A Dual-Framework Approach for Interpreting and Predicting Social Media Discourse through AI and Data Science Techniques

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Abstract

In the age of digital consumerism, electronic Word of Mouth (eWOM) significantly influences customer opinions and decision-making processes. Social media platforms, such as Twitter, Facebook, and Instagram, have become vital channels for public discourse, generating vast amounts of unstructured data. This thesis addresses the need for innovative analytical approaches to harness the value of social media data, proposing a comprehensive dual framework that integrates sentiment analysis (SA) and network analysis.

The research aims to fill gaps in existing methodologies by developing a framework that identifies key influencers, patterns of information spread, and major themes, while also analysing public sentiment and its changes over time. The methodology involves advanced natural language processing (NLP) techniques, including a sentiment classifier that incorporates emoji features to enhance classification accuracy. Additionally, network analysis techniques, such as link analysis and community detection, are employed and applied at the user level and tweet level, respectively, to evaluate online user engagement.

Case studies focusing on the United Kingdom’s (UK's) cost of living crisis and movie box office performance were conducted to validate the framework's effectiveness in terms of comprehensiveness, accuracy, robustness, and practical utility. The results demonstrate the framework's ability to provide actionable insights, revealing a range of public responses and identifying key topics and influencers. Notably, the study revealed a significant impact of online user engagement on business performance. The findings indicate the utility of the dual-framework in various domains, from governmental policy analysis to business strategy and crisis management.

This research addresses several gaps in existing Social Media Analytics (SMA), studies, particularly the integration of sentiment and network analysis and the handling of informal social media language. By enhancing methodological transparency and developing standardised guidelines, this thesis contributes to knowledge about the reliability and validity of social media research, offering a valuable tool for understanding the complexities of online discourse.

Keywords: Social Media Analytic, Network Analysis, Sentiment Analysis, Dual-Framework, Public Sentiment, Emoji-Incorporated BiLSTM-CNN Model, Online User Engagement, Business Performance, Policy Analysis

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Contents

List of Abbreviations

Abbreviation	Full Term
ACF	Autocorrelation Function
AI	Artificial Intelligence
BERT	Bidirectional Encoder Representations from Transformers
BRCAN	Bidirectional Recurrent Convolutional Neural Network Attention-Based
CPI	Consumer Price Index
CML	Conventional Machine Learning
CNN	Convolutional Neural Network
DL	Deep Learning
DWP	Department for Work and Pensions
EE	Emoji Embeddings
E-BiLSTM-CNN	Emoji-Incorporated BiLSTM-CNN Model
ER	Entity Replacement
ES	Emoji Scores
eWOM	electronic Word of Mouth
FN	False Negative
FP	False Positive
HITS	Hyperlink-Induced Topic Search
IBM	International Business Machines Corporation
IMDB	Internet Movie Database
KNN	K-Nearest Neighbours
LIME	Local Interpretable Model-Agnostic Explanations
LR	Logistic Regression
LSTM	Long Short-Term Memory
mBERT	Multilingual BERT
ML	Machine Learning
NB	Naïve Bayes
NLTK	Natural Language Toolkit
NLP	Natural Language Processing
PACF	Partial Autocorrelation Function

PIP	Personal Independence Payment
PR	Public Relations
RF	Random Forest
RNN	Recurrent Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARIMAX	Seasonal Autoregressive Integrated Moving Average with eXogenous regressors
SA	Sentiment Analysis
SHAP	SHapley Additive exPlanations
SMA	Social Media Analytics
SNA	Social Network Analysis
SVM	Support Vector Machine
TF	Term Frequency
TN	True Negative
TP	True Positive
UK	United Kingdom
US	United States
VADER	Valence Aware Dictionary and sEntiment Reasoner
WDW	Walt Disney World
XAI	Explainable Artificial Intelligence

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Chapter 1 Introduction

1.1 Background and Context

In the era of digital consumerism, electronic Word of Mouth (eWOM) plays a significant role in shaping customer opinions and influencing decision-making processes (Biswas et al., 2022; Stöckli & Khobzi, 2021). Online reviews from traditional customer review sites such as TripAdvisor, Yelp, and Amazon are common sources that inform decision-making. However, there is a risk of these reviews being manipulated, with companies creating artificial positive reviews or competitors generating malicious negative reviews (Hajek & Sahut, 2022). This manipulation can elevate the stakes for decision-making processes, such as marketing analysis and preference prediction based on these reviews. Consequently, businesses are shifting towards social media for a more genuine representation of customer sentiment.

Social media platforms have evolved into vital information channels, not only for business but also for social, political, and economic dialogue. Users generate large amounts of unstructured data, including comments, posts, and opinions related to various topics (Al-Bakri et al., 2021). This data is a valuable resource in today's digital era, as it contains real-time, volunteered, and comparatively unbiased information that covers a wide range of topics in this fast-changing world. It provides low-cost yet promptly valuable new insights for businesses, governments, and organisations.

However, due to the vast volume of social media reviews, innovative approaches are required to efficiently help various stakeholders understand public reactions, needs, and preferences, improve their products, services, or policies, and enhance overall satisfaction (Lamrhari et al., 2022).The discipline of big data analytics, which focuses on efficient data storage, access and processing, has shown potential in addressing this problem. Notably, social media analytics (SMA), which includes techniques like sentiment analysis (SA) and network analysis, has emerged as a vital tool in this field (Yan et al., 2021; Rahman and Islam, 2022). These techniques provide the ability to extract meaningful insights from vast amounts of social media data, supporting data-driven decision-making across various domains.

However, existing research is still limited. Firstly, within the informal language spectrum of social media, the usage of slang, abbreviations, emojis, and the rapid evolution of language, present significant challenges for traditional analysis methods. In addition, most of the existing studies analysing social media data use these two methods individually. Among the studies combining these two methods, the focus is mostly on the sentiment of users, ignoring the depth of such sentiment, that is, how they perceive different aspects of the discussed targets and further, how these sentiments change over time. Therefore, these two approaches need to be synthesised into a more comprehensive SMA framework. Finally, although there are a number of studies on the impact of online customer engagement on business performance, few of them have assessed this impact from the perspectives of graph theory and natural language processing (NLP) techniques.

1.2 Literature Review Summary

SMA literature illustrates that the value of social media data for research is immense. The growing popularity of platforms such as Twitter, Facebook, and Instagram has changed how data are collected and analysed, allowing researchers to gain real-time insights into societal trends and public opinions. Social media data, thus, represent an instant, rich source of evidence to trace the developments of current events, public opinion, and market trends.

In the existing literature, social network analysis (SNA) and SA are the two most commonly used methods for analysing social media data. SASA, an NLP technique, derives opinions, emotions, and sentiments from written language (Agüero-Torales et al., 2019). Widespread applications of SA have been found in fields such as marketing, politics, disaster management, and many others to understand public opinions and make or adjust decisions (Salur & Aydin, 2020; Singla et al., 2022). Techniques in SA include lexicon-based methods (Baccianella et al., 2010; Dang et al., 2020; Grljevic et al., 2020; Abd et al., 2021), machine learning (ML) models (Daeli and Adiwijaya, 2020; Al-Bakri et al., 2021; El-Affendi et al., 2021; Salur & Aydin, 2020; Kastrati et al., 2021), and hybrid approaches (Gopi et al., 2020; Dashtipour et al., 2020; Shrivastava and Kumar, 2020). These methods have been used to classify sentiments in various contexts, from product reviews to political tweets, demonstrating their versatility and applicability.

As another major SMA method, network analysis examines relationships and interactions within social media networks. It identifies key influencers (Jastania et al., 2020; Milani et al., 2020; Singh et al., 2020), tracks information dissemination (Loukianov et al., 2023; Han et al., 2020; Díaz Ferreyra et al., 2022), and understands the dynamics of social interactions (Suitner et al., 2022; . Wang et al., 2020; Pascual-Ferrá et al., 2022). Network analysis techniques, such as ego network analysis (Crossley et al., 2015; Burt, 1992; Everett & Borgatti, 2020; Hoffmann et al., 2020), link analysis (Camacho et al., 2020; Tabassum et al., 2018), and community detection (Jin et al., 2021; Madhulika et al., 2023), are employed to study the structure of social networks and user behaviour.

Together, these techniques provide a comprehensive view of how information flows and how influence is exerted within social media environments.

Despite these advancements, there are notable gaps in existing research. While SA and network analysis are both well-researched individually, few studies have combined these methods to provide a comprehensive view of social media discourse. This integrated approach can not only identify key influencers and the dissemination of information, it can also provide an in-depth look at the most discussed topics, people's sentiments towards them, and how these sentiments change over time. Integration is crucial for understanding how sentiments spread through networks and how influencers impact public opinion. Secondly, from the perspective of existing techniques, manual and rule-based classifications are laborious and vulnerable to bias, making it difficult to adapt to the changing nature of social media language. Therefore, this study aims to build the SA component based on deep learning (DL) techniques. However, current SA techniques face limitations in handling the informality of social media language, particularly the use of emojis. As of September 2023, the Unicode standard has included more than 3,700 emojis. Emojis encapsