Cyberbullying and the Mental Health Burden on Young Women in STEM Fields in the U.S.

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Abstract- Online discourse about women in STEM fields frequently triggers targeted harassment and cyberbullying behaviors. Using text mining, this study examined the prevalence and nature of cyberbullying directed at young women in STEM on TikTok in the U.S. Analysis of 33,615 comments from 50 TikTok videos revealed that non-cyberbullying comments occurred significantly more than expected. Among cyberbullying behaviors, gendered slurs dominated responses (34.1% of all cyberbullying comments), followed by sexualization (29.6%) and mansplaining (29.0%), while traditional harassment tactics occurred less frequently than anticipated. Sentiment analysis revealed a predominance of neutral sentiment over positive or negative expressions. These findings demonstrate that while overt cyberbullying remains relatively infrequent on TikTok due to platform moderation, gender-based harassment becomes the predominant form of harmful behavior, with distinct patterns requiring targeted intervention strategies to support women's participation in STEM fields.

Keywords: cyberbullying, women in STEM, TikTok, gender-based harassment, social media

I. INTRODUCTION

Cyberbullying poses a significant mental health burden, particularly on young women in STEM fields within the United States. The impact of cyberbullying extends beyond mere psychological distress, affecting various aspects of mental well-being. Recent research confirms that cyberbullying is a complex and persistent form of bullying that can lead to significant negative consequences, with 26.5% of American teenagers (aged 13 to 17) being victims of cyberbullying in 2023, an increase from 23.2% in 2021 (Bright Path Behavioral Health, 2024). It is associated with anxiety and avoidance behaviors, such as diarrhea, palpitations, and nausea during exams, particularly evident in female victims (Rusillo-Magdaleno et al., 2024). The larger research culture within STEM fields contributes to this mental health burden. The competitive and often exclusionary nature of research environments, exacerbated by factors such as contract precarity and the need for diversity, further influence the mental health struggles of women in these fields (Limas et al., 2022). This environment can contribute to a cycle where mental health issues are viewed as personal failings rather than responses to systemic pressures, thereby exacerbating the effects of cyberbullying.

Studies show that the digital landscape allows bullying to manifest in new and pervasive ways. Current data reveals that 59.2% of female teens experience cyberbullying at some point in their lives compared to 49.5% of males, with females being more likely to experience severe psychological impacts (Bright Path Behavioral Health, 2024). Cybervictims, particularly females, tend to engage in negative health behaviors as responses to victimization (Nikolaou, 2022). This can include substance use and other harmful behaviors, showing the extended effect of cyberbullying beyond immediate psychological distress. While gender plays a significant role, with female students often being more frequent cybervictims, there is a notable lack of significant associations regarding mitigation or negotiation of these dynamics (Carvalho et al., 2021). This suggests a need for more targeted interventions that address gender-specific dynamics in cyberbullying.

Young women in STEM fields in the U.S. experience various forms of cyberbullying, which significantly impact their mental health. Common forms of cyberbullying include online harassment, exposure to unsolicited sexual content, and hurtful comments, often facilitated by the anonymity of digital platforms (Gaur & Maini, 2023). Current statistics indicate that among all social networks, TikTok ranks third highest for cyberbullying incidents at 64%, following YouTube at 79% and Snapchat at 69% (Vigderman, 2024). These behaviors are prevalent in college settings, where female students frequently encounter degrading comments, hate speech, and the posting of explicit or unwanted pictures (Selkie et al., 2016). The impact of such cyberbullying is profound, leading to increased stress, depression, anxiety, and even suicidal ideation among victims (Wilkins-Yel et al., 2022; Ghowrui et al., 2024). Recent systematic reviews demonstrate that depression shows significant association with cyber-victimization in 80% of studies (prevalence: 15–73%), while anxiety is significant in 80% of studies (27–84.1%) (Arif et al., 2024).

The psychological toll is exacerbated by the traditionally male-dominated nature of STEM environments, which can marginalize women and contribute to a "chilly climate" that affects their persistence in these fields (Wilkins-Yel et al., 2022). Cyberbullying is also linked to emotional problems more strongly in females than in males, highlighting a gendered dimension to its impact (Kim et al., 2018). Furthermore, cyberbullying can lead to social withdrawal, shame, and social anxiety, which are common responses among female victims (Gaur & Maini, 2023). Addressing these issues requires increased awareness, timely reporting, and institutional support to mitigate the adverse effects on young women's mental health and their participation in STEM fields (Ghowrui et al., 2024; Wilkins-Yel et al., 2022). Although existing research highlights the prevalence of gender-based harassment and its detrimental effects on women's mental health, a critical gap remains in understanding how diverse forms of cyberbullying on social media, particularly on TikTok, affect the mental well-being of young women pursuing science, technology, engineering, and mathematics careers in the United States. Given the growing importance of TikTok as a platform for social interaction, professional networking, and identity formation among youth, addressing this gap is essential for developing targeted, evidence-based interventions to mitigate psychological distress and promote retention of young women in STEM fields, thereby advancing public health and gender equity priorities at the national level.

