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CBSoft 2025

Pain in a Safe Space: Mapping Emotions and Discourse in the Womenintech Subreddit

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ABSTRACT

Women in Information Technology (WIT) continue to face systemic challenges, including career stagnation, lack of recognition, workplace bias, and professional isolation. In response, external support networks such as the *r/womenintech* subreddit have emerged, offering a dedicated and inclusive space for women in Software Engineering (SE) to exchange experiences, seek advice, and build community. This study investigates the discursive landscape of this subreddit by analyzing 2,367 posts published between April 2024 and April 2025. We applied a set of natural language processing (NLP) techniques, using the Twitter-based RoBERTa model, to conduct a multi-dimensional analysis that includes emotion detection, sentiment analysis, hate speech classification, irony detection, and offensive content identification. Our findings show that 99.9% of the posts are free of hate speech, reinforcing the subreddit's role as a safe space for women in tech to share experiences. However, the prevalence of the emotion *Sadness* (45%) reveal that the experiences reported are often distressing and unpleasant. In addition, we explore temporal trends in politically charged contexts of DEIA law. Our study highlights the importance of better understanding the underlying structural and cultural factors that contribute to these emotions and open new directions for further analysis.

KEYWORDS

Crowdsourcing in Software Engineering, Reddit, Human Aspects

1 Introduction

The technology industry remains male-dominated, with women facing challenges such as workplace bias, career stagnation, and professional isolation [27, 30]. Canedo et al. [7] demonstrate that entrenched cultural norms and gender stereotypes continue to create significant obstacles to equity for women in Software Engineering (SE). Despite organizational efforts to promote diversity, equity, inclusion, and accessibility (DEIA) in SE, many women still lack trusted forums to voice their experiences and seek peer support outside formal corporate channels [16]. In response, digital communities have emerged as vital support networks where women can share experiences, ask for advice, and build solidarity. A grey literature study of 44 DEV Community posts highlights how these forums surface both persistent barriers and peer-driven solutions [20].

Among these platforms, Reddit stands out as a prominent social media site structured around user-generated communities known as subreddits, each dedicated to specific topics. Reddit's design, featuring pseudonymous participation, moderation tools, and community-driven rules, makes it a compelling subject for research into online behavior and community dynamics. In fact, Reddit is a rich and underexplored platform for collecting crowdsourced data on the *Human Aspects* of SE, especially from the standpoint of women in Information Technology [31].

In this context, the *r/womenintech* [24] subreddit has become a prominent *"safe space"*, offering pseudonymous participation, upvote/down-vote moderation, and community-driven rules that foster inclusive and candid discussions. Prior studies have leveraged Reddit's rich, threaded discourse to investigate online behavior, sentiment dynamics, and hate speech across various communities [18, 34], most focus on controversial or extremist forums [26], not support-oriented spaces. Despite Reddit's positive reputation, little is known about the emotional burden carried by its members or how these affective states evolve over time.

To address this gap, we uncover the emotional and discursive landscape of the *r/womenintech* subreddit by tracing these emotions and sentiments over a one-year timeline, including before and after the implementation of the recent DEIA legislation [33] - shedding light on the temporal dynamics of online support spaces and their interplay with broader policy contexts. By focusing on emotional patterns and community interactions, our work contributes to SE by exploring the human dimensions of developer support networks and providing empirical guidance for the design of more inclusive, empathetic tools, processes, and workplace policies. This paper makes the following key contributions:

- We built an annotated dataset of 2,367 posts and 1,596 users interactions from the support-oriented *r/womenintech* subreddit. Each post is enriched with labels for emotion, sentiment, hate speech, irony, and offensive content, thus enabling further exploration of online discourse around gender, technology, and support networks.
- We conducted an exploratory temporal analysis of this discursive space, uncovering how emotions and sentiments evolve over time, particularly in response to how policy shifts may influence online discourse among women in tech.
- We find that although *r/womenintech* remains free from hate speech (99.9%), many posts express negative emotions, especially sadness, suggesting that even in supportive communities, distressing experiences remain prevalent.

