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Online Female Mutual Support Communities: Themes and Engagement Mechanism

By

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Abstract

Online mutual support communities provide vital spaces for individuals to seek guidance, share experiences, and engage in collective discourse. This study examines engagement dynamics within Douban's *Women in Academia* group, a digital support community for women in higher education. Using a large-scale dataset spanning over three years, this research employs Latent Dirichlet Allocation (LDA) to identify prevalent discussion topics and utilizes machine learning modeling to investigate factors influencing post engagement. The findings reveal that discussions primarily center around research advice, emotional expression, and feminist discourse, aligning with broader literature on online social support and gendered digital engagement. The results highlight that historical user activity, emotional intensity, and participatory behaviors strongly predict engagement levels. Additionally, interaction effects suggest that emotional expression plays a particularly significant role in feminist discussions. These insights contribute to the understanding of digital support mechanisms and provide practical recommendations for optimizing engagement strategies in online feminist and academic communities.

Keywords: Online Communities; Social Support; Feminist Discourse; Digital Engagement; Machine Learning; Network Analysis; Sentiment Analysis

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1 Introduction

The proliferation of digital communication has significantly reshaped the dynamics of social support, transforming the ways individuals seek informational and emotional resources. Online mutual support communities, particularly those tailored to historically underrepresented populations, offer crucial spaces for addressing professional challenges, emotional concerns, and structural inequalities. Among these groups, *Women in Academia* have increasingly leveraged online platforms to navigate barriers related to career advancement, mental health, and gender-based discrimination, highlighting a distinct need for scholarly exploration of these digital spaces.

However, existing literature has predominantly focused on general social media or broader online forums, with limited attention to the specific mechanisms and engagement dynamics within female-oriented digital support communities. This gap hinders comprehensive understanding of how women utilize these platforms to foster professional growth, emotional solidarity, and feminist advocacy. Additionally, there remains insufficient empirical investigation into culturally specific digital environments, particularly within Chinese online contexts, where platforms such as Douban provide unique spaces for discourse and mutual support.

Addressing these gaps motivates the current study, which systematically examines the thematic content and engagement patterns within Douban's *Women in Academia* group. This group represents an exemplary instance of an active, professionally oriented, feminist-inflected online support community. Preliminary observations indicate frequent exchanges around emotional expression, peer mentoring, and feminist commentary, suggesting structured patterns of interaction deserving rigorous academic inquiry. Accordingly, two primary research questions are proposed to guide the analysis:

Firstly, understanding prevalent discussion topics provides essential insights into the informational and emotional needs of the community members. Identifying dominant themes allows for a nuanced exploration of the core purposes these communities serve and helps clarify how participants engage with issues specific to their professional and personal lives. Therefore, RQ1 is raised:

RQ1: What topics are prevalent within the female mutual support community?

Secondly, identifying factors that contribute to the success of posts in terms of engagement is crucial for comprehending how interactions are fostered within online support communities. By determining which characteristics—such as emotional tone, user participation, or network positioning—drive visibility and response, this analysis can inform strategies for community moderation and enhancement of user experience. Therefore, RQ2 is raised:

RQ2: What factors contribute to the success of posts in terms of engagement?

To answer these questions, this study employs a mixed-methods computational approach, analyzing a comprehensive dataset spanning over three years of user-generated content and interactions within Douban's *Women in Academia* group. Specifically, Latent Dirichlet Allocation (LDA) is utilized to identify salient discussion topics, while XGBoost, a robust machine learning framework, is implemented to quantify the relative importance of content-level characteristics, user activity patterns, and network structural attributes in predicting post engagement.

The contributions of this study are threefold. First, it extends the theoretical and empirical understanding of online social support by integrating computational analysis with frameworks from feminist discourse studies and network theory. Second, it enriches the existing scholarship by introducing empirical data from Douban, a prominent yet underexplored Chinese social media platform, thereby enhancing the cross-cultural comprehension of digital feminist support environments. Third, the study identifies critical engagement drivers such as emotional intensity, historical user participation, and structural network positioning, providing actionable insights into community engagement optimization.

The findings of this research bear significant implications for both scholarly and practical realms. For academics, the analysis deepens theoretical insights into digital social support mechanisms, feminist digital activism, and networked engagement behaviors. For practitioners, the results inform strategic decisions in designing and moderating inclusive and effective online support communities. Overall, this research contributes substantively to interdisciplinary conversations across computational social science, communication studies, gender studies, and digital platform governance.

2 Literature Review

2.1 Online Social Support

Social support plays a crucial role in the well-being of its recipients, providing significant psychological and physical benefits (Baum et al., 2020; Goldsmith, 2004; Thompson et al., 2011). Historically, social support has been characterized as communication that imparts emotional, informational, or referential value, reducing stress or uncertainty (Walther & Boyd, 2002). With the proliferation of media technology, social support has seamlessly integrated into computer-mediated contexts, making online support communities increasingly appealing to those who prefer digital over face-to-face interactions (Chung, 2013).

Online social support offers numerous advantages. It connects individuals facing similar challenges across different geographical regions, providing a platform for support in situations where face-to-face interaction might lead to judgment or stigma (Parker & Thorson, 2009; Rains & Meng, 2022). These attributes are particularly beneficial in professional settings, where perceived similarity and credibility can facilitate the exchange of professional guidance and support. Online platforms enable individuals to find and interact with like-minded peers, overcoming barriers often encountered in traditional settings (Walther & Boyd, 2002; Wright et al., 2010).

This is particularly relevant for women, who frequently encounter significant barriers within offline academic settings due to gender disparities and the social distancing protocols enforced during the COVID-19 pandemic. For instance, women represent only 27.7% of the academic workforce in China, and this proportion diminishes further in higher academic ranks (National Science Library, 2022), reflecting a widespread "glass ceiling" effect (Cotter et al., 2001). Such gender imbalances are prevalent across various professional spheres in society. In response to the cessation of offline activities in 2020, the *Women in XXX* groups on Douban emerged as crucial platforms for networking and professional support, offering women vital resources for advancing their careers.

2.2 Online Feminism

Online feminism has become a formidable force in contemporary feminist activism, leveraging digital platforms to challenge gender inequalities and advocate for women's rights (Bailey et al., 2016; Trott, 2021). These online feminist communities enhance the empowerment of women by fostering open dialogue on critical issues such as gender discrimination, sexual harassment, and rights equality (Talbot & Pownall, 2022). Utilizing the vast reach and networking capabilities of social media, these groups expand feminist engagement by incorporating a wide array of voices and experiences (Crossley, 2018).

In this study, the proliferation of *Women in XXX* communities on Douban represents an extension of the broader trend of online feminism. These communities serve not only as support platforms but also as advocacy spaces that catalyze discussions on topics affecting women in China. The role of online feminism within these communities extends beyond support provision to include the cultivation of a collective identity that challenges existing social norms and stimulates discourse on gender-specific issues (Dixon, 2014; Morrow et al., 2015).

2.3 Network Structure and Social Support

Exploring network structures within online communities provides deep insights into the dynamics of social support (Granovetter, 2023; Wellman & Frank, 2017). Network theory suggests that the configuration of connections among individuals within a community significantly impacts the availability and quality of support (Hayat, 2022). For women in mutual support communities, the network structure determines how effectively members can access information, emotional support, and resources. Dense and interconnected networks typically facilitate rapid and comprehensive support distribution, while sparser networks might restrict access (Borgatti et al., 2009).

Moreover, an individual's position within a network, such as those in central or brokerage roles, often affects their ability to give and receive support (Monge & Contractor, 2003). Central members, because of their access to resources and information, are better positioned to provide support to others (Burt, 1992). This study will examine these dynamics by exploring how network structures within the *Women in XXX* communities on Douban affect the distribution and reception of support, thus providing a deeper understanding of the support mechanisms and their effectiveness in fostering environments conducive to women's empowerment and advocacy.

2.4 Female Mutual Support Communities

Female mutual support communities represent dynamic online spaces where women come together to exchange emotional, informational, and instrumental support tailored to their unique experiences. Grounded in social support theory, these communities have been shown to reduce stress and foster psychological well-being by creating networks of mutual aid and understanding (Goldsmith, 2004; Thompson et al., 2011). Unlike broader social networks, female mutual support communities specifically address challenges such as workplace discrimination, societal expectations, and the pressures of balancing professional and personal roles (Cotter et al., 2001).