Research Questions

1. What is extent and style of cyberbullying in TikTok content created by young women pursuing STEM careers in the United States?
2. What are the most frequently discussed topics in TikTok posts by young women in STEM fields in the U.S.?
3. What is the overall sentiment expressed by TikTok users toward young women in STEM who post about their academic and professional experiences?

II. BACKGROUND

The underrepresentation of women in STEM education and careers in the United States is shaped by a complex interplay of cultural, institutional, and individual factors. Persistent gender stereotypes and biases within STEM fields contribute to environments where women often feel marginalized, which can discourage both their entry into and advancement within these areas (Cho, 2017; Beede et al., 2011; John, 2022). Although women comprise nearly half of the overall U.S. workforce, current data shows they occupy only 26% of STEM positions, a gap that has remained despite gains in women's workforce participation more broadly, with global statistics indicating women comprise only 29.2% of the STEM workforce in 146 nations evaluated (Smith, 2025). This disparity is even more pronounced for women of color, particularly Black women, who often contend with compounded challenges stemming from racial bias and a lack of representation in STEM roles (Charleston et al., 2014; Owuondo, 2022). Recent data shows that Black students earned only 7% of STEM bachelor's degrees as of 2018, below their share of all bachelor's degrees (10%) or their share of the adult population (12%) (Fry et al, 2021). The Field-specific Ability Beliefs (FAB) hypothesis offers additional insight, suggesting that women are less likely to enter fields believed to require innate brilliance, a quality that is often stereotypically associated with men (Meyer et al., 2015). Beyond cultural and perceptual barriers, structural issues such as the gender pay gap and the scarcity of family-friendly policies in STEM workplaces further hinder women's ability to thrive in these fields (Beede et al., 2011; Owuondo, 2022). Addressing these challenges requires multifaceted strategies, including policy reforms, targeted mentorship, and initiatives aimed at creating more inclusive and equitable environments in both STEM education and professional settings (Nweje et al., 2025).

Cyberbullying among adolescents in the United States remains a pressing and increasingly prevalent issue, with recent data showing significant growth in reported incidents. Current statistics indicate that approximately 55% of students reported experiencing cyberbullying at some point in their lifetimes, with 27% experiencing it within the most recent 30 days, representing an increase from previous years (Patchin & Hinduja, 2024). Nearly half of U.S. teens ages 13 to 17 (46%) report ever experiencing at least one of six cyberbullying behaviors, with social media platforms serving as the most common context for these incidents (Vogels, 2022). There is a notable overlap between traditional and cyberbullying, as many adolescents who are bullied in person also face online harassment (Giumetti & Kowalski, 2015). The psychological consequences of cyberbullying are well-documented, with victims frequently experiencing heightened levels of anxiety, depression, and suicidal ideation. Recent research shows that nearly all victims of cyberbullying (93%) report negative mental health effects, with cyberbullying increasing suicidal thinking among victims by nearly 15% and suicide attempts by almost 9% (Joshua, 2024). In some cases, the emotional distress caused by cyberbullying escalates to self-harm or suicide attempts (Perwitasari & Wuryaningsih, 2022; Agustiningsih et al., 2024; Deol & Lashai, 2022). Importantly, the harmful effects are not limited to victims alone; perpetrators and bystanders may also experience adverse psychological, physical, and social consequences (Hafizi, 2024).

Gender plays a critical role in influencing both the prevalence of cyberbullying and its psychological and behavioral consequences. Current data reveals significant gender disparities, with adolescent girls being more likely to have experienced cyberbullying in their lifetimes (59.2% vs. 49.5% for boys), and 15- to 17-year-old girls standing out as particularly likely to have faced cyberbullying compared with younger teen girls and teen boys of any age (Patchin & Hinduja, 2024; Vogels; 2022). Studies show that gender differences exist in both perpetration and victimization, as well as in how adolescents respond to and cope with cyberbullying (Jankowiak et al., 2024). Girls are more likely to experience written forms of cyberbullying and are generally more receptive to educational and help-seeking strategies aimed at addressing it (Perasso et al., 2020; Chun et al., 2021). In contrast, boys tend to report higher rates of perpetration and a greater tolerance for such behavior (Wang et al., 2023). Girls are also more frequently identified as victims of cyberbullying incidents (Iorga et al., 2022). These patterns are further shaped by psychological and social factors. For example, gender influences mechanisms such as moral disengagement and peer affiliation, particularly with deviant groups, which can increase the likelihood of cyberbullying involvement (Liang et al., 2022). Family dynamics also play a critical role; supportive family environments have been shown to reduce the risk of victimization across both genders (Perasso et al., 2020). Given the gendered dimensions of cyberbullying and its profound psychological and behavioral impacts, it is essential to design interventions that account for these differences. The widespread and harmful nature of cyberbullying reinforces the urgent need for targeted strategies to protect adolescent mental health (Carter & Wilson, 2015; Bottino et al., 2015; Hamm et al., 2015).

III. METHODOLOGY

This study employed a mixed-methods approach to investigate gender-based harassment and its mental health impact on young women in STEM on TikTok. It combined qualitative content analysis with text mining to capture both nuanced patterns of online cyberbullying in user responses.

Data Collection

Data collection focused on TikTok videos identified using a defined set of hashtags related to women's participation in STEM, with comments subsequently extracted via exportcomments.com (https://exportcomments.com/). Nine hashtags were used to identify relevant posts: #WomenInSTEM, #GirlsWhoCode, #ScienceTok, #STEMTok, #EngineerLife, #SheCanSTEM, #WomenInTech, #BreakingBarriers, and #RepresentationMatters. These hashtags were selected for their clear association with science, technology, engineering, and mathematics content created by women, particularly those in student or early-career roles. A purposive sampling strategy was applied to select videos created by users identified as young women in STEM fields based in the United States. Indicators used to identify relevant users included bios referencing STEM roles or education (e.g., "CS major," "pre-med student," "aspiring engineer"), usernames linked to STEM identities, visual content markers such as lab environments or code demonstrations, and location cues like university names, campus apparel, or regional references. Location was further confirmed through captions or bios mentioning U.S. cities, universities, or states. Sampling was stratified by creator type to include high school students, undergraduate students, graduate students, early-career STEM professionals, and influencers ranging from micro-level (1,000+ followers) to macro-level accounts. Efforts were made to include creators representing diverse racial backgrounds, geographic regions, and educational institutions, including Historically Black Colleges and Universities (HBCUs) and Hispanic-serving institutions (HSIs), as well as varied STEM subfields such as computer science, engineering, life sciences, and data science. Videos from brands, news organizations, or institutional accounts were excluded to maintain focus on individual perspectives and peer-driven content. A total of 50 TikTok videos were collected, and all publicly available comments were extracted, resulting in a dataset of 33,615 user comments.

Codebook Development

Using NVivo (version 24), an inductive coding approach was used to manually analyze 1,500 user comments from TikTok videos featuring women in STEM. This approach allowed patterns and themes to emerge directly from the data rather than relying on predetermined categories. The process began with open coding, in which each comment was reviewed line by line and assigned initial codes capturing key phrases, sentiments, or emotional tones. These codes were grounded in the users' own language and reflected the tone and meaning of the responses. Similar or overlapping codes were then merged and refined into broader thematic categories through multiple iterative reviews. This cyclical process supported the development of themes related to gender-based harassment, stereotyping, and other audience reactions toward women in STEM. Coding definitions were updated as needed to remain closely aligned with the context and content of the data. To ensure reliability, two independent coders conducted the analysis and reached an interrater agreement of 88%. Table 1 presents the categories of gender-based harassment identified through this process. This qualitative framework was then applied to large-scale text mining in R to systematically examine harassment trends across all 33,615 user comments.

Code	Definition	Example
Belittlement	Demeaning the creator's intelligence, skills, or contributions	"This is basic stuff, anyone can do that." / "You're not a real engineer."
Discrediting	Undermining legitimacy, expertise, or qualifications	"You probably just got hired for diversity points."
Gendered Slurs	Use of sexist, demeaning, or derogatory terms targeting gender	"Stupid b*tch." / "Dumb blonde."
Sexualization	Inappropriate comments focused on appearance rather than content	"You're too hot to be doing science." / "I'd fail your class on purpose 😉"
Gatekeeping	Asserting that STEM is not a space for women or questioning belonging	"STEM isn't for girls." / "Women just don't have the logic."
Mansplaining	Patronizing explanations assuming the creator lacks knowledge	"What you meant to say was…" / "Actually, it's more complicated than you understand."
Invalidation	Rejecting or minimizing the experience of sexism, harassment, or barriers	"Stop playing the victim." / "Not everything is about gender."

Table 1. Codebook

IV. DATA ANALYSIS

Keyword Matching

Data preprocessing was carried out using the R packages dplyr (Wickham et al., 2023) and stringr (Wickham, 2022). Each comment in the dataset was assigned a unique identifier with the row_number() function to support systematic tracking and organization. Regular expressions were then applied to identify specific words and phrases associated with gender-based harassment toward women in STEM. The keyword lists used for classification were developed directly from the inductive qualitative analysis described earlier, ensuring that computational categorization reflected the actual language and expressions found in TikTok comment sections on this topic. A rule-based classification framework was created to group comments into seven thematic categories: Belittlement, Discrediting, Gendered Slurs, Sexualization, Gatekeeping, Mansplaining, and Invalidation. Classification was performed using the case_when() function in combination with str_detect() in R, allowing each comment to be sequentially evaluated against the predefined keyword lists. Comments were assigned to the first matching category, and those that did not match any were labeled as Uncategorized. This approach ensured that the computational text mining remained grounded in user-generated language patterns while maintaining methodological consistency and contextual accuracy. The rule-based method provided a scalable and replicable process for detecting and quantifying forms of gender-based harassment, forming the basis for subsequent quantitative analysis of trolling directed at women in STEM on TikTok.