Our study reveals underexplored dimensions, such as the deeper analysis of posts (*e.g.*, comments), and offers data-driven evidence for organizations seeking to better support women in tech. Our findings can inform the development of more effective workplace policies, targeted interventions, and inclusive practices aimed at mitigating distress and promoting equity.

2 Background and Related Work

Reddit is a prominent social media platform hosting over 100,000 active user-generated communities called subreddits, each centered on specific topics such as politics, entertainment, professional development, and mental health [1, 23]. Its scale and diversity, combined with features like pseudonymous participation, upvote/downvote mechanisms, and community-specific moderation [9, 12, 22]. This makes Reddit a valuable corpus for studying collective behavior and complex emotional or ideological discourses in ways that differ from other social media platforms like Twitter or Facebook [10, 15, 35].

Given its discursive richness, Reddit has increasingly been used in NLP research for tasks such as sentiment analysis [35], hate speech detection [34], and emotion classification [2]. However, Reddit posts tend to be longer and more nuanced than tweets, and community-specific contexts heavily influence tone, requiring analytical models that handle informal language while capturing emotional subtleties. Subreddits like *r/womenintech* have become a key digital space for women in tech to share experiences, seek advice, and find support, filling gaps left by formal institutions [32]. The semi-anonymous environment encourages disclosures that might be suppressed in formal settings [32].

Complementing these community-driven insights, a recent survey of 192 Brazilian women ICT professionals revealed mismatches between career expectations and reality, with concerns about pay, advancement, and workplace culture [13]. Conversely, a study with 217 male developers found limited recognition of sexism on their teams, often attributing women's underrepresentation to a presumed lack of coding affinity rather than to structural bias [8].

Recent NLP studies highlight online platforms as support spaces and sources of gendered insight for women in STEM [14, 16]. Jacobs et al. [16] use topic modeling on subreddits like *r/womenEngineers* and *r/xxSTEM* to reveal concerns such as harassment and identity conflict. We extend this by applying a multidimensional NLP pipeline to the subreddit *r/womenintech*, enabling finer-grained analysis of sentiment, emotion, and implicit harms like offensive content and hate speech, thus adding emotional depth to prior thematic findings. Focusing on a support-oriented community rather than extremist or controversial spaces allows us to explore emotional burdens present even in so-called *"safe spaces"*. While Fouad and Alkooheji [14] analyzes 250,000 tweets using BERT and TimeLMs, reporting mostly positive sentiments. In contrast, our Reddit analysis reveals dominant tones of sadness, frustration, and neutrality. We also explore temporal shifts around DEIA-related policy changes.

While advances in emotion detection and hate speech analysis using Reddit data exist [18, 19, 26], to our knowledge no prior work has examined the impact of DEIA-related policies within Reddit-based tech communities. Additionally, although Stack Overflow is the primary platform for studying developer communities in SE [31], Reddit's diverse and informal topic-specific communities enable richer, more nuanced discussions. This makes Reddit better suited for exploring social and emotional aspects in SE, especially sensitive issues like gender dynamics and DEIA policies. While Reddit is widely used in other fields, its application in SE remains emergent, revealing a gap that this work addresses by focusing on a key Reddit community.

3 Methodology

To guide our investigation, we adopted the Goal-Question-Metric (GQM) approach [6], and defined our goal as follows: **analyze** the online discourse in the *r/womenintech* subreddit; **for the purpose of** understanding patterns of toxicity and emotional expression over one year; **with respect to** linguistic trends; **from the viewpoint of** women; **in the context of** the *r/womenintech* subreddit. We detail each research questions (RQs) as follows:

RQ$_1$: What is the volume of hate speech, irony, and offensive content, and what are the main discussed terms? – RQ$_1$ investigates linguistic patterns in the *r/womenintech* subreddit by quantifying the occurrence of hate speech, irony, and offensive content. Identifying low levels of toxic discourse would support its value as a safe, welcoming environment. Moreover, analyzing frequently discussed terms allows us to map key concerns – ranging from discrimination and burnout to career advice. To this end, we applied NLP techniques to identify linguistic patterns in English-language content.