The digital nature of these communities offers additional advantages. Online platforms provide a safe space for candid discussion, where anonymity and accessibility reduce the stigma often associated with sharing personal experiences (Chung, 2013). This virtual environment enables women from diverse backgrounds to overcome geographical and social barriers, fostering inclusivity and collective empowerment. The tailored focus of these groups not only facilitates the exchange of practical advice but also nurtures a sense of solidarity and collective identity, which is critical in challenging traditional gender norms.

Network dynamics within these communities further enhance their impact. Dense interconnections and active engagement among members promote rapid information diffusion and coordinated support, while central actors often play key roles in mobilizing community efforts and sustaining dialogue (Borgatti et al., 2009; Burt, 1992). Moreover, recent work on online feminism underscores that these communities are not merely support platforms; they are active agents in feminist advocacy, contributing to broader social movements that aim to redress gender imbalances (Bailey et al., 2016; Trott, 2021). In sum, female mutual support communities stand at the nexus of digital innovation and feminist activism, offering both immediate support and long-term empowerment in the face of ongoing societal challenges.

2.5 Main concepts and how does it relate to literature

2.5.1 Engagement Metrics

Engagement metrics such as likes, shares, and comments are widely recognized as effective tools for measuring social media users' involvement and assessing the virality of online posts (Brodie et al., 2011; Drivas et al., 2022; Yoon et al., 2018). These metrics provide immediate, quantifiable feedback on the reach and resonance of digital content. Likes are typically seen as a basic endorsement that signals user approval or interest, while shares facilitate the dissemination of content across personal networks, thus amplifying its visibility and potential for viral spread. Comments allow for more nuanced user interaction by capturing detailed opinions, questions, and discussions that enrich the overall conversation (Brodie et al., 2011; Drivas et al., 2022).

Academic research underscores the efficacy of these low-barrier interactions in gauging audience engagement and predicting content virality. Brodie et al. (Brodie et al., 2011) demonstrate that such metrics can serve as early indicators of both user sentiment and the likelihood of a post becoming viral. Complementarily, the qualitative insights gleaned from comments provide an in-depth understanding of the audience's reactions, thereby offering a fuller picture of user involvement (Brodie et al., 2011; Yoon et al., 2018).

Moreover, these engagement metrics are integral components of digital analytics frameworks employed by both researchers and industry practitioners. By monitoring these indicators over time, analysts are able to identify emerging trends, determine peak periods of interaction, and assess the effectiveness of various content strategies. This data-driven approach is crucial for real-time content optimization, ensuring that social media posts are not only reaching but also resonating with their intended audiences (Yoon et al., 2018).

In summary, engagement metrics such as likes, shares, and comments are highly effective and commonly used measures for evaluating social media involvement and post virality (Brodie et al., 2011; Drivas et al., 2022; Yoon et al., 2018). Their combined quantitative and qualitative insights provide a robust framework for understanding and enhancing digital content performance in today's dynamic online landscape.

2.5.2 Active Users

Active users are typically defined as those members who contribute significantly more posts or replies than the average community participant. These individuals are pivotal to the vitality of online communities, as their heightened activity not only sustains ongoing conversations but also plays a critical role in amplifying engagement metrics such as likes, shares, and comments. Research indicates that posts originating from active users are more likely to attract attention and prompt further interactions (Hemmings-Jarrett et al., 2017).

The concept of active users is underpinned by the widely recognized 90-9-1 principle, which observes that a small minority of users account for the vast majority of content creation in online environments (Carroll & Rosson, 1987). Moreover, empirical evidence suggests that active users benefit from a virtuous cycle (Chen et al., 2014; Ozimek et al., 2023): their increased visibility leads to more likes, shares, and comments, which further enhances their influence within the community. This pattern justifies the methodological decision to define active users as those with substantially higher posting and replying behaviors. By focusing on these key participants, researchers can gain deeper insights into the dynamics of digital engagement and better understand how content virality is driven by user activity (Ozimek et al., 2023).

In summary, active users serve as the backbone of social media communities. Their prolific posting behavior is strongly associated with higher engagement, making them critical targets for studies that seek to understand and leverage online community dynamics.

2.5.3 Network Centrality

Network centrality is a fundamental concept in social network analysis that captures the structural importance of individuals within a network. It determines the influence and connectivity of users by assessing their position relative to others (Borgatti et al., 2009; Monge & Contractor, 2003). Centrality measures such as in-degree, out-degree, and betweenness provide insights into how information flows through a network and how individuals contribute to engagement. Higher centrality often correlates with increased visibility and interaction, making it a crucial factor in understanding social dynamics within online communities (Burt, 1992; Monge & Contractor, 2003).

In-degree and out-degree centrality measure the direct connections an individual has within a network. In-degree centrality refers to the number of connections directed toward a user, signifying their popularity or authority in a given community. A high in-degree suggests that a user frequently receives responses or interactions from others, indicating a strong presence in the network (Bakshy et al., 2011; Contractor et al., 2011; M. E. J. Newman, 2010). Out-degree centrality, on the other hand, reflects the number of connections a user initiates by responding to others. Users with high out-degree centrality are active participants who frequently engage with content and contribute to discussions (Burt, 2000; Contractor et al., 2011; Shen et al., 2014). Both metrics are essential for evaluating user engagement, as individuals with higher degrees of centrality tend to generate more interactions and influence community discourse.

Betweenness centrality measures the extent to which a user acts as a bridge within a network, connecting different subgroups that might not otherwise interact (Bakshy et al., 2011; M. Newman et al., 2011). A user with high betweenness occupies a strategic position that facilitates information flow, making them an essential node in network cohesion (Burt, 1992, 2005; M. E. J. Newman, 2010). Studies have shown that individuals with high betweenness centrality often have greater social capital because they control access to information and can influence discussions by introducing new perspectives (Burt, 1992, 2005; Granovetter, 2023). In online communities, these users frequently mediate interactions between different clusters, leading to higher engagement with their posts (Contractor et al., 2011; Lungeanu et al., 2023; Pan et al., 2020; Shen et al., 2014). Their visibility and role in shaping discussions make them more likely to attract likes, shares, and comments, reinforcing their influence within the network.

Centrality is a critical determinant of user engagement and support provision in online communities (Bakshy et al., 2011; Contractor et al., 2011; Monge & Contractor, 2003; M. Newman et al., 2011). Users with high centrality metrics—whether measured through in-degree, out-degree, or betweenness—are more likely to receive engagement due to their established visibility and network position (Dambanemuya et al., 2024; Pan et al., 2020; Shen et al., 2014). Posts from highly central users are more likely to be liked, shared, and commented on because these users are perceived as credible and influential within the community. Additionally, high betweenness centrality positions users as gatekeepers of information, making their content more valuable for knowledge dissemination and discussion (Dambanemuya et al., 2024; Pan et al., 2020; Shen et al., 2014; Talbot & Pownall, 2022). The structural advantages conferred by network centrality highlight its role in shaping social interactions and fostering active participation in digital communities.

2.5.4 Male-inclusion policy

A key aspect of this study is examining the impact of male participation on engagement and interaction patterns within female-oriented communities. The dataset is divided into two periods: before and after July 2022, when stricter gender-verification rules were implemented in the *Women in Academia* group. This policy shift followed heightened discussions about male involvement in feminist spaces, leading to the group becoming exclusively female.

Before July 2022, male users could participate in discussions, contributing to engagement dynamics that included interactions between genders. After July 2022, the implementation of stricter verification rules aimed to foster a female-only space, potentially altering the nature of discussions, support dynamics, and overall community engagement.

This division allows for a direct comparison of community behavior under different inclusion policies while keeping the dataset structurally unified. By analyzing engagement metrics, sentiment trends, and network structures across both periods, this study also assesses whether male participation influenced users' engagement level. This approach provides better control over external variables and enables a clearer understanding of how gender composition affects community interactions. The findings will offer insights into the role of male inclusion policies in shaping digital feminist communities.

3 Data and Methods

3.1 Data

The dataset for this study was collected from the Douban Group *Women in Academia* using a Python web crawler. The dataset comprises 5,254 original posts and 13,657 post-reply pairs, which represent the network's edges in the reply network. The data spans from the group's inception on September 18, 2020, to December 31, 2023.

For each original post, the following attributes were extracted: post content, author name, publishing time, engagement metrics (including the number of likes, comments, reposts, and collections), and the timestamp. The reply data includes an edgelist capturing the reply relationships within the community, detailing the original post, the name of the original post's author, the comment, the name of the comment's author, and the timestamp of the comment. These structured data points were specifically selected because they directly contribute to addressing the study's two primary research questions by enabling content analysis for identifying prevalent topics and quantitative modeling for understanding factors influencing post engagement. Additionally, these attributes were reliably accessible and systematically extractable through automated web crawling from Douban.

The chosen approach—collecting and analyzing engagement and network data from the Douban Group *Women in Academia*—is optimal for answering the research questions as it captures real user behaviors and interactions in an organic, unfiltered manner. This method ensures high ecological validity by examining user-generated content and engagement metrics as they naturally occur. Specifically, this dataset provides direct measures of topic prevalence (RQ1) and engagement factors (RQ2). To investigate RQ1, Latent Dirichlet Allocation (LDA) is applied to the large-scale collection of original posts to uncover the underlying thematic structure of discussions and identify the most prevalent topics within the community. To address RQ2, sentiment analysis, active user detection, and social network features are combined within an XGBoost regression framework to model and evaluate the relative importance of various content-level, user-level, and structural factors in predicting engagement outcomes, while controling the male-inclusion policy's potential impact. This integrated methodological approach enables a comprehensive understanding of how female mutual support communities function both in terms of what is discussed and how different types of content and users drive interaction. Furthermore, the dataset's longitudinal nature (spanning over three years) enables the study of long-term trends, making it particularly suitable for assessing engagement dynamics over time.

Alternative methodological approaches, such as surveys or experimental designs, would introduce several limitations. Surveys, while useful for capturing subjective experiences, suffer from self-report bias, where users may misrepresent their engagement levels due to memory recall issues or social desirability bias. Additionally, surveys often fail to capture the full scope of interactions, especially those from passive users (lurkers) who engage with content but do not actively contribute. In contrast, experimental methods, such as manipulating post content to observe engagement changes, present ethical and feasibility challenges. Experimentation would require direct intervention in an existing community, which could disrupt organic interactions and reduce the authenticity of the findings. Moreover, experimental studies are often constrained in duration, limiting their ability to capture long-term engagement trends.

Compared to these alternatives, the chosen approach offers a robust, data-driven perspective on engagement in online support communities. By leveraging naturally occurring data, this study avoids the biases associated with self-reported engagement and artificial experimental conditions. The availability of structured engagement metrics—likes, shares, and comments—along with network centrality measures, provides a reliable basis for evaluating user influence and content virality. Furthermore, the use of network analysis enables the identification of key actors and structural relationships within the community, shedding light on how social capital is distributed and how engagement propagates through the network. The combination of content analysis and network modeling ensures that the study can comprehensively address its RQs, making this approach the most effective and feasible choice for examining engagement patterns, user activity, and support mechanisms in the *Women in Academia* community.

3.1.1 Data Structure

The main unit of observation in this study is the individual post within the Douban Group *Women in Academia*. Each post represents a unique instance of user-generated content, along with its associated engagement metrics (replies, likes, collects, and reposts) and textual characteristics. In total, the dataset comprises 5,254 observations, corresponding to 5,254 original posts. Descriptive statistics of engagement metrics and the lengths of the posts are shown below:

Based on the box plots presented in Figure 1, there are significant outliers across all engagement metrics, including replies, likes, collects, and reposts, as well as in the length of text. These outliers correspond to posts that have received exceptionally high engagement

Table 1: Descriptive Statistics of Engagement Metrics and Text Length

	Reply	**Like**	**Collect**	**Repost**	**Length of Text**
Count	5254	5254	5254	5254	5254
Mean	14.675	1.808	2.159	0.737	222.056
Std	25.209	2.221	2.410	1.584	388.730
Min	0.000	0.000	0.000	0.000	1.000
25%	3.000	0.000	0.000	0.000	55.000
50% (Median)	8.000	1.000	1.000	0.000	115.000
75%	19.000	3.000	3.000	1.000	242.000
Max	1115.000	9.000	9.000	9.000	9262.000

compared to the majority of posts in the dataset. While extreme values can sometimes indicate errors or anomalies, in this context, they are likely to represent posts that were particularly influential, informative, or resonated strongly with the community.

Rather than excluding these outliers, I retained them in the dataset because they provided critical insights into the posts that generate the most engagement. Removing them would risk discarding highly informative cases that help explain key patterns of interaction within the *Women in Academia* community. However, to mitigate potential statistical challenges posed by these extreme values—such as skewed distributions or heteroscedasticity—I implemented threshold-based transformations where necessary. Specifically, engagement metrics such as likes, replies, reposts, and collections were categorized into binary variables using thresholds based on their median values (e.g., high-like vs. low-like, high-reply vs. low-reply). For instance, posts receiving replies above the median count were classified as "high-reply," while those below the median were labeled as "low-reply." These binary transformations were applied in subsequent statistical analyses, particularly in engagement modeling with XGBoost, to enhance model robustness while preserving the explanatory significance of highly engaged posts.

3.1.2 Transformations

In the preparatory stages of textual data analysis, several transformations were applied to structure the data for computational handling. These transformations were necessary to accommodate both the characteristics of social media text and the linguistic properties of the Chinese language.

First, standard preprocessing techniques were employed, including tokenization, normalization, and lemmatization. Tokenization involved segmenting the text into meaningful units, which, in the case of Chinese, required specialized word segmentation tools due to the absence of spaces between words. The segmentation process was conducted using `jieba.cut()`, ensuring that individual words could be effectively analyzed. Subsequently,

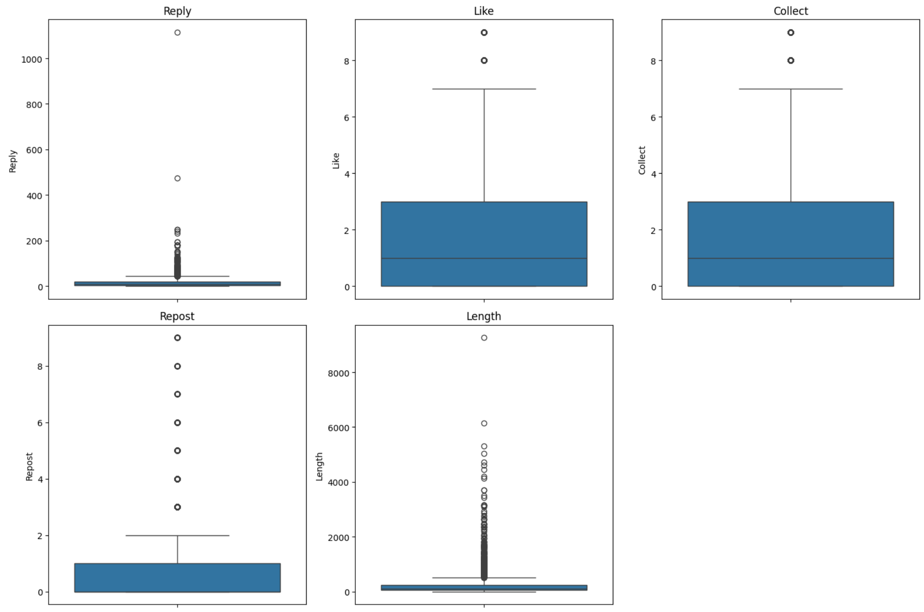

Figure 1: Box plot of engagement metrics and text length, showing significant outliers.

tokenized text was normalized by removing punctuation and other non-essential characters to improve the consistency of textual representations.

To facilitate advanced textual analysis, sentence-level tokenization was also performed, generating structured lists where each sentence was represented as an ordered sequence of words. This step ensured that subsequent natural language processing (NLP) techniques, such as topic modeling or sentiment analysis, could be applied efficiently. Given the unique complexities of processing Chinese text, multiple formatted datasets were created to ensure compatibility with various analytical methodologies. The transformations applied to textual data are summarized in Table 2.

Beyond textual transformations, engagement metrics were also adjusted where necessary. To address potential skewness in engagement distributions, threshold-based binarization was considered. For example, high-like vs. low-like categories were introduced to reduce the impact of extreme values while preserving meaningful engagement patterns. This transformation was particularly useful when statistical challenges such as heteroscedasticity or non-normality arose.

Overall, these transformations enhanced the dataset's analytical utility, ensuring that it was well-prepared for computational processing while maintaining the integrity of user interactions and engagement patterns.

Table 2: Text Processing

Original text	**Segmented text**	**Tokenized text**	**Normalized text**	**Tokenized sentences**
The original post.	Segment the original post with spaces (with help of `jieba.cut()`)	Tokenize the original post. (with help of `jieba.cut()`)	Delete the punctuations from tokenized text.	Create a list of lists, where each inner list consists of all the tokens from a single sentence.

3.1.3 Exploratory Data Analysis (EDA)

Figure 2 presents the monthly distribution of posts from September 2020 to December 2023. A clear downward trend is observed over the four-year period, with the highest volume of posts occurring at the group's inception. This initial peak can be attributed to the establishment of community guidelines and discussions around group norms. Additionally, a recurring seasonal pattern emerges, with noticeable peaks in the first and fourth quarters of each year. This trend likely reflects the academic cycle, where members of *Women in Academia* engage in job searches and Ph.D. applications during the fourth quarter and subsequently prepare for interviews in the first quarter. These observations suggest that user engagement follows a seasonal pattern, which should be considered when conducting comparative analyses to account for temporal variations.

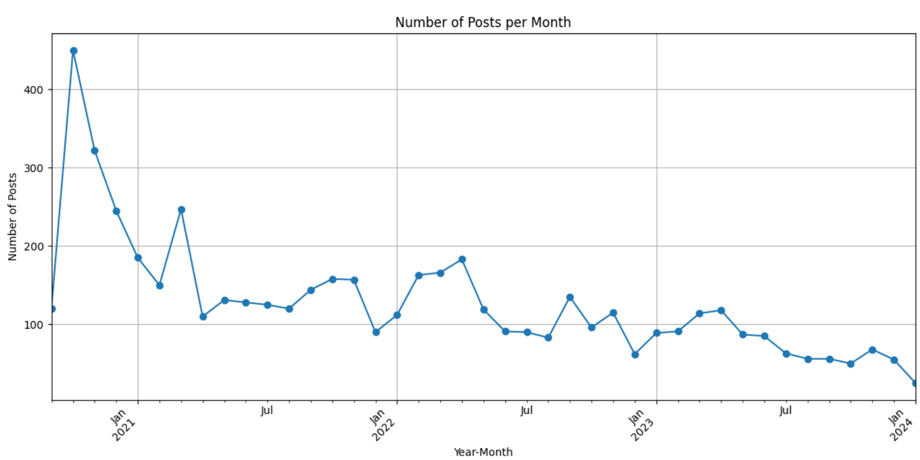

Figure 2: Monthly distribution of posts from September 2020 to December 2023.

Figure 3 displays the correlation matrix of engagement metrics, illustrating the relationships between replies, likes, collects, reposts, and text length. The color intensity and numerical values indicate that the highest correlation coefficient is 0.31, while most values remain below 0.3, suggesting no strong multicollinearity among these variables. In statistical analysis, multicollinearity becomes problematic when correlation coefficients exceed 0.7 or 0.8, as it can inflate variance and distort regression estimates. Since all observed correlations are significantly lower, multicollinearity is not a concern in this dataset.

Moreover, this matrix highlights the distinct contribution of each variable to engagement. While some metrics, such as likes and collects (0.30) or reposts and replies (0.31), share moderate associations, each metric captures a unique dimension of user interaction. Likes reflect content approval, replies indicate active discussion, collects suggest information value, and reposts measure content amplification. The relatively low correlations confirm that these metrics do not redundantly measure the same behavior, justifying their inclusion in statistical models. Overall, this visualization confirms that engagement metrics provide complementary insights rather than overlapping information, ensuring their robustness for further analysis.

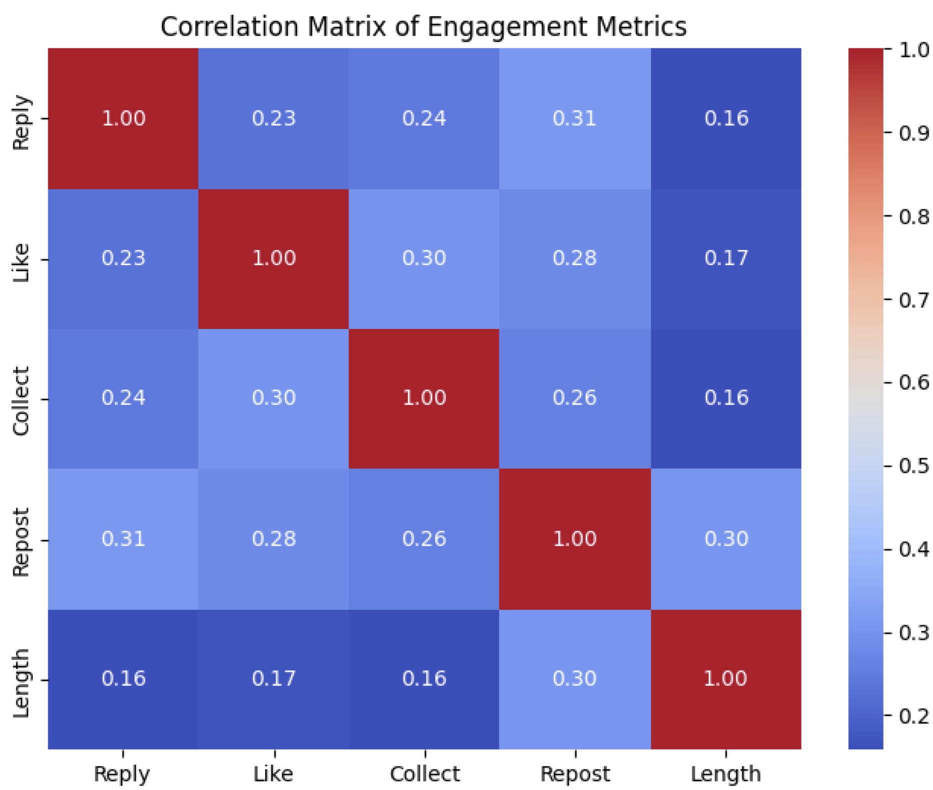

Figure 3: Correlation matrix of engagement metrics, showing relationships between replies, likes, collects, reposts, and text length.

While multiple engagement metrics—such as likes, reposts, collects, and replies—were extracted from Douban, this study specifically employs the number of replies as the primary measure of engagement. Replies were chosen as they represent active, conversational interactions and therefore best capture the dynamics of user-to-user support exchanges within online mutual support communities. Unlike passive engagement indicators (e.g., likes or collects), replies explicitly reflect reciprocal communication and deeper involvement in discussions, aligning closely with the study's theoretical framework emphasizing interactive social support. Moreover, replies facilitate the construction of user interaction networks, allowing analysis of structural dynamics such as centrality and reciprocity. This choice, therefore, enables a richer and more nuanced examination of the social mechanisms underlying community engagement patterns.

3.2 Methods

3.2.1 Sentiment Analysis

To determine the sentiment tendencies of each post, I tested two approaches: Hugging Face Transformers and SnowNLP, both of which are designed for Chinese text sentiment analysis. Their performance was evaluated on 100 randomly selected posts, revealing that SnowNLP achieved full accuracy, while Hugging Face Transformers correctly classified only 41 of the 100 posts. The likely reason for this discrepancy is that Hugging Face Transformers was trained primarily on online merchant reviews, which may not generalize well to feminist community discussions.

Based on these findings, I selected SnowNLP for sentiment analysis of the entire dataset. SnowNLP generates a continuous sentiment score for each post, ranging from 0 (most negative) to 1 (most positive). To incorporate sentiment into the engagement model, it was necessary to further transform this score into a measure of *sentiment intensity*, reflecting the extremity of emotional expression regardless of polarity.

Specifically, sentiment intensity was operationalized as the absolute distance of the sentiment score from the neutral midpoint of 0.5, following approaches recommended in the literature for capturing the strength, rather than just the direction, of affective language (Hoemann & Barrett, 2017; Liu et al., 2016). This transformation is formalized as follows:

$$\text{Sentiment Intensity} = |\text{Sentiment Score} - 0.5|$$

A value close to 0 indicates a neutral or weakly expressed sentiment, while a value closer to 0.5 reflects higher intensity—either strongly positive or negative. This approach enables the model to account for posts that, while differing in polarity, may equally drive engagement due to their emotional vividness.

The rationale for using sentiment intensity instead of a simple positive/negative dichotomy is grounded in research demonstrating that posts with stronger emotional expression, regardless of valence, are more likely to elicit engagement and interaction in online communities (Ferrara et al., 2015; Stieglitz & Dang-Xuan, 2013). Intensity-based measures provide a more granular and predictive indicator of user response than binary sentiment labels. Consequently, sentiment intensity was included as a continuous predictor in the engagement modeling framework to capture the nuanced effects of emotional expression on community dynamics.

