# Threading the Line: Emotion, Structure, and Engagement on Twitter

A Multi-faceted Analysis of User Interactions in Twitter Threads


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Social media threads, like Twitter threads, offer unique avenues for extended conversations and content delivery. However, the interplay between emotional tone, thread structure, and user engagement on these platforms remains under-explored [10]. This study delves into this multifaceted relationship to understand how emotions and structural elements influence user interaction. We leverage a combination of sentiment analysis using the BERT model and user engagement metrics (likes, retweets, comments) to analyze a dataset of Twitter threads [2]. Our investigation explores the impact of different emotions on engagement, the role of thread length and sentiment variation, and the influence of emotional shifts within threads. Additionally, we examine how other thread attributes like topic and timestamp might influence engagement. This research aims to not only illuminate these relationships but also translate findings into actionable strategies. We propose methods for content creators and platforms to foster healthier online interactions by optimizing thread structure and emotional tone. Our findings hold significant value for researchers studying user behavior in digital environments, content creators seeking to cultivate positive online communities, and platform developers aiming to design interfaces that promote healthier user experiences.



CCS CONCEPTS • Human-Computer Interaction • Social and Information Networks • Information Retrieval

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# 1 INTRODUCTION

The ever-growing popularity of social media platforms like Twitter has given rise to new forms of online interaction. Twitter threads, specifically, offer a unique avenue for users to engage in extended conversations and deliver content in a structured format that goes beyond the limitations of single tweets. These threaded conversations create a dynamic space where emotional expression and content delivery can be interwoven. However, despite the increasing prominence of Twitter threads, a crucial gap exists in our understanding of how emotional tone and thread structure interact to influence user engagement.

This research delves into this multifaceted relationship to illuminate the complex interplay between emotions, thread structure, and user interaction on Twitter. By analyzing user engagement metrics alongside sentiment analysis, we aim to shed light on how the emotional tenor and structural characteristics of threads influence user behavior. Understanding these dynamics can not only provide valuable insights into user psychology in online environments, but also pave the way for the development of actionable strategies to promote healthier online interactions.

This study addresses the following research question: How do the emotional tone and structure of Twitter threads affect user engagement, and what strategies can individuals and platforms employ to foster healthier online interactions through threads? To answer this overarching question, we will explore several sub-questions: (1) Do different emotions within a thread lead to different user engagement, and why? (2) Do thread attributes influence user engagement, and if so, how? (3) How does a shift in sentiment within a thread impact user engagement? (4) Do other thread attributes like topic and timestamp play a role in user engagement, and if so, to what extent?

By investigating these sub-questions, we aim to gain a comprehensive understanding of the factors influencing user engagement within Twitter threads. This knowledge can then be translated into practical strategies. We will explore how content creators can optimize their threads by tailoring emotional tone and structure to foster positive interactions. Additionally, platforms can leverage these findings to design interfaces that promote healthier user experiences.

## 1.1 Importance

The significance of this research extends beyond the realm of user engagement on Twitter. It contributes to a broader understanding of user behavior in digital environments, particularly the role of emotions and content structure in online interactions. These insights hold value for researchers, content creators, platform developers, and the general public.

For researchers, this study offers valuable insights into the intricate dynamics of user behavior within digital environments. For content creators, the findings from this research will equip content creators with actionable strategies to optimize their Twitter threads for positive user engagement. For platform users, this research empowers platform users to navigate the social media landscape more effectively. Finally for the general public, this research contributes to the development of methods that minimize the negative impacts of social media and promote mental health [7][8][10].

# 2 RELATED WORK AND RELEVANT LITERATURE

The exploration of user behavior in online social networks has been a burgeoning area of research within the field of computer science and information systems. This section delves into existing literature that informs our investigation into the interplay between emotional tone, thread structure, and user engagement on Twitter threads.

## 2.1 User Behavior in Online Social Networks

A substantial body of research has focused on user behavior in online social networks, with a particular emphasis on understanding factors that influence user engagement and content creation [3][4].

These studies provide a foundational understanding of user behavior within online social networks, laying the groundwork for our investigation into the specific context of Twitter threads.

### 2.2 Sentiment Analysis and User Engagement

The field of Natural Language Processing (NLP) has seen significant advancements in sentiment analysis techniques, enabling the automated extraction of emotional tone from text data. This technology has been leveraged by researchers to explore the relationship between sentiment and user engagement on social media platforms [5][6].

These studies demonstrate the potential value of sentiment analysis in understanding the role of emotions in user engagement. We aim to build upon this foundation by applying sentiment analysis specifically to the context of Twitter threads, exploring the interaction between emotional tone and thread structure.

### 2.3 Gap in Existing Literature

While the aforementioned research provides valuable insights into user behavior and engagement online, a critical gap exists in our understanding of how emotional tone and thread structure interact to influence user engagement specifically within Twitter threads. Existing studies that analyze the relationship between emotions and engagement often focus on individual posts or comments, not the cohesive structure of a thread. Our research aims to bridge this gap by analyzing the interplay of emotional tone, thread structure (length, sentiment variation), and user engagement within the context of Twitter threads.

By incorporating insights from related work and addressing the limitations of existing research, our study aims to shed light on the multifaceted relationship between emotions, thread structure, and user engagement within Twitter threads. This knowledge can not only inform user behavior within Twitter but also contribute to a broader understanding of user psychology in online environments.

## 3 PROPOSED STUDY DESIGN

### 3.1 Data Source

#### *3.1.1 Twitter Thread*

Our primary data source for analyzing the relationship between emotional tone, thread structure, and user engagement will be a publicly available dataset of Twitter threads from Kaggle (Daniel, 2018) [2]. Unlike individual tweets, threads provide a structured context for extended conversations and content delivery. This allows us to analyze the interplay of emotional tone and structure within a cohesive unit of communication.

The dataset consists of approximately 100 threads per CSV file, with a total of 5 CSV files. Each thread comprises individual tweets from the same user, forming a cohesive conversation. Each CSV file contains twitter threads in a specific length. The presence of threads with different lengths allows us to explore how thread length interacts with emotional tone and user engagement. This can provide valuable insights into how users engage with content across varying lengths of conversation.

#### *3.1.2 Sentiment Analysis Data*

To enhance the accuracy of our sentiment analysis within the context of Twitter threads, we will utilize a separate dataset specifically focused on social media language emotion classification. This secondary dataset, also available from Kaggle by Saravia et al, offers several benefits:

Social Media Focus: The dataset consists of English Twitter messages, ensuring the language and emotions align closely with the Twitter thread data we are analyzing.

Predefined Emotion Labels: The dataset provides pre-labeled examples of tweets with emotions like sadness, joy, love, anger, and fear. This pre-classification allows us to fine-tune the sentiment analysis model for optimal performance on our Twitter thread data.

With this dataset, we can fine-turn a pretrained model for emotion classification tasks.

### 3.2 Data Preprocessing

Data preprocessing is a crucial step in preparing the Twitter thread and sentiment analysis datasets for further analysis. We will utilize Python's Pandas library for efficient data cleaning and manipulation.

#### *3.2.1 Twitter Thread*

Removing Irrelevant Data: We will identify and remove any irrelevant data points within the Twitter thread dataset. This may include entries that contain non-textual content like url which cannot be further used.

Handling Missing Values: If the dataset contains any missing values (e.g., missing tweets within a thread), we will impute missing values using techniques of median imputation or removing threads with excessive missing data points.

Formatting Data: We will ensure the data is formatted consistently for further analysis. This might involve tasks like standardizing timestamps, removing unnecessary characters, and tokenizing the text content of each tweet within a thread.

#### *3.2.2 Sentiment Analysis Data*

Text Cleaning: Similar to the Twitter thread data, we will clean the text content within the sentiment analysis dataset. This may involve removing special characters, URLs, and other non-essential elements that could potentially impact the sentiment analysis model's performance.