RQ$_2$: What are the prevalence sentiments and emotions expressed, and how do they relate to the most discussed terms? – RQ$_2$ provides insight into the emotional tone behind posts. By detecting emotions, *e.g.* sadness, anger, joy, or fear, we gain insight into the emotional impact of tech industry experiences on women. We cross-analyzed the results to determine the distribution of emotions across different sentiment categories. Moreover, we map sentiments and emotions to specific terms.

RQ3: How have patterns of hate speech, sentiment, and emotion evolved, before and after the implementation of DEIA policy shifts? – RQ$_3$ explores the temporal dynamics of the *r/womenintech* subreddit, focusing on how external DEIA policy changes (*e.g.*, reduced federal DEIA requirements) affect discursive trends. Tracking shifts in hate speech and emotional tone before and after key policy events enables us to evaluate whether such policies influence community sentiment, positively or negatively.

3.1 Study Phases and Procedures

To ensure the reproducibility of this study, it was organized into six distinct phases (Figure 1). Next, we describe each phase.

(1) Data Extraction. In this phase, we identified which subreddits host the desired discussions. We selected the subreddit *r/womenintech*, which describes itself as "An inclusive space for all women working in the tech industry - whether technical, non-technical, or somewhere in between. Connect, build community, and support each other here." Then, we mined data using the Python Reddit API Wrapper (PRAW) [5]. PRAW has certain limitations that influenced the design of our data mining strategy. First, it restricts the number of posts that can be mined per subreddit to 1,000 by request. Second, it does not allow filtering data by date range.

Since we aimed to analyze one year of data, we developed three complementary mining strategies. First, we applied two standard Reddit filters - *Top* and *Hot* - while varying the `time_filter`

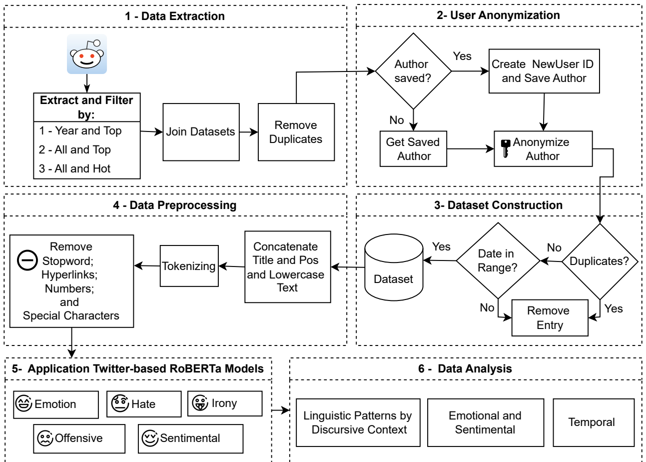


Figure 1: Overview of the study phases

parameter. All of our requests were configured to retrieve a maximum of 1,000 posts. For posts up to December 2024, we used the *Top* filter with the `time_filter` set to `"year"`, which returns the most relevant posts from the twelve months preceding the date of extraction. It yielded 993 posts spanning from April to December 2024. The second extraction used the *Hot* filter, which retrieves posts that are rapidly gaining attention through comments, votes, and shares over a rolling three-month window. This resulted in 965 posts. However, this approach did not capture posts from January.

To address this gap, we performed a third extraction using the *Top* filter again, this time with the `time_filter` set to `"all"`, manually selecting only the posts published from January onward. This final strategy provided an additional 453 posts. The raw dataset initially contained 2,411 posts. We identified and removed 44 duplicate entries, resulting in a final dataset of 2,367 unique posts.

(2) User Anonymization. Our dataset includes a column named *Author*, which contains the user ID of the post creator. To protect user privacy, we anonymized this information. Additionally, it is important to note that a single user may have authored multiple posts; therefore, anonymization must preserve this by assigning the same pseudonym to all posts from the same user. To address this, we developed a Python script [25] that generates consistent pseudonyms following the pattern `user_num`, where `num` ranges from 1 to N. Resulting in 1,596 unique pseudonyms.

(3) Dataset Construction. The dataset comprises 2,367 records distributed across nine fields, as detailed in Table 1. The temporal distribution of posts is uneven, with a lower volume observed in February (17%), March (18.3%), and April (17.15%) 2025. This variation is a result of the data extraction strategy described in Phase (1). In 2024, April recorded the lowest number of posts (0.8%), whereas October had the highest activity (8.5%).

(4) Data Preprocessing. As an initial step in this phase of the study, we concatenated the title and body of each post, aiming to treat the post as a single input unit for the model. Then, we performed preprocessing by converting all text to lowercase, tokenizing it, and removing stopwords, hyperlinks, special characters, numbers, isolated letters, line breaks, tabs, and formatting symbols.

(5) Application of the Twitter-based RoBERTa Model. We used five RoBERTa models fine-tuned with the SuperTweetEval dataset [3]. Table 2 lists the models used in our study, their output labels, and a brief description of how each model contributes to our analysis. We selected those because they were fine-tuned on approximately 58 million labeled tweets, ensuring a high diversity of data sourced from social media platforms. Additionally, these models achieve state-of-the-art performance in tasks such as irony detection, offensive content classification, and emotion recognition [29].

Table 1: Overview of the dataset fields

Field	Description
ID	A unique identifier for each Reddit post.
Date	The date the post was published on the platform.
Subreddit	The name of the subreddit to which the post belongs.
URL	The post's direct link on the Reddit platform.
Title	The title of the post.
Text	The body of the post. It may contain null values, as some posts include only videos, images, or links. These cases were excluded from this study.
Author	The anonymized nickname of the post's author.
Score	The total score of the post, calculated based on upvotes and downvotes.
#comments	The number of comments the post had at the time of data extraction.

Table 2: NLP models used for text classification

Model	Output labels	Description
Twitter-RoBERTa-emotion	*anger, anticipation, disgust, fear, joy, love, optimism, pessimism, sadness, surprise, trust*	Returns a ranked list of emotions with corresponding confidence scores; only the top-ranked emotion is considered in our analysis.
Twitter-RoBERTa-hate	*hate, non-hate*	Binary classification model trained to detect hate speech[1].
Twitter-RoBERTa-irony (via TweetNLP)	*irony, non-irony*	Binary classifier for identifying ironic expressions in text.
Twitter-RoBERTa-offensive	*offensive, non-offensive*	Binary classifier for detecting offensive language in tweets.
Twitter-RoBERTa-sentiment	*positive, neutral, negative*	Classifies overall sentiment of text into one of three categories.

(6) Data Analysis. We performed a quantitative analysis to examine the distribution of the data generated by the five models. This phase was divided into two parts: *(i)* a class-wise analysis of the entire dataset, and *(ii)* a temporal analysis of each class.

4 Results and Discussion

We discuss the results of our research questions (RQs) as follows.

4.1 RQ$_1$: Mapping Linguistic Patterns

While our models classify hate speech, offensive language, and irony as linguistic patterns, these results should be interpreted within a broader discursive context. The absence of hate speech, as illustrated in Figure 2, suggests that *r/womenintech* successfully serves its intended purpose as a safe space where women can share experiences and build supportive networks.