3.2.2 Active User Detection

Active users were identified based on two engagement criteria: posting frequency and replying frequency. The interquartile range (IQR) method was applied to detect users with significantly higher engagement levels.

The IQR method defines outliers using the range between the first quartile (Q1) and the third quartile (Q3). A user was classified as an active user if their engagement exceeded the upper bound, calculated as:

$$\text{Threshold} = Q3 + 1.5 \times \text{IQR}$$

For both posting frequency and replying frequency, the threshold was determined to be 3.5. Users who posted or replied more than 3.5 times were marked as active users. Two binary features were created to distinguish active users by each criterion, and users meeting both thresholds were classified as active under both criteria. The analysis revealed that 73.13% of users identified as active by one criterion were also active by the other, confirming consistency in user engagement patterns.

3.2.3 Topic Modeling (LDA)

To analyze the thematic structure of discussions within the *Women in Academia* community, Latent Dirichlet Allocation (LDA) was applied to uncover latent topics present in user-generated posts. LDA is an unsupervised probabilistic model that identifies recurring themes by capturing word co-occurrence patterns, allowing for the categorization of posts into distinct topics. Six topics were extracted from the dataset, providing a structured understanding of the primary areas of discussion.

The Intertopic Distance Map generated through pyLDAvis, revealed significant thematic overlap among Topics 1, 2, 3, and 4, indicating shared linguistic and conceptual features. A qualitative analysis of the top-30 most relevant terms within each topic, along with representative posts, led to the identification of three overarching themes that characterize user engagement in this online community.

Research Advice (Topics 1, 2, 3, and 4) consists of discussions surrounding academic methodologies, writing strategies, career progression, and research-related challenges. Users frequently seek guidance on PhD applications, journal submissions, and balancing research with other commitments. For instance, one post exemplifies this theme:

> *As the title says, I see that many applicants apply for PhD after they have some work experience. In normal job hunting, having a work background in a famous company will be helpful. When applying for a PhD, which one will be more important, work experience or academic research experience (publication, conference, research, etc.)?*

Emotional Expression (Topic 5) is a significant aspect of the community, reflecting the need for a supportive space where users can express feelings of stress, self-doubt, and career uncertainty. Posts in this category often address struggles with concentration, productivity, and mental well-being, reinforcing the role of the platform as a space for empathy and solidarity. A representative post highlights this sentiment:

> *Recently I can only read 20 pages of a book in more than an hour. I often lose focus. When it is serious, I can't turn over a few pages of the book in the whole morning. I am distracted by various things. When I was an undergraduate, I not only had less distraction, but I could also concentrate on reading boring books and papers. Is it because I am getting older and my physical strength is not good enough? Recently, when I looked in the mirror, I noticed wrinkles at the corners of my eyes. I can't stay up late anymore. I am so sad.*

Feminism Discussions (Topic 6) captures conversations about gender-related experiences in academia, including sexism, bias in hiring and mentorship, and broader discussions on feminist ideology. This theme highlights the ways in which women in academic settings confront and navigate structural inequalities. One post exemplifies these challenges:

> *I am in my second year of graduate school. My current supervisor is an experimentalist, but he is a bit biased towards boys and thinks boys are more suitable for doing experiments. My senior said that the supervisor supports our idea. I also mentioned to the supervisor that I want to study abroad for a doctorate, but the supervisor's reaction was a bit cold. He said that he hadn't contacted the school for a long time and asked if they wanted students when the time comes.*

3.2.4 Classification with Large Language Models (LLMs)

To classify posts as either **support-seeking** or **support-provision**, I utilized the DeepSeek-V3 API, which has demonstrated strong performance in Mandarin Chinese text processing.

The API's advanced NLP capabilities will help distinguish subtle differences in intent and sentiment within posts. By applying this classification, the directed network can be reconstructed, enabling more precise insights into how users seek and provide support within the community.

3.2.5 Network Analysis

To examine the structural relationships that characterize user interactions within the *Women in Academia* community, an initial network analysis was performed utilizing the reply data. An edgelist was constructed based on directional interactions, specifically mapping connections from repliers to the authors of the original posts. This foundational network structure was developed using the `networkx` library, which enabled systematic computation of relevant network metrics.

Key measures included in-degree (in-replies), representing the number of replies a user received and thus serving as a proxy for the level of attention or influence their posts commanded within the community. Conversely, out-degree (out-replies) was calculated to capture the extent of a user's active engagement, reflected by the number of replies they contributed to others. Additionally, betweenness centrality was assessed to determine the degree to which individual users acted as intermediaries or bridges connecting disparate parts of the network, highlighting their potential role in facilitating information flow and support distribution.

Preliminary efforts to detect cohesive sub-communities within this network did not yield notable clusters, a limitation likely attributable to the insufficient directionality in the initial network construction. To address this, it was determined that a more granular classification distinguishing between support-seeking and support-provision posts is required. Introducing this distinction will enable the creation of a directed network that more accurately captures the direction and nature of support exchanges, thereby enhancing the capacity to analyze community structure and interaction dynamics.

3.3 Modeling

Building on the justification for XGBoost, this section details the modeling process employed to analyze user engagement. The methodology follows a structured pipeline consisting of feature selection, baseline model implementation, hyperparameter optimization, interaction term testing, and feature interpretation.

First, feature selection and preprocessing were conducted to ensure the inclusion of relevant variables. Features were categorized into four distinct levels: content-level, user-level, structure-level, and rule-level (see Table 3). Several variables, including sentiment intensity, topic classifications (e.g., feminism, research advice), and support-providing indicators, were generated using computational methods such as SnowNLP, DeepSeek-V3 API, and Latent Dirichlet Allocation (LDA). Given that these features were automatically derived, their reliability was assessed using Cohen's kappa score, which compares computer-generated labels with human-coded annotations. As illustrated in Figure 4, the kappa scores exceeded 0.8, indicating a substantial level of agreement and supporting the validity of these features for modeling.

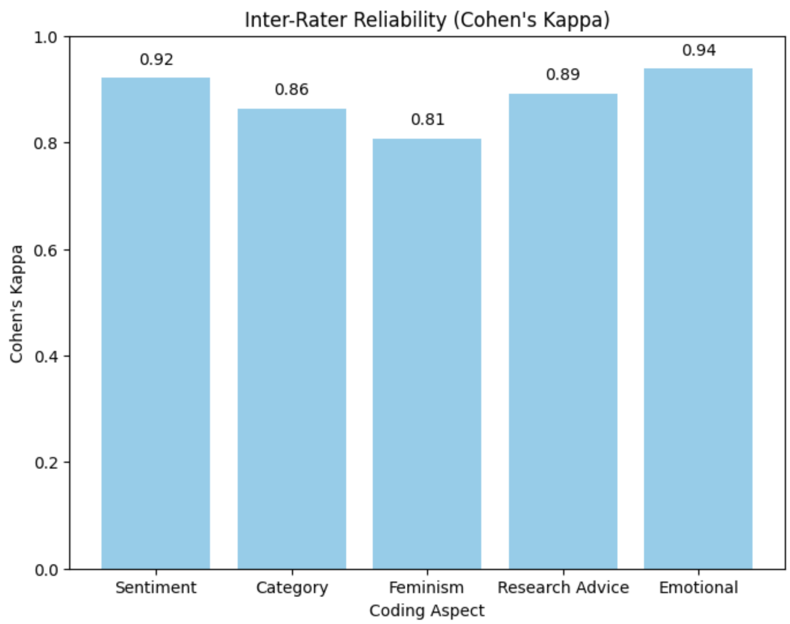

Figure 4: Cohen's Kappa Score for Computationally Generated Labels

Following feature selection, a baseline XGBoost model was trained using all selected features to establish an initial benchmark for performance. The model's effectiveness was evaluated using standard regression metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). This step provided insights into the overall predictive power of the model before optimization.

To enhance model performance, hyperparameter optimization was conducted through GridSearch, which systematically tuned key parameters such as maximum tree depth (max_depth), number of estimators (n_estimators), learning rate (learning_rate), and regularization strength (reg_lambda). The optimized model yielded improved performance metrics and refined feature importance rankings, thereby enhancing its predictive accuracy.