Category	Selected Keywords/Phrases
Belittlement	you're dumb, stupid, idiot, moron, retard, dummy, brain dead, clueless, hopeless, pathetic, useless, waste of space, loser, failure, joke, embarrassing, cringe, trash, garbage, worthless, incompetent, amateur, terrible, awful, disgusting

Discrediting	you're wrong, that's not right, fake, lying, making it up, no proof, unreliable, untrustworthy, biased, misleading, false, exaggerating, unprofessional, unqualified, lacks credentials, no evidence, baseless, nonsense, irrelevant, shallow, questionable, doubtful, suspicious, fraudulent, deceptive
Gendered Slurs	bitch, slut, whore, hoe, thot, girl, female, woman, bimbo, gold digger, attention whore, drama queen, princess, queen, girly, feminine, lady, chick, broad, doll, honey, sweetie, baby, darling
Sexualization	hot, sexy, fine, beautiful, gorgeous, pretty, cute, attractive, stunning, perfect, body, legs, chest, ass, boobs, curves, smile, eyes, hair, lips, face, figure, shape, look good, looking fine, damn girl, babe, honey, sweetie, fine af, baddie
Gatekeeping	not for you, you don't belong, stay in your lane, not qualified, not smart enough, prove yourself, you can't, not cut out, don't deserve, not worthy, outsider, imposter, fake, pretending, trying too hard, not real, doesn't count, amateur, beginner, newbie, inexperienced, unfit, inappropriate, wrong field, misplaced
Mansplaining	let me explain, actually, well actually, you don't understand, listen, here's how, that's not how, you're wrong, let me teach you, allow me, trust me, I know, you need to, you should, clearly you, obviously you, simple, basic, elementary, fundamental, easy, just, simply, merely, only, common sense
Invalidation	you're overreacting, not a big deal, get over it, stop complaining, quit whining, too sensitive, too emotional, dramatic, exaggerating, making it up, imagining things, not that serious, happens to everyone, normal, deal with it, toughen up, grow up, stop crying, calm down, relax, chill, whatever, so what, who cares, don't care

Table 2. Keyword matching

Sentiment Analysis

Sentiment analysis was conducted on the full dataset of 33,615 comments collected from 50 TikTok videos featuring women in STEM. All data preprocessing and analysis were performed using R (R Core Team, 2023). The comment text was tokenized into lowercase words using the unnest_tokens() function from the tidytext package (Silge & Robinson, 2016). Common English stop words, such as “the,” “and,” and “is,” were removed to concentrate on meaningful terms. Sentiment classification utilized the Bing Liu lexicon (Hu & Liu, 2004), which categorizes words as either positive or negative. Tokenized words were matched with the sentiment lexicon via inner joins to extract emotion-related vocabulary. Sentiment scores for each comment were calculated by comparing the counts of positive and negative words, leading to classification into positive, negative, or neutral categories. Classification followed established conventions where comments with equal positive and negative words were labeled neutral, those with more positive words were labeled positive, and those with more negative words were labeled negative (10e, 2018, August 10). This approach aligns with standard sentiment analysis practices, where neutral serves as the baseline for comments without clear emotional polarity (Wikipedia contributors, 2025, July 26). The three-category system (positive, negative, neutral) is widely used in sentiment research, offering clear distinctions between emotional tones while accounting for neutral content (Nandwani & Verma, 2021). A word cloud was also created to highlight prominent vocabulary patterns across the dataset. Finally, a sentiment distribution plot illustrated the proportion of comments in each emotional category, providing insight into the overall tone of audience responses to women’s participation in STEM on TikTok.

Topic Modeling

Latent Dirichlet Allocation (LDA) topic modeling was applied to analyze thematic patterns within the TikTok comment dataset focusing on women in STEM. The analysis included 33,615 comments and aimed to identify core discussion themes related to gender-based harassment and experiences of women in STEM. Data preprocessing was conducted in R (R Core Team, 2023) using the tm package (Feinerer & Meyer, 2008). The comments were cleaned by converting all text to lowercase, removing punctuation and numbers, filtering out standard English stop words, and normalizing whitespace. Comments with no meaningful content after preprocessing were excluded to preserve analytical accuracy. A Document-Term Matrix (DTM) was then created to represent word frequency distributions throughout the dataset. The LDA model was run using the topicmodels package in R (Grün & Hornik, 2011), with the number of topics fixed at five. This decision was informed by model evaluation metrics including perplexity and topic coherence, which balance interpretability and predictive performance (Gan & Qi, 2021; Zhao et al., 2015). This method aligns with common practices in topic modeling, where multiple topic counts are assessed to find the optimal trade-off between model complexity and clear topic differentiation (Zhao et al., 2015). The selection of five topics provided stable and well-separated themes, consistent with recommendations for datasets of this size and complexity (Gan & Qi, 2021). To ensure reproducibility, a fixed random seed was applied. For each topic, the ten terms with the highest probability weights (β values) were extracted for interpretation. Visualizations of topic-term associations were produced using ggplot2 (Wickham, 2016), offering a detailed overview of prominent themes emerging from TikTok comments concerning harassment and women’s experiences in STEM.

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V. FINDINGS

4. What is extent and style of cyberbullying in TikTok content created by young women pursuing STEM careers in the United States?

On TikTok, significantly more non-cyberbullying comments on content created by young women pursuing STEM careers were found than cyberbullying comments, χ^2 (1, N = 33,615) = 32,147.28, p < .001. Gendered slurs were the most common cyberbullying tactic (34.10% of all cyberbullying comments), followed by sexualization (29.64%), mansplaining (29.04%), belittlement (2.79%), invalidation (2.06%), discrediting (1.88%), and gatekeeping (0.49%). A chi-square test of independence was performed to examine the relationship between the different cyberbullying tactics. The results were statistically significant, χ^2 (6, N = 5,916) = 6,095.69, p < .001, with significantly more gendered slurs, sexualization, and mansplaining tactics and significantly less belittlement, invalidation, discrediting, and gatekeeping than the other cyberbullying tactics. Based on the adjusted standardized residuals with critical value ±1.96, gendered slurs, sexualization, and mansplaining were used significantly more on TikTok than expected, while belittlement, invalidation, discrediting, and gatekeeping were used significantly less than expected.

Tactic	Non-cyberbullying		Cyberbullying			X^2	*df*	*N*	*p*
	#	%	#	%	Adjusted standardized residuals				
Gendered Slurs			2,017	34.10	40.31	6,095.69	6	5,916	< 0.001
Sexualization			1,754	29.64	31.26				
Mansplaining			1,718	29.04	30.02				
Belittlement			165	2.79	-23.39				
Discrediting			111	1.88	-25.25				
Gatekeeping			29	0.49	-28.07				
Invalidation			122	2.06	-24.87				
Total	27,699	82.40	5,916	17.6		32,147.28	1	33,615	< 0.001

Table 3. Extent and style of cyberbullying

2. What are the most frequently discussed topics in TikTok posts by young women in STEM fields in the U.S.?

The analysis revealed that the most frequently discussed topics in TikTok posts by young women in STEM fields in the U.S. encompassed five distinct categories. STEM Advocacy discussions centered on promoting women's participation and representation in science, technology, engineering, and mathematics disciplines. Skill Validation represented content demonstrating technical competencies and professional abilities within STEM contexts. Personal Desires emerged through expressions of individual motivations, aspirations, and personal connections to STEM careers. Future Planning involved discussions about educational pathways, career trajectories, and long-term professional goals within STEM fields. Social Commentary reflected broader observations and critiques regarding gender dynamics, workplace culture, and societal perceptions of women in STEM environments. These topics collectively demonstrate the diverse nature of content creation among young women in STEM on the platform, encompassing both personal narratives and advocacy efforts aimed at challenging traditional gender barriers in technical fields.

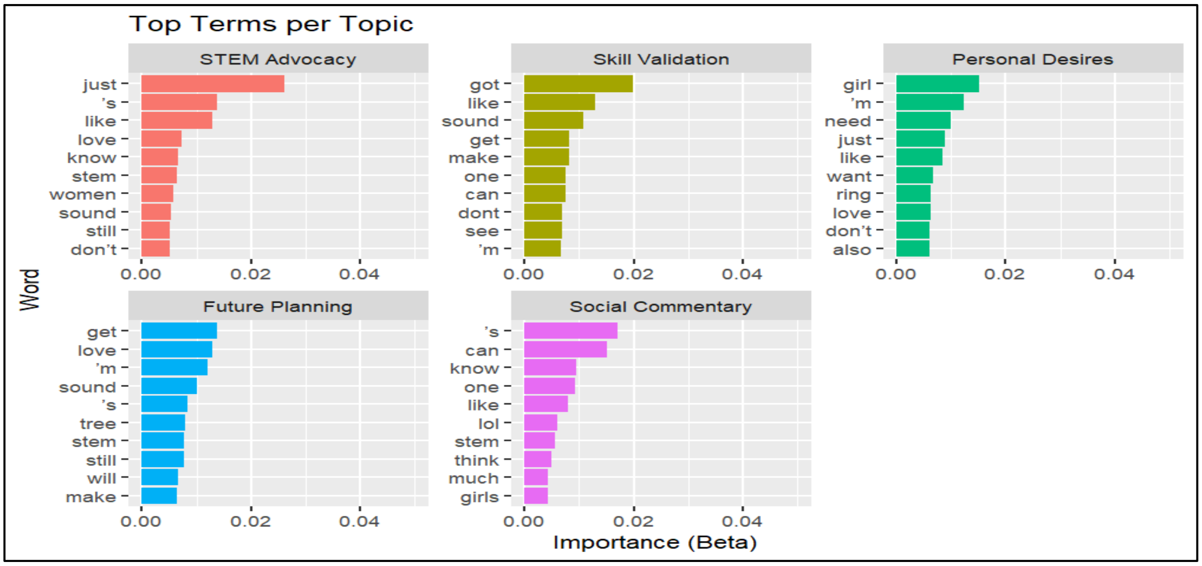

Figure 1. Topics discussed

3. What is the overall sentiment expressed by TikTok users toward young women in STEM who post about their academic and professional experiences?

The analysis revealed significantly more neutral sentiment expressed towards young women in STEM who post about their academic and professional experiences on TikTok than positive or negative sentiment. Neutral comments comprised the largest proportion of user responses, followed by positive sentiment, while negative sentiment constituted the smallest category of responses. The sentiment distribution demonstrated that users predominantly responded with non-judgmental reactions to STEM-related posts.

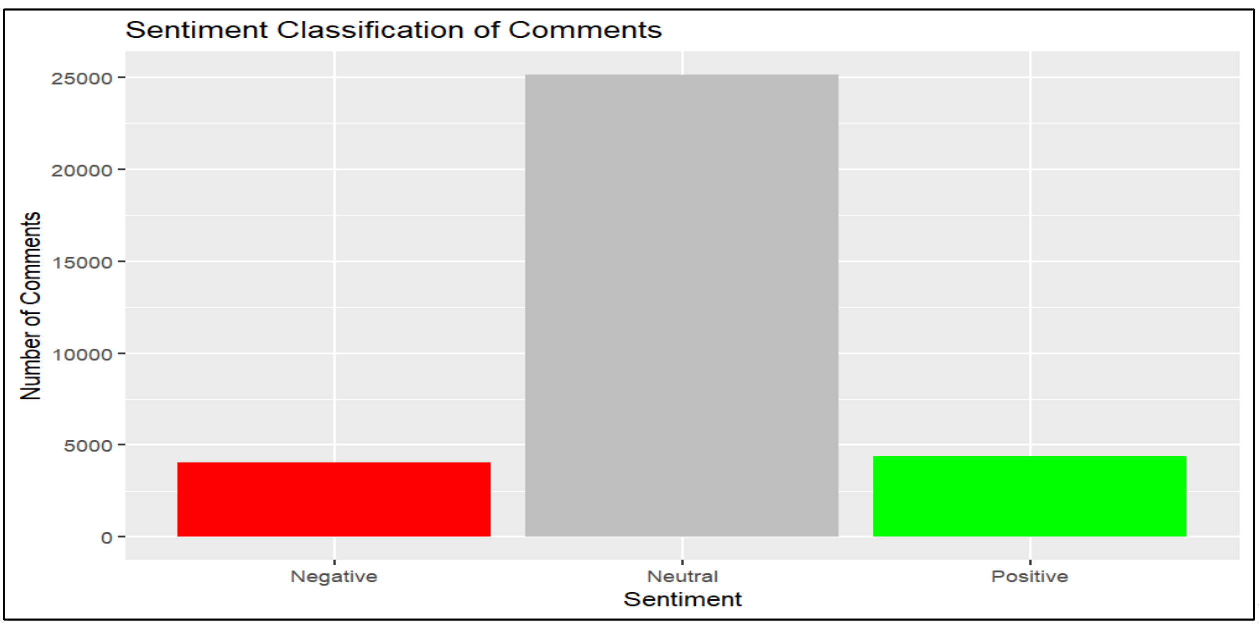

Figure 2. User sentiments

The word cloud analysis showed the most frequently used terms across all comments. The most prominent words included "love," "sound," "stem," "women," "engineering," "girl," and "don't," indicating that discussions frequently centered on career enthusiasm and field-specific language. Other notable terms included "amazing," "smart," "degree," "proud," "queen," and "cute," suggesting supportive discourse around academic achievements and professional aspirations. Education-related terms such as "school," "college," "science,"

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"coding," and "physics" also appeared prominently, reflecting the connection between STEM identity discussions and specific academic disciplines in the comment sections.