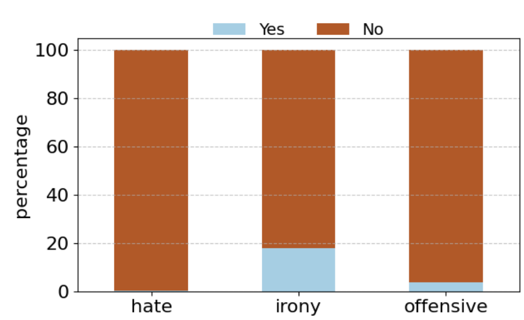


Figure 2: Percentage of hate, irony and offensive content

Additionally, the presence of irony in only 18% of posts implies that most contributors prefer clear, cohesive communication. However, the use of irony in the remaining posts may reflect an implicit type of criticism or resistance related to the topic under discussion. Interestingly, ironic posts were most frequently associated with the emotion *joy* (44%), followed by *anger* (25%), *sadness* (21%), and *optimism* (9.7%), suggesting a complex interplay between emotional tone and rhetorical style. For instance, irony paired with joy appears in a post where #user_1216 reflects on team dynamics, *"[...] These guys normally react to messages with the standard 👍 emoji, but celebrate each other's achievements in our group chat with the ❤ emoji! It warms my heart every time I see it, they're such sweeties."* In contrast, irony paired with anger emerges in posts such as #user_1476's, *"[...] Thank you for the opportunity, boss! I'm thrilled we didn't do anything to resolve the root cause, or expect a basic standard or decency from all our people. That sounds hard. [...]"* and *"[...] this is my favourite part, I have to be the project manager's mommy. I'll coax him and coddle him into doing the bare minimum, asking him if maybe, for me, could he stop rolling his eyes when the client speaks? That would be so great, buddy!"* Irony also surfaces alongside sadness, as in #user_2088's reflection *"[...] about burnout in tech and realized the issue is a lot larger than tech. All my stay at home mom friends are burned out on raising kids!"*

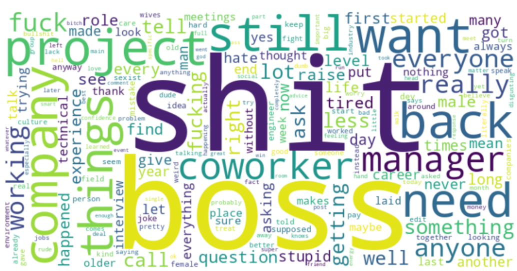


Figure 3: Offensive word cloud

Figure 3 shows posts classified as offensive content (3.6%) may include emotionally charged language, such as the terms *"s*@t"*, *"stupid"*, *"sexist"*, and *"f*ck"*. These expressions do not necessarily constitute direct attacks on individuals, but most reflect frustration or emotional outbursts related to the situation being described. For instance, #user_523 stated a personal experience:*"[...] On my first day at work, a colleague told me, 'I'm sexist and make sexist jokes, so be prepared'. [...]"* #user_200, #user_1159 and #user_1026, on the other hand, expressed personal frustrations: *"[...] I think that men, especially older men, feel automatically threatened by a woman who is smart and knows her s*@t, and the older I get, the less patience I have for it. [...]"*, *"[...] They believe that even if you got the job, you're still stupid, so they search for your mistakes and blow them out of proportion. [...] "* and *"[...] If women screamed at each other the way they do, we'd all be unemployed. Must be nice to say whatever the f*ck you want, can't relate."*

4.2 RQ$_2$: Sentiment and Emotion Dynamics

According to Sailunaz and Alhajj [28], analyzing emotions in text is a challenging task, as emotions are intrinsic to human personality. While emotions are often easily recognized through facial expressions or vocal tone, their written representation depends heavily on the reader's interpretation of context. For this reason, sentiment classification (Negative, Neutral, and Positive) is more commonly applied to textual data [11]. In this study, we performed both sentiment and emotion classification, as well as an agreement analysis between the two dimensions.

The sentiment analysis results showed a relatively balanced distribution between positive (25%) and negative (26%) posts, with the majority being classified as neutral (48%). This motivated us to examine how emotions are distributed within each sentiment category, as illustrated in Figure 4.

The *Twitter-RoBERTa-emotion* model outputs one of ten possible emotion categories (see Table 2). However, in our dataset, only four emotions were identified: *anger* (23%), *joy* (20%), *optimism* (12%), and *sadness* (45%). A large portion of the posts shared by users reflect negative experiences faced by women, with approximately 68% of the posts expressing either *anger* or *sadness*. In contrast, more positive emotions (*joy* and *optimism*) account for only 32%, suggesting that users feel comfortable sharing negative experiences.

Within the *negative sentiment*, the emotional breakdown included: *anger* (12.8%), *joy* (0.08%), and *sadness* (13.4%).The *neutral sentiment* was composed of: *anger* (9%), *joy* (9%), *optimism* (6%), and *sadness* (24%). The *positive sentiment* consisted of: *anger* (0.9%), *joy* (11%), *optimism* (6%), and *sadness* (7.4%).