To further explore potential interaction effects, additional interaction terms were introduced into the model. Specifically, the study examined whether feminism-related discussions

Feature	**Definition**	**Purpose**
Content-Level		
Length	Total number of characters in the post	Captures post verbosity and potential impact on engagement
sentiment_intensity	Intensity of sentiment (positive/negative) using SnowNLP	Measures emotional strength, influencing reply engagement
Provide	Binary indicator of support-providing posts	Differentiates support-seeking from support-providing, influencing engagement
Feminism	Binary indicator of feminism discussion in the post	Identifies feminism-related content influencing engagement
Research_Advice	Binary indicator of research advice in the post	Captures educational support, influencing guidance-seeking
Emotional	Binary indicator of emotional expression in the post	Reflects emotional disclosure, enhancing empathetic interactions
User-Level		
PostCount	Number of posts the author published before the current post	Identifies active users with higher visibility and credibility
ReplyCount	Number of replies the author commented on before the current post	Captures engagement behavior and social reciprocity
Structure-Level		
In_Replies	Number of incoming replies received by the author	Indicates author's influence and social standing
Out_Replies	Number of outgoing replies posted by the author to others	Reflects proactive engagement in conversations
In_Betweenness	Betweenness centrality from incoming replies	Shows author's role as a conversation mediator
Out_Betweenness	Betweenness centrality from outgoing replies	Captures author's influence in initiating discussions
Rule-Level		
male_excluded	Binary indicator of male exclusion in the discussion	Captures gender dynamics and homophily effects on engagement

Table 3: Features Used in the Model

interact with male exclusion (Feminism $\times$ male_excluded) and whether feminist discourse is amplified by sentiment intensity (Feminism $\times$ sentiment_intensity). The revised model's performance was compared against the previous iteration, revealing that the inclusion of interaction terms did not significantly improve predictive accuracy. This suggests that individual features sufficiently captured engagement dynamics without requiring additional interaction modeling.

Lastly, feature importance and interpretability were assessed using both XGBoost's built-in importance scores and Shapley Additive explanations (SHAP) analysis. Feature importance rankings highlighted ReplyCount, PostCount, and male_excluded as the most influential predictors, underscoring the role of user activity and gender-related discussion dynamics in engagement levels. SHAP analysis further elucidated the direction and magnitude of these effects, enhancing interpretability and supporting theoretical insights into user interaction patterns.

By following this structured approach, the final model was designed to be both robust and interpretable, leveraging machine learning techniques to uncover key drivers of engagement in online feminist and knowledge-sharing communities.

4 Results

4.1 Prevalent Topics

The topic modeling results provide insights into the RQ1: *What topics are prevalent within the female mutual support community?* Discussions in this community primarily revolve around research guidance, emotional expression, and feminist discourse. The prevalence of research advice as the dominant theme highlights the practical and career-oriented nature of many interactions, with users frequently seeking strategies for academic success. These discussions emphasize PhD application strategies, research methodologies, and balancing professional and personal growth within academia.

At the same time, emotional expression emerges as a crucial aspect of the community, demonstrating the need for a supportive space where users can share concerns related to stress, self-doubt, and career uncertainty. Posts in this category frequently address struggles with concentration, productivity, and mental well-being, reinforcing the role of the platform as a space for empathy and solidarity.

The presence of feminism discussions underscores the unique challenges faced by women in academia. Posts in this category frequently address issues of gender bias, unequal access to opportunities, and the navigation of male-dominated academic environments. The discussion of gender-related experiences suggests that the community not only serves as a support system but also as a platform for addressing systemic inequities.

These findings align with the broader literature on online mutual support communities, demonstrating that such platforms facilitate both informational and emotional exchanges, with an added layer of advocacy and identity-based discourse in feminist-leaning spaces. The results suggest that engagement within these communities is shaped by a combination of pragmatic advice-seeking behaviors, emotional reinforcement, and collective discussions on gender-based challenges.

4.2 Factors Influencing Engagement

4.2.1 Initial Model

The initial model was developed to assess the predictive capacity of various content-level, user-level, structure-level, and rule-level features in determining the number of replies a post receives. Given the long-tailed distribution of the reply count, a log-transformation was applied to the target variable to improve model stability and performance. XGBoost was selected as the primary modeling approach due to its ability to capture non-linear relationships, manage imbalanced data, and provide interpretability through feature importance analysis.

To enhance model performance, hyperparameter tuning was conducted using GridSearch. The optimized parameters included an increased number of estimators (`n_estimators` = 1000), a depth constraint on individual trees (`max_depth` = 6), a lower learning rate (`learning_rate` = 0.01) to refine updates during training, and sub-sampling strategies (`subsample` = 0.8, `colsample_bytree` = 1.0) to reduce overfitting. Additionally, an L2 regularization term (`reg_lambda` = 10) was applied to control model complexity and prevent excessive variance.

Following these refinements, the model achieved a Mean Absolute Error (MAE) of 4.4658 and a Mean Squared Error (MSE) of 106.3576, with an R-squared value of 0.6789. Compared to the untuned version, the optimized model demonstrated a better fit, reducing error rates while maintaining interpretability. The performance metrics are summarized in Table 4.

Table 4: Performance Metrics of the Optimized XGBoost Model

Metric	**Value**
Mean Absolute Error (MAE)	4.4658
Mean Squared Error (MSE)	106.3576
R-squared (R^2)	0.6789

A comprehensive feature importance analysis was conducted to identify the key predictors of engagement. As illustrated in Figure 5, ReplyCount and PostCount emerged as the most influential features, underscoring the significance of prior user activity in shaping engagement levels. Sentiment intensity and Emotional expression were also among the top-ranked predictors, suggesting that emotionally charged content tends to elicit a higher number of replies. In contrast, Out_Betweenness exhibited consistently low importance, indicating its limited relevance in engagement prediction.

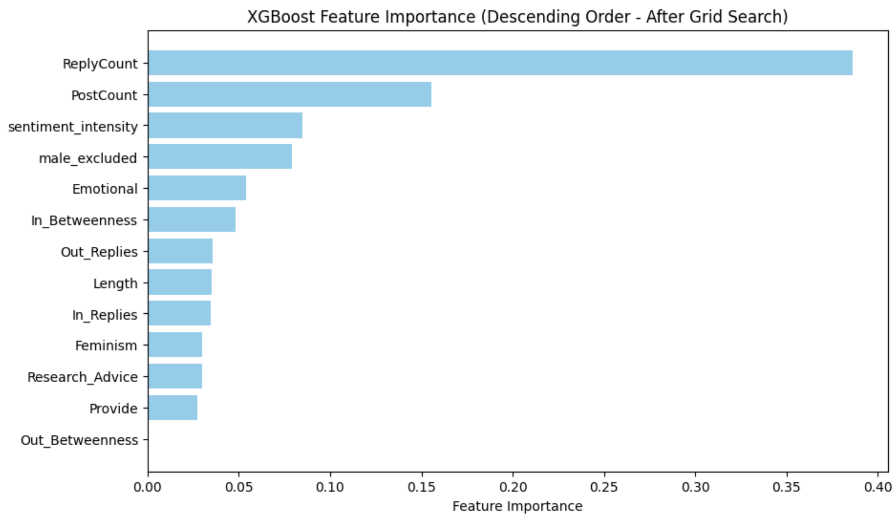

Figure 5: Feature Importance in the Optimized Model

To further examine the impact of individual features, SHAP (SHapley Additive exPlanations) analysis was employed, as depicted in Figure 6. The results confirm that higher values of ReplyCount positively impact engagement, reinforcing the notion that users who frequently engage with others are more likely to receive replies themselves. Conversely, an increase in PostCount appears to be associated with fewer replies, which may indicate a saturation effect where highly active users experience diminishing engagement returns. Notably, sentiment intensity displayed a clear relationship with reply counts, with both strongly positive and strongly negative posts receiving more engagement than neutral ones. This suggests that emotionally expressive content fosters user interaction. Additionally, posts containing emotional expressions tended to receive more replies, further reinforcing the importance of affective communication in online discussions.