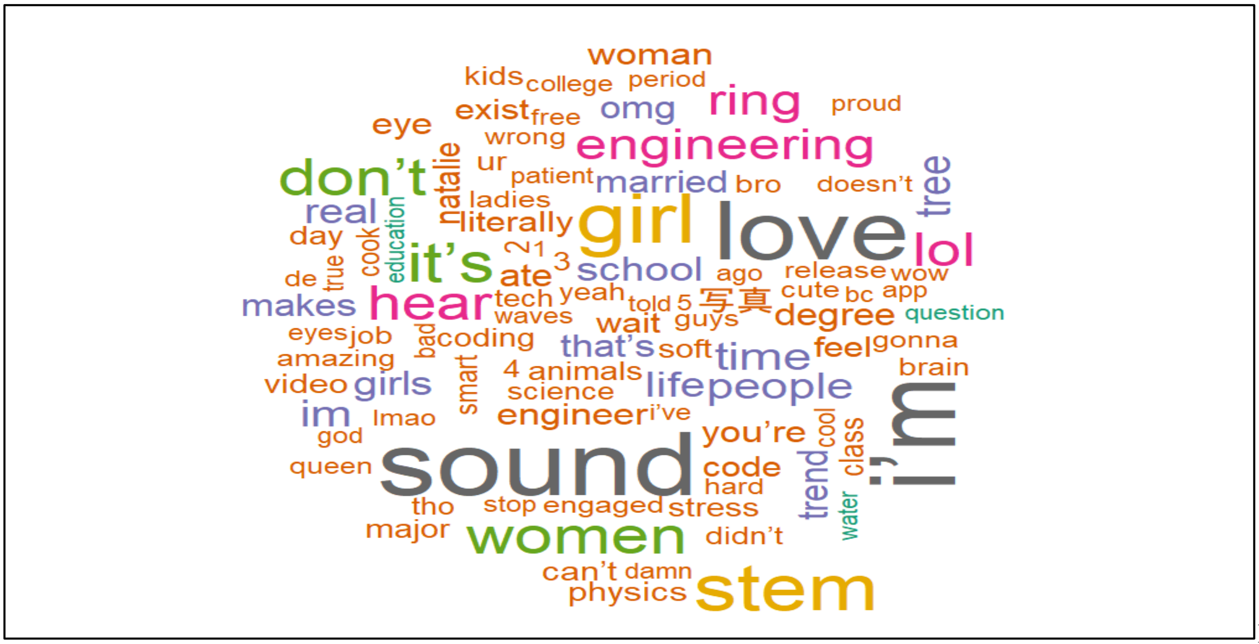

Figure 3. Word cloud

VI. DISCUSSION

This section begins by outlining the differences in both the extent and style of cyberbullying comments directed at young women in STEM careers. It then discusses the findings of the sentiment analysis. On TikTok, content created by young women in STEM received significantly more non-cyberbullying comments than cyberbullying ones. Content created by young women in STEM on TikTok received significantly more non-cyberbullying comments than cyberbullying ones. TikTok creators can moderate their comment sections directly, and the platform's community-driven ranking system amplifies popular responses, which are typically positive (Zeng & Kaye, 2022). These features help boost supportive comments while reducing the prominence of harmful content. Additionally, TikTok's audience consists mainly of young users between 16 and 24 who engage with the platform for self-expression and educational content (Yang & Zilberg, 2020). This younger demographic may respond more empathetically and supportively to STEM creators rather than with hostility. These characteristics may explain this pattern. Gendered slurs, sexualization, and mansplaining were directed at young women in STEM who post on TikTok significantly more often than expected, whereas belittlement, invalidation, discrediting, and gatekeeping occurred significantly less frequently than expected. These patterns reflect specific mechanisms of gender-based harassment. Sexist slurs function strategically to reinforce traditional gender norms and assert dominance, particularly targeting women who deviate from expected gender roles (Felmlee, 2020). Rather than being random attacks, these comments aim to degrade and marginalize women who challenge social hierarchies. Similarly, sexualized remarks work to objectify women, reducing their perceived humanity and diminishing empathy from other users (Galdi & Guizzo, 2021; Ligman et al., 2024). This dehumanization process makes women in STEM more vulnerable to sexualized harassment online. Mansplaining represents another form of dominance assertion that specifically targets women's expertise. This behavior stems from cultural biases and social power imbalances, which are often amplified by online anonymity and platform designs that favor male voices (Robinson, 2024, December 21). These factors could explain why certain types of gender-based harassment appear more frequently than others when targeting women STEM creators on TikTok. The sentiment analysis revealed significantly more neutral sentiment expressed towards young women in STEM who post about their academic and professional experiences on TikTok than positive or negative sentiment. This pattern may relate to both TikTok's algorithmic design and the nature of STEM content itself. TikTok's recommendation system favors content that generates high engagement, including likes, comments, and shares. Videos that attract supportive responses are more likely to be promoted, creating a reinforcing cycle of visibility and positivity (Zhou, 2024). This dynamic can unintentionally suppress cyberbullying by reducing its reach. However, the predominance of neutral sentiment may reflect how audiences typically engage with educational STEM content, which often prompts informational or factual responses rather than emotionally charged reactions. These algorithmic and content-specific factors could explain why neutral sentiment dominates the response patterns toward women STEM creators on the platform. Building on these findings, the following section outlines key policy implications that can guide platform regulation, youth protection initiatives, and targeted prevention strategies to address cyberbullying and its mental health burden on young women in STEM fields in the U.S.