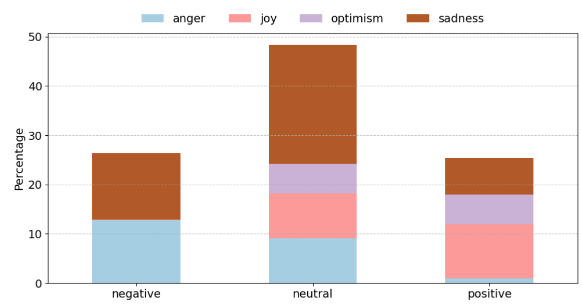


Figure 4: Distribution of emotions within each sentiment

By comparing sentiment and emotion outputs, we confirm the complexity of emotional expression in text, as noted by Sailunaz and Alhajj [28]. All three sentiment categories include a significant proportion of *sadness* in their emotion subsets. For instance, negatively classified posts generally expressed sadness through personal burnout and regret, as stated by #user_769, *"I put in extra hours, volunteered for everything, and got praised as a top performer. But instead of rewards, I got more work, more stress, and watched people who did less climb the ladder. [...]"* and #user_144, *"Existential crisis I am in my 40's and unemployed. [...]"*.

Neutral posts report statistics – *"Around 76% of high-performing women receive negative feedback on their personality [...]"*, #user_3 and *"[...] My channel viewership is 99.9% male. I don't know if that's just a product of robotics/AI being male dominated, or if YouTube just has significantly more men on the platform? [...]"*, #user_864 – conveying sadness not through subjective emotion, but through the implicit weight of systemic bias. Positive posts can be observed in how individuals navigate challenging professional circumstances, as highlighted by #user_7, *"[...] Can't find anything now - overqualified for lower positions, not cool and connected enough to get a senior position again. [...]"*, #user_76, *"I used to like working at Amazon but this year it feels like an unsustainable and unhealthy relentless grind.*

[...]", and #user_47, *[...] Today is my last day before maternity leave, and guess what? No card, no $. [...]*. These examples illustrate how sadness may emerge from frustration, perceived injustice, or unacknowledged efforts, highlighting the nuanced interplay between sentiment polarity and emotional depth.

Despite this, the highest combined percentages of *joy* and *optimism* were still found within the positive sentiment category. For instance, several positively classified posts expressed optimism or joy through their love for tech, as stated by #user_5, *"[...] I love tech, I love my career path, but I'm so done fighting for my seat at the table that I've already earned several times over. [...]"*, #user_393 *"[...] My initial thoughts were just, 'I love data. I love solving complex problems. Data is used for EVERYTHING. I should go for it!' [...]"*, and #user_238 *"[...] I love coding and being a part of tech. [...]"*. In contrast, neutral posts labeled with optimism or joy often involve sharing information, experiences, or resources within a community context, or recounting small, positive interactions and achievements. #user_232, #user_379 and #user_795, respectively highlighted: *"So I figured I'd share a funny story instead of just a horror story [...]"*, *"We're recruiting an all-women game dev team! [...]"*, and *"[...] I knitted and spun yarn and walked my dogs. And today my 2 rescue dogs passed their 3 odor recognition tests. [...]*. These results suggest a reasonable level of agreement between the emotion and sentiment classification models used in our study.

4.3 RQ$_3$: Impact of Policy Shifts on DEIA

Our dataset covers the period from April 2024-2025, with a key turning point on January 20, 2025, marked by a significant shift in U.S. federal support for DEIA policies [33]. We acknowledge that a one-year dataset may be limited in capturing the long-term effects of public policy changes. However, our goal was to explore whether there was any short-term shift in discourse in this period. To support this temporal comparison, we divided the dataset around the critical turning point of January 20, 2025; where 44% of the posts were published before this date, while 56% were published after it.

Figure 5 presents three charts on the temporal distribution of classifications across the following dimensions: (a) Linguistic patterns, including the detection of hate speech, irony, and offensive content; (b) Emotional classification of the posts; (c) Sentiment analysis. Our goal with these charts is to conduct an exploratory analysis to identify interesting patterns, aiming to delve deeper into them later. The y-axis of each chart represents the percentage volume of posts, while the x-axis corresponds to the timeline (year–month). A higher volume of posts in February, March, and April is expected due to the data extraction rules defined in Section 3.1.

In Figure 5(a), we observe the absence of hate speech even after the repeal of the DEIA policy. The figure shows an increase in ironic content in January 2025, followed by a slight drop in February, and a rising trend starting in March 2025. This may suggest increased user engagement with this rhetorical device, potentially indicating dissatisfaction expressed through humor or sarcasm. This leads us to believe that posts containing ironic content require further investigation to identify potential relationships among them, as well as recurring topics.

Regarding emotional distribution (Figure 5(b)), as anticipated, *sadness* was the most frequent emotion throughout the observed period. However, unexpectedly, *joy* became the second most frequent emotion between January and April 2025. This finding prompted us to seek additional validation methods, such as manual annotation or qualitative analysis, to better understand this outcome.

For the sentiment analysis (Figure 5(c)), as expected, neutral posts dominated the dataset, comprising 48% of the total. What stands out is the reversal between positive and negative sentiment volumes starting in March 2025. To determine whether this shift reflects a long-term trend or is merely seasonal—possibly related to International Women's Day celebrations in March—we intend to collect additional data beyond April 2025.

After analyzing the word frequency in offensive content (see Section 4.1), we identified some interesting findings. This led us to apply a follow-up analysis comparing patterns in the data before and after the implementation of the DEIA policy changes. Figure 6 presents word clouds of emotionally charged language: (a) before and (b) after the DEIA policy shift.

Both word clouds contain aggressive language, such as *st*, *fk*, among others. However, the occurrence of such terms increased after the defined turning point. Additionally, new terms emerged, including *a***, *toxic*, *freak*, and *uneducated*, suggesting that the tone of the offensive content may have become more intense.

Following our exploratory analysis of the data from the perspective of DEIA-related policies, we recognized the need to expand the data collection period to better evaluate public policies. Additionally, we plan to apply filters within the dataset to focus specifically on posts addressing this topic, which may yield more robust results in future analyses.

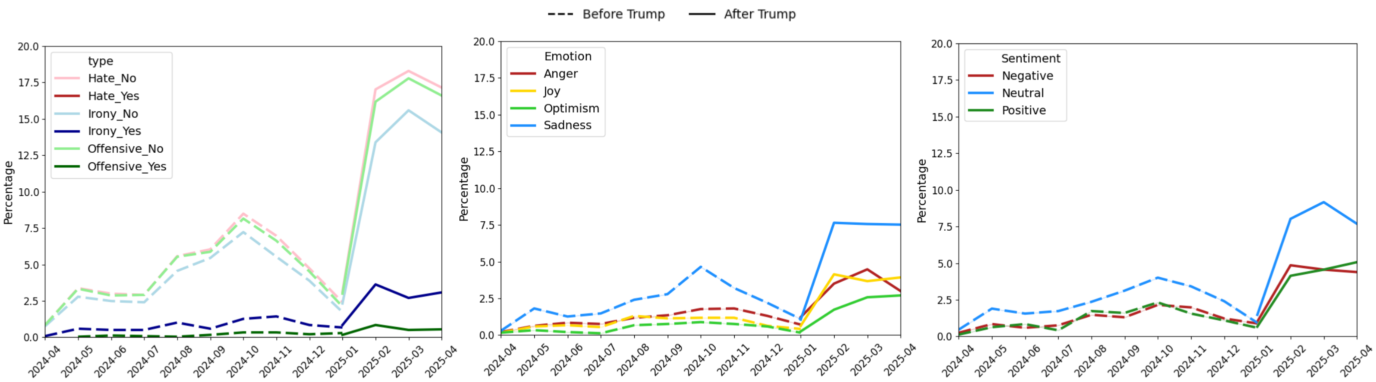
4.4 Threads to Validity

The RoBERTa model, fine-tuned on Twitter data, may misinterpret Reddit's longer post formats, subreddit-specific jargon, and sarcasm markers (*e.g.*, "/s"). These domain mismatches can misclassify the output labels. Future work will fine-tune the model in order to mitigate this threat. Moreover, the use of Reddit's "Top" filter may bias the dataset toward popular posts, excluding niche or time-sensitive discussions and potentially skewing sentiment and topic distributions. Additionally, our focus on a single women's subreddit from April 2024 to April 2025, capturing discourse before and after the January 20 DEIA policy repeal, limits the generalizability of results across platforms, communities, and timeframes.