The results of this analysis highlight the central role of user engagement history and emotional expressiveness in predicting the number of replies a post receives. While hyperparameter tuning improved the model's predictive capability, potential interaction effects between key variables remain unexplored. Specifically, the interplay between Feminism and male_excluded, as well as between Feminism and sentiment_intensity, may contribute to variations in engagement patterns. Therefore, the next phase of analysis will involve incorporating interaction terms into the model to evaluate their potential influence on en-

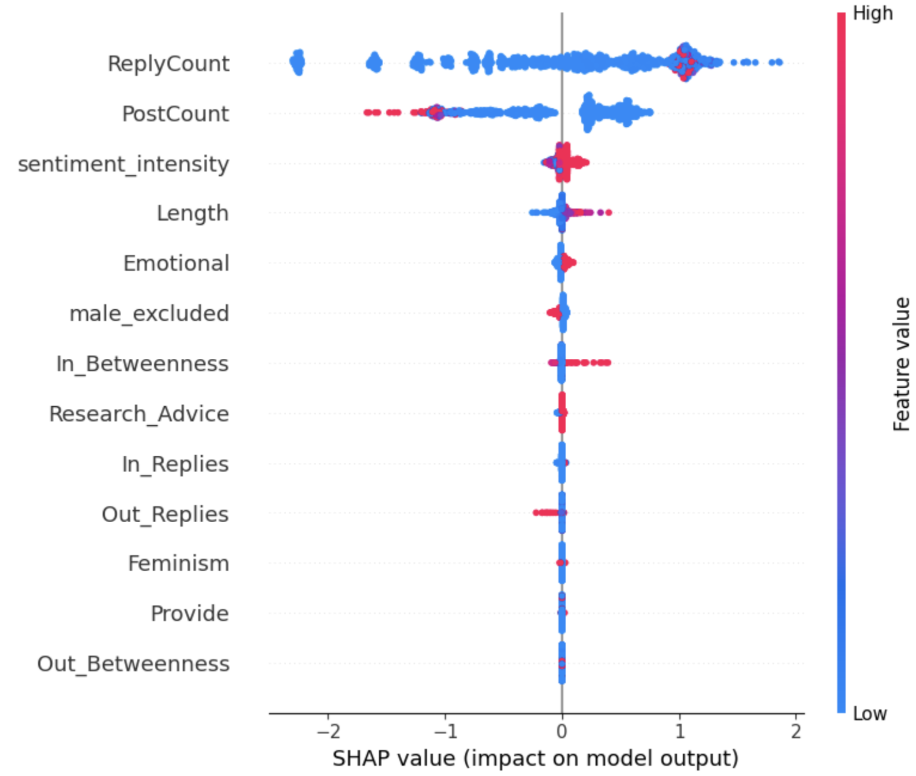

Figure 6: SHAP Summary Plot for the Optimized Model

gagement prediction.

4.2.2 Integrating Interaction Terms

To further explore potential moderating effects in user engagement, interaction terms were introduced into the model. Specifically, two interaction terms were considered:

- *Feminism* × *male_excluded*, which examines the influence of gender dynamics on engagement within feminism-related discussions.
- *Feminism* × *sentiment_intensity*, which investigates the impact of emotional intensity within posts discussing feminism.

The inclusion of these interaction terms aimed to capture nuanced relationships that could better explain engagement variations. The model was retrained with these additional terms, maintaining the optimized hyperparameters from the previous GridSearch tuning.

The updated model's performance metrics indicate an improvement in explanatory power. The mean absolute error (MAE) was recorded at 4.2852, while the mean squared error (MSE) was 102.9566. Notably, the R-squared (R^2) value increased to 0.6892, the highest among all tested models, suggesting that the interaction terms contributed to explaining additional variance in user engagement.

Figure 7 presents the feature importance rankings (based on the variable importance scores) for the final model. The interaction term *Feminism* $\times$ *sentiment_intensity* demonstrated non-negligible importance, implying that emotional intensity played a significant role in driving engagement in feminism-related discussions. Meanwhile, *Feminism* $\times$ *male_excluded* had lower importance but still suggested a potential moderation effect of gender dynamics.

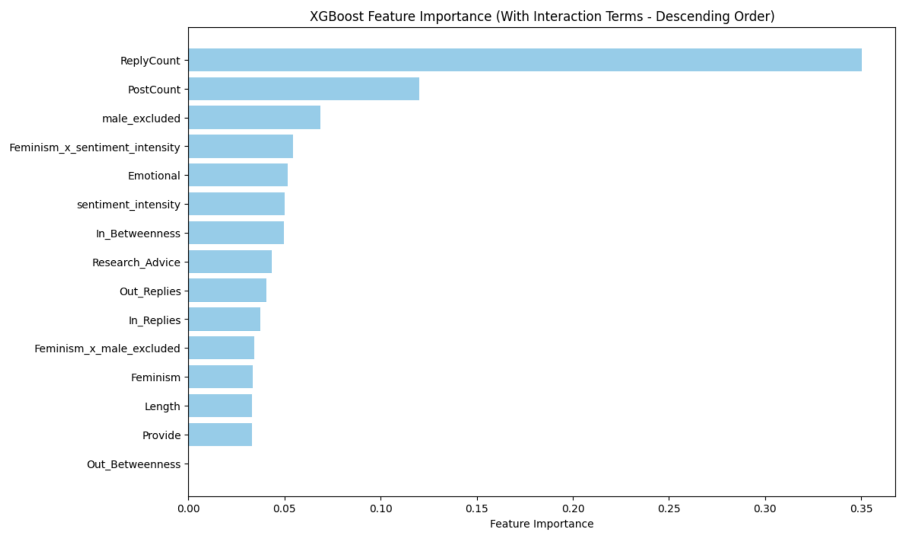

Figure 7: Feature importance of the final model with interaction terms

To further assess these relationships, SHAP analysis was conducted, as shown in Figure 8. The results reinforce the finding that posts exhibiting strong sentiment, particularly in feminism-related contexts, were associated with higher engagement levels. While the interaction term involving male exclusion had a relatively weaker impact, its presence in the model highlights the relevance of gendered discourse in shaping community interactions.

In summary, integrating interaction terms enhanced the model's performance and provided insights into the role of sentiment intensity and gender exclusion within feminism-related discussions. These findings suggest that engagement in online communities is influenced by both content-specific attributes and the broader social dynamics underlying discourse participation.

4.2.3 Model Interpretations

The modeling results provide empirical insights into the factors shaping post engagement, addressing RQ2: *What factors contribute to the success of posts in terms of engagement?*.

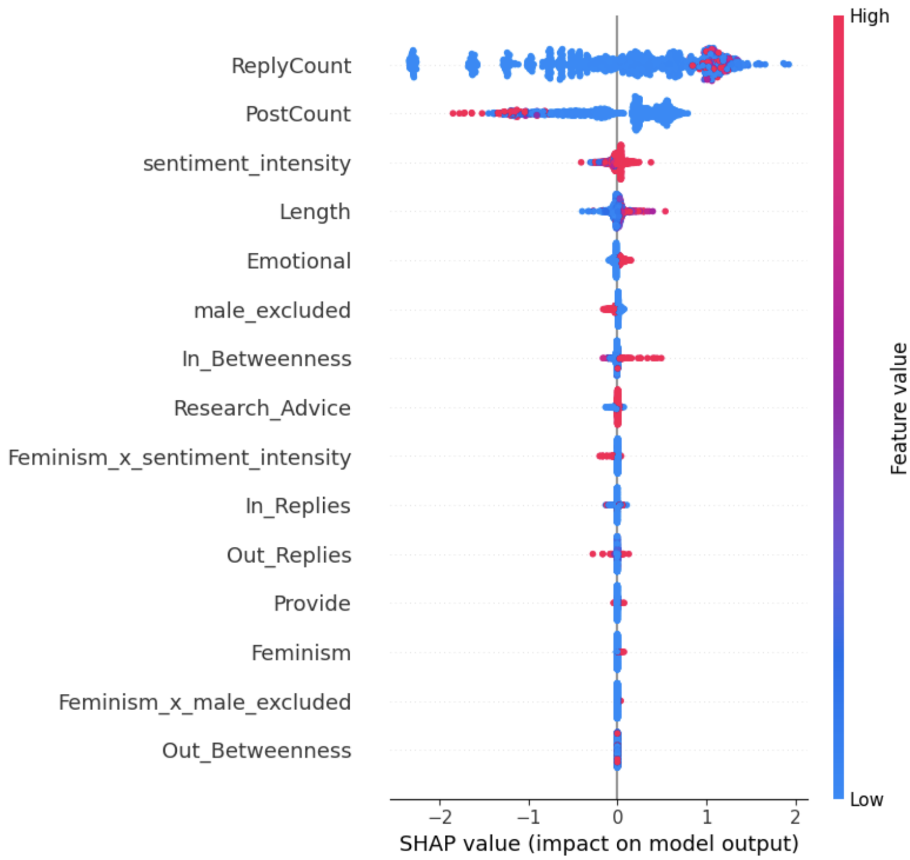

Figure 8: SHAP analysis of the final model with interaction terms

The analysis identifies three primary determinants of engagement: sentiment and emotional expression, user participation patterns, and network centrality.

