- Belsey B. (2005). Cyberbullying: An emerging threat to the “always on” generation. *Recuperado el*, (5), 2010.
- Fairclough, N. (1989). *Language and power*. New York: Pearson Education.
- Kliem, S. et al. (2020). General and specific trends in cyberbullying: results of representative surveys among pupils in lower saxony. *Kheit Und Entwicklung*, 29(2), 67-74.
- Li, W. Q. (2020). The language of bullying: Social issues on Chinese websites, *Aggression and Violent Behavior*, 53(101453), 1359-1789.
- Mautner, G. (1995). *Only connect critical discourse analysis and corpus linguistics*. Lancast: UCRL.
- Orpin, D. (2005). Corpus linguistics and critical discourse analysis: Examining the ideology of sleaze. *International Journal of Corpus Linguistics*, (1), 37-61.
- Patchin, J. W. & Hinduja, S. (2006). Bullies move beyond the schoolyard: A preliminary look at cyberbullying. *Youth violence and juvenile justice*, (2), 148-169.
- Stubbs, M. (1996). *Text and corpus analysis: Computer-assisted studies of language and culture*. Oxford: Blackwell Publisher.
- VanDijk, T. A. (1998). Ideology: A multidisciplinary approach. *Ideology*, (2), 1-384.
- Yuan, P. P., & Liu, W. W. (2023). The study of cyber-bullying from the perspective of critical discourse analysis: A case study of Tik Tok comment area language. *Journal of Literature and Art Studies*, 13(2), 82-88.