Our temporal analysis is inherently correlational and cannot disentangle the effect of the policy change from other contemporaneous events within our one-year, single-forum window. Community dynamics, policy contexts, and discussion norms vary across different platforms and over time, so our findings may not hold in other subreddits, mixed-gender tech communities, or periods beyond early 2025. Finally, to manage model input constraints, we truncated Reddit posts, enabling classification but causing some context loss, especially in longer or rhetorically complex texts. This may impact label accuracy for subtle cues like sentiment or burnout. Future work will explore hierarchical encoding or sliding windows to better preserve context.

5 Future Plans

As future steps, we plan to conduct a qualitative analysis of the findings related to offensive content, emotions, and sentiment. We aim to improve our temporal analysis, as our initial exploratory



(a) Linguistic patterns **(b) Emotional tone** **(c) Sentiment analysis**

Figure 5: Temporal analysis from 04/01/2024 to 01/19/2025 (before the DEIA policy shift) and from 01/20/2025 to 04/20/2025 (after the DEIA policy shift)

(a) Before the DEIA policy shift

(b) After the DEIA policy shift

Figure 6: Temporal analysis of offensive word cloud

study revealed interesting patterns worth deeper investigation, such as the increase in the emotion *joy*, the rise in irony, and the intensification of offensive content starting in January 2025.

As we are working with long texts, we plan to perform our experiments using more recent chunking methods to identify the most suitable approach. We intend to apply topic modeling techniques, such as Latent Dirichlet Allocation (LDA) [17], BERTopic [4, 21], and Large Language Models (LLMs) [4, 21], to identify the main discussion topics, and map them to sentiment and emotion classifications, helping uncover recurring patterns in user experiences.

Since we have already collected the comments associated with each post, we aim to build an "emotion network" [28] by analyzing the emotional content of comments in response to emotion-labeled posts. This will allow us to detect patterns by sentiment and by user, identifying the most active participants in the interaction network. We also plan to include unexplored engagement metrics, such as comment count and post score, in future analyses. Finally, to improve model accuracy – since current models were trained on Twitter data – we will fine-tune RoBERTa on a manually annotated subset of our Reddit corpus.

6 Conclusion

The use of Reddit as a data source for crowd-based studies is not new; however, its application in the field of Software Engineering (SE) remains limited, primarily due to the need for carefully mapping the relevant communities [31]. For this reason, we chose to map the subreddit *r/womenintech*, a space built by and for women working in technology, where they can freely share their experiences and receive mutual support. Our main findings include the absence of hate speech and the predominance of the emotion *sadness* over a one-year period. The most prominent posts were personal accounts of negative experiences, suggesting that other users may have felt compelled to share similar stories or to offer support. To validate these assumptions more rigorously, we intend to investigate the emotional network structure through emotion graphs. Regarding offensive content, we observed that many posts include full quotations of aggressive language originally directed at the authors by others. In some cases, coworkers reportedly identified themselves as sexists and made sexist jokes openly (see Section 4.1). This highlights the need to implement actions or methodologies related to gender disparity and/or DEIA in these work environments.

ARTIFACT AVAILABILITY

The authors declare that the research artifacts supporting the findings of this study are accessible at Zenodo repository https://doi.org/10.5281/zenodo.17054583.

ACKNOWLEDGMENTS

This research was partially funded by the Brazilian funding agencies CAPES (Grant 88881.879016/2023-01), FAPESP (Grant 2023/00811-0), CNPq, and the Binational Cooperation Program CAPES/COFECUB (Ma1036/24). We also acknowledge the Brazilian company Stone[2] for their financial support.

[2]https://www.stone.com.br/

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