Policy implications and national relevance

The economic consequences of losing women from STEM fields represent a critical threat to American innovation and competitiveness. Women held only 35% of tech jobs in the U.S. at the end of 2023, despite comprising nearly half of the workforce (Radulovski, 2020). The global information technology industry is worth trillions of dollars and expected to grow by 8% annually, yet women comprise less than one-third of employees and only 22% of artificial intelligence professionals (Özdemir, 2025). STEM jobs are projected to grow 10.4% between 2023 and 2033, compared to 3.6% for non-STEM jobs, with median annual wages of $101,650 versus $46,680 for non-STEM positions (Smith, 2025). The U.S. will need to fill about 3.5 million jobs by 2025, yet as many as 2 million may go unfilled due to the skills gap (Smith, 2025). The U.S. faces unprecedented competition in critical technologies, with the National Security Commission on Artificial Intelligence identifying a severe STEM talent shortage as a primary threat, stating that "the United States government needs digital experts now or it will remain unprepared to buy, build, and use AI and its associated technologies" (National Security Commission on Artificial Intelligence, n.d.). The Department of Defense's STEM Strategic Plan for fiscal years 2021-2025 emphasizes the urgent need to diversify the STEM pipeline to maintain military technological superiority (Department of Defense, 2021). The findings that 34.10% of cyberbullying comments targeting women STEM creators involve gendered slurs, with an additional 29.64% consisting of sexualization, directly threaten these workforce development goals. Research indicates that achieving gender parity in STEM fields could increase GDP per capita by 0.7-0.9% by 2030 and 2.2-3.0% by 2050 (Wikipedia contributors, 2025). Current data shows women remain significantly underrepresented in leadership positions, with major tech companies reporting female leadership rates ranging from just 26% to 34% (Radulovski, 2020).

This research provides critical evidence supporting multiple federal initiatives. The findings align directly with the Kids Online Safety Act (KOSA), reintroduced in the 119th Congress in May 2025, which requires platforms to implement duty of care standards for users under 17 (Schneid, 2025). The documentation that gendered slurs and sexualization comprise 63.74% of cyberbullying comments offers specific evidence for implementing KOSA's platform accountability measures (Kids Online Safety Act, 2023). The duty of care provisions require social media companies to prevent and mitigate specific harms including sexual exploitation, mental health disorders, and cyberbullying (Blumenthal, R., n.d.). The research also supports the Surgeon General's 2023 Advisory on Social Media and Youth Mental Health (U.S. Public Health Service, 2023) and informs the Federal Trade Commission's ongoing investigations into youth protection on social media platforms (U.S. Department of Justice, n.d.). The Department of Commerce's Women in STEM Ambassador Program, launched in March 2024, specifically aims to raise awareness about opportunities for women in the semiconductor industry (U.S. Department of Commerce, 2024).

The identification of specific harassment patterns (gendered slurs: 34.10%, sexualization: 29.64%, mansplaining: 29.04%) provides platforms with targeted content moderation priorities that could be implemented through algorithmic detection systems. Recent research demonstrates that cyberbullying detection systems can achieve accuracy rates exceeding 80% when trained on specific harassment patterns (Talpur & O'Sullivan, 2020). The National Science Foundation reports that more than 36 million people work in STEM occupations, with workers in STEM occupations having higher employment rates and higher median earnings than their non-STEM counterparts (National Center for Science and Engineering Statistics, 2024). Research indicates that increasing women's participation in STEM careers could boost women's cumulative earnings by $299 billion over the next ten years (Guest Blogger, 2017). Recent statistics indicate that over a fifth (21.34%) of women in 2024 believed that eliminating the gender pay gap would encourage more women to pursue STEM careers (AIPRM, 2025). This research provides federal agencies with actionable evidence for developing targeted interventions that protect a critical national resource, the pipeline of women entering STEM fields.

VII. LIMITATION

This study presents two major limitations that should be considered when interpreting the findings. First, the analysis relied on publicly available comments only, which may not capture the full scope of harassment experienced by women in STEM on TikTok. Private messages, direct messages, and comments that were deleted by creators or removed by platform moderation before data collection could contain more severe forms of cyberbullying, potentially underestimating the true extent and intensity of gender-based harassment. Second, the keyword-based classification approach, while grounded in qualitative analysis, may have missed subtle forms of harassment that do not contain explicit terminology.

VIII. CONCLUSION

This study addresses a gap in the literature on cyberbullying comments directed at young women in STEM in the U.S. on TikTok. This study is significant because it examines harassment patterns on a platform predominantly used by young audiences, providing insights into how gender-based cyberbullying manifests in educational STEM content. The findings contribute to understanding platform-specific harassment dynamics and inform strategies for supporting women in STEM fields. On TikTok, content created by young women in STEM received significantly more non-cyberbullying comments than cyberbullying ones. Gendered slurs, sexualization, and mansplaining were directed at young women in STEM who post on TikTok significantly more often than expected, whereas belittlement, invalidation, discrediting, and gatekeeping occurred significantly less frequently than expected. The sentiment analysis revealed significantly more neutral sentiment expressed towards young women in STEM who post about their academic and professional experiences on TikTok than positive or negative sentiment.

Future research could pursue two critical directions to advance understanding of gender-based harassment in STEM spaces. First, longitudinal studies tracking harassment patterns over time could examine how cyberbullying toward women STEM creators evolves as platform algorithms, community guidelines, and user demographics change. Second, comparative cross-platform research examining harassment patterns across multiple social media platforms could reveal platform-specific factors that either amplify or mitigate gender-based cyberbullying, informing evidence-based recommendations for platform design features and moderation policies that better protect women pursuing STEM careers.

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