The strongest predictor of engagement is historical user activity, specifically ReplyCount and PostCount. However, the nature of this activity significantly influences engagement outcomes. Users who actively reply to others tend to receive more replies when they post, reinforcing the importance of interaction reciprocity. In contrast, those who primarily engage by posting frequently experience diminishing responses over time, suggesting that an excessive posting frequency does not necessarily translate to higher engagement. This finding highlights the importance of participatory engagement over mere content generation.

Emotional content also plays a pivotal role in driving engagement. Both sentiment intensity and explicit emotional expression in posts are positively correlated with reply volume, emphasizing the impact of emotional disclosure in online interactions. This aligns with prior literature suggesting that emotionally expressive content tends to elicit stronger reactions, facilitating deeper and more interactive discussions. Moreover, interaction effects reveal that sentiment intensity is particularly influential in feminism-related discussions, where heightened emotional expression tends to amplify engagement. In contrast, the interaction between feminism-related content and male exclusion exhibited limited predictive power, indicating that gender composition alone is a weaker determinant of engagement compared to emotional tone.

Beyond individual-level factors, the structural positioning of users within the discussion network also contributes to engagement. In-replies, out-replies, and in-betweenness centrality influence the visibility and reach of a post. However, the model suggests that direct engagement behaviors (e.g., replying) play a more substantial role in fostering interactions than passive structural prominence.

These findings underscore the multifaceted nature of engagement within online communities. Posts that elicit high engagement tend to be authored by users who are actively involved in conversations, contain emotionally expressive content, and maintain an optimal balance between replying and posting. The results suggest that strategies for fostering engagement should prioritize interaction reciprocity and emotional resonance over sheer posting frequency. Additionally, sentiment expression in feminist discussions should be considered when designing engagement strategies, as emotional intensity significantly enhances user interaction.

5 Discussion

The findings of this study contribute to the growing body of research on online mutual support communities, particularly those centered around women in academia. By addressing the two research questions, this study situates engagement dynamics within the broader theoretical frameworks of social support, online feminism, and network theory. The results demonstrate that engagement in these communities is driven by a combination of informational and emotional exchanges, user participation patterns, and structural positioning within the network. These insights align with and extend previous research on digital support environments and gendered online discourse.

The topic modeling analysis reveals that discussions within the *Women in Academia* group predominantly revolve around three overarching themes: research advice, emotional expression, and feminist discourse. This aligns with prior research suggesting that online support communities serve both instrumental and emotional functions (Chung, 2013; Goldsmith, 2004). The prominence of research advice reflects the group's role in providing practical career support, reinforcing previous findings that informational support is a primary driver of engagement in professional online spaces (Rains & Meng, 2022). Similarly, the significant presence of emotional expression underscores the community's role in fostering solidarity and psychological well-being, echoing studies that highlight the therapeutic benefits of social support in digital contexts (Parker & Thorson, 2009; Thompson et al., 2011).

The engagement modeling results further contextualize the factors influencing post visibility and interaction. The strongest predictor of engagement is historical user activity, specifically the number of replies and posts an individual has contributed. However, the way users participate matters significantly. Individuals who actively reply to others receive more replies when they post, supporting the concept of engagement reciprocity. This finding aligns with previous work on networked communication, which suggests that users with a high degree of interactivity and embeddedness in discussions tend to receive more engagement (Borgatti et al., 2009; Wellman & Frank, 2017). Conversely, those who predominantly post without replying exhibit diminishing engagement over time, reinforcing the notion that participatory engagement is more impactful than passive content generation (Burt, 1992).

Emotional content also emerges as a key determinant of engagement, with sentiment intensity and explicit emotional disclosure positively correlated with reply volume. These results are consistent with studies indicating that emotionally expressive content tends to elicit stronger audience reactions and fosters deeper online interactions (Brodie et al., 2011; Yoon et al., 2018). Furthermore, the interaction analysis reveals that emotional intensity is particularly influential in feminism-related discussions. This finding suggests that feminist discourse, when framed with heightened emotional expression, amplifies engagement, supporting previous research on digital feminist activism, where emotional rhetoric is often a key driver of participation (Bailey et al., 2016; Crossley, 2018).

In addition to individual-level factors, the structural positioning of users within the discussion network also influences engagement. In-replies, out-replies, and betweenness centrality contribute to post visibility, but the findings suggest that direct engagement behaviors, such as replying, play a more substantial role in fostering interactions than passive structural prominence. This aligns with network theory, which posits that active engagement enhances social capital and strengthens relational ties, increasing visibility and response likelihood (Burt, 2005; Granovetter, 2023).

These findings also provide insights into gendered participation in online support communities. The limited impact of the *Feminism* $\times$ *male_excluded* interaction suggests that male participation alone does not strongly influence engagement patterns. This contrasts with existing literature that argues for the disruptive effects of male intrusion in female-centered spaces (Talbot & Pownall, 2022). However, the feminist discussions within this community appear to be more reactive to emotional intensity rather than gender composition, implying that the tone and framing of discussions play a more critical role in shaping engagement.

Overall, these results underscore the complexity of engagement within female mutual support communities. Engagement is not merely a function of post frequency but is deeply embedded in social and emotional exchanges. The findings emphasize that users benefit most from a strategy that balances content creation with active participation in discussions. Furthermore, emotional intensity enhances engagement, particularly in feminist discourse, suggesting that affective communication plays a crucial role in digital advocacy spaces. By integrating these insights with prior literature, this study contributes to a deeper understanding of how support, sentiment, and social structures interact to shape engagement in online feminist communities.

This study presents several strengths that enhance its contribution to research on online mutual support communities. One notable strength is the large-scale dataset, which spans over three years of discussions within the *Women in Academia* group. This extensive data collection allows for an in-depth examination of engagement trends over time, providing a comprehensive perspective on the evolution of support-seeking and support-providing behaviors. Additionally, the combination of topic modeling and engagement prediction through machine learning offers a robust methodological approach, capturing both content dynamics and structural factors influencing interaction.

Moreover, the study benefits from an interdisciplinary framework, drawing from computational social science, network theory, and feminist discourse analysis. This integration allows for a nuanced understanding of how digital support operates within gendered communities. The use of SHAP analysis further enhances interpretability, ensuring that the machine learning model's results are transparent and theoretically meaningful.

However, the study also has limitations. First, while the dataset provides a rich source of organic user interactions, it is limited to one online community, raising concerns about generalizability. The findings may not necessarily extend to other female mutual support groups that operate under different cultural or platform-specific dynamics. Additionally, the reliance on computational methods for sentiment analysis and topic classification introduces potential biases. Despite the validation efforts using Cohen's kappa, algorithmic limitations in processing nuanced feminist discourse may still affect classification accuracy.

Another limitation pertains to the engagement metric used in this study. While replies serve as a proxy for interaction levels, they do not fully capture all forms of engagement, such as passive reading or non-verbal expressions of agreement (e.g., likes or collects). Future research could incorporate multimodal engagement metrics to provide a more holistic assessment of participation.

6 Conclusion

This study examines the structure and engagement dynamics of an online female mutual support community, using computational methods to analyze prevalent discussion topics and factors influencing post visibility. The findings reveal that the community primarily engages in discussions related to research advice, emotional expression, and feminist discourse. Engagement analysis further highlights that historical user activity and emotional intensity significantly impact the likelihood of a post receiving responses. Furthermore, emotional intensity shows extra predictive power in the context of feminist discussion.

The results have implications for understanding how digital support communities operate and how engagement can be optimized. The emphasis on replying as a key engagement factor suggests that fostering interactive discussions is more effective than increasing sheer posting frequency. Additionally, the findings underscore the role of emotional resonance in driving engagement, particularly in feminist discourse.

Overall, this study contributes to the growing body of research on online social support and digital feminist spaces. By leveraging broad machine learning techniques and network analysis, it offers empirical insights into how women in academia navigate professional and emotional challenges in digital spaces. Future research could expand on these findings by exploring cross-platform comparisons or investigating the impact of external events on community engagement patterns.

Data and Code Availability Statement

The dataset analyzed in this study was collected from the Douban Group *Women in Academia* through publicly accessible web content, using automated data collection methods that complied with the platform's terms of service at the time of retrieval. To protect user privacy, identifiable information has been anonymized, and data sharing is limited to non-identifiable, aggregated formats.

All code used for data collection, preprocessing, analysis, and modeling is available in a public GitHub repository for transparency and reproducibility. The repository includes scripts for web scraping, data transformation, topic modeling, sentiment analysis, network construction, and XGBoost modeling.

The data and code can be accessed here.

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