Label Verification: We will verify the pre-defined emotion labels within the dataset to ensure their accuracy and consistency. This involves manual inspection of some samples.

### 3.3 Sentiment Analysis

We will leverage the power of the Bidirectional Encoder Representations from Transformers (BERT) model for sentiment analysis. BERT is a state-of-the-art pre-trained language model with exceptional capabilities in understanding the nuances of natural language. While BERT offers robust performance, we will further enhance its accuracy by fine-tuning the model specifically for the context of Twitter threads. We will utilize the sentiment analysis dataset obtained from Kaggle (described in section 3.1.2) for this purpose. This dataset provides labeled examples of tweets with specific emotions (sadness, joy, love, etc.).

Once the fine-tuning process is complete, we will employ the sentiment analysis model to assign an emotional label (positive, negative, neutral, or potentially more nuanced categories) to each tweet within a Twitter thread. By implementing this sentiment analysis approach, we aim to accurately capture the emotional tone of Twitter threads and pave the way for exploring its relationship with user engagement [9].

### 3.4 User Engagement Metrics

For this research, we will focus on three commonly used metrics to quantify user engagement on Twitter threads. We will extract the user engagement metrics (likes, retweets, comments) for each thread within the Twitter thread dataset. It's important to acknowledge that these user engagement metrics might not capture the full scope of user interaction. However, by focusing on these established metrics, we can establish a baseline for understanding user engagement patterns and their relationship to emotional tone and thread structure.

Furthermore, we plan to use the Analytic Hierarchy Process (AHP) model to create a more comprehensive engagement score. The AHP is a multi-criteria decision-making method that allows us to incorporate various factors into a single score. We will create a Pairwise Comparison Matrix in addition to user engagement metrics (likes, retweets, comments) for AHP. In this way, AHP allows us to create a more holistic picture of user engagement that goes beyond basic metrics.

### 3.5 Data Analysis

Having preprocessed the data and implemented sentiment analysis, we can now delve into the core of our research: analyzing the relationship between emotional tone, thread structure, and user engagement on Twitter threads. Here's an outline of the specific data analysis techniques we will employ.

#### *3.5.1 Comparing Engagement Across Emotional Threads*

This analysis aims to understand how the overall emotional tone of a thread influences user engagement metrics. We will categorize the threads within our dataset based on their dominant sentiment as determined by the thread-level sentiment analysis (Section 3.3). For each sentiment category (positive, negative, neutral), we will calculate average engagement scores using the defined metrics (likes, retweets, comments). Also, we will employ appropriate statistical tests to compare the average engagement scores across different sentiment categories. This will help us determine if there are statistically significant differences in user engagement based on the emotional tone of the thread.

#### *3.5.2 Thread Attributes and Engagement*

This analysis explores how thread attributes within the thread interact to influence user engagement.

Thread Length: We will categorize threads into different length groups (e.g., short, medium, long) based on the total number of tweets within a thread, and then compare user engagement metrics (likes, retweets, comments) across different thread length categories.

Topic Category: We will categorize threads based on their thematic content (e.g., news, entertainment, sports). This will allow us to explore potential variations in user engagement across different topics.

Time of Day Posted: We will analyze the time of day a thread was posted (e.g., morning, evening) and compare engagement metrics across different time periods. This analysis is exploratory, acknowledging the limitations of timestamps in capturing user behavior across various time zones.

#### *3.5.3 Sentiment Shifts and Engagement*

This analysis focuses on how shifts in sentiment within a thread (e.g., transitioning from positive to negative) impact user engagement. We will develop a method to identify threads with significant sentimental shifts. This might involve detecting transitions from positive to negative sentiment or vice versa within the sequence of tweets in a thread. Then, we will compare user engagement metrics (likes, retweets, comments) between threads with sentiment shifts and threads with consistent sentiment throughout. This will provide insights into how emotional transitions within a conversation influence user interaction.

## 4 ADDRESS PROBLEMS FROM FEEDBACK

### 4.1 Address Problems from Professor's Feedback

We address feedback provided by the professors.

Why twitter/twitter threads? Our research extends to the structural elements of social media threads, delving into thread length, sentiment variation, and the dynamics of emotional shifts. By elucidating the role of thread structure in shaping user engagement, we anticipate providing valuable insights that extend beyond emotional tone.

Where does hypothesis come from? Negative comments are sometimes associated with controversial or polarizing topics. Discussions around controversial issues tend to attract more attention and engagement as people express diverse opinions and engage in debates. The hypothesis arises from previous research [7][8][10].

Who should care about this and why? Importance is mentioned in section 1.1.

### 4.2 Address Problems from Peer Feedback

We address feedback provided by peers.

Answering Group 5 line 166: If this research would like to be continued, it could be expanded to include other platforms besides twitter. The reason our team chose to use twitter to initially answer our research question, is because Twitter is a very popular social media platform where individuals as well as businesses engage in multiple interactions. We considered using the API, but multiple calls would have to be made to it and it would take a long time and much more effort. Perhaps we can find a more efficient way to use the API later.

Answering Group 5 line 182: We will preprocess and organize the data. We would Ensure that user information is adequately captured and associated with each tweet within the thread. Include user identifiers, usernames, or other relevant details to distinguish contributors to the thread.

Answering Group 5 line 187: we will Identify the most crucial sub-questions that align with the core objectives of your research and outline the steps involved in data pre-processing and cleaning.

## 5 PROPOSED TIMELINE

By March 8th the project proposal report will be written, revised, and submitted by all team members. Then, by March 18th, Tianyi will preprocess the data and fine tune the sentiment analysis model as well as the AHP model. By March 28th, Mike will compare engagement across emotional threads, Jack will analyze thread attributes and engagement, Yuxuan will analyze sentiment shifts and engagement. In each of the sections, other group members can help each other if necessary. By April 18th the team will summarize conclusions and by April 25th, a paper on the project will be written.

## 6 EXPECTED PROJECT OUTCOME

We aim to uncover insightful patterns regarding the emotional impact on user engagement. Through a meticulous analysis of sentiment using the BERT model, our research endeavors to discern how various emotions manifest within social media threads and influence user interactions, quantified through metrics like likes, retweets, and comments.

Our research extends to the structural elements of social media threads, delving into thread length, sentiment variation, and the dynamics of emotional shifts. By elucidating the role of thread structure in shaping user engagement, we anticipate providing valuable insights that extend beyond emotional tone.

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## A APPENDIX

In the appendix section, we will provide our collaboration plan.

Yuxuan Chen: I formatted the draft of the proposal paper into CHI Publication Format. For the project, I will preprocess the data and help Tianyi fine tune the sentiment analysis model (Tianyi will be leading the fine tuning). I will participate in all teamwork assignments including scheduling, objectives, writing final paper, and coding. I will analyze sentimental shifts and engagement.

Tianyi Huang: I completed the majority of the draft of the proposal paper. For the project, I will preprocess the data and fine tune the sentiment analysis model as well as the AHP model. I will participate in all assignments and engagements that require team effort such as determining project details (objectives, schedule, among others), writing paper, developing posters, and preprocessing data. For the final paper, every team member will write the part they contributed, and the rest will be worked together. I will contribute to the methodology of finetuning and the AHP model.

Mike He: I plan to conduct a thorough data preprocessing phase as part of my research, ensuring that the data is cleaned and organized effectively. Additionally, I will engage in correlation analysis to explore relationships within the dataset. I have already incorporated relevant citations from existing papers into our proposal, providing a solid foundation for my research. Furthermore, I am committed to actively participating in all team assignments, including tasks related to sentiment analysis and correlation analysis.

Jack Dayan: I, Jack Dayan will contribute to the team; I will participate on all assignments and engagements that require team effort such as determining project details (objectives, schedule, among others), writing paper, developing posters, and preprocessing data. On the more technical side, I will analyze thread attributes and engagement. This means that I will analyze how thread attributes within the thread interact to influence user engagement. I look forward to analyzing results collected from the dataset and presenting them to the rest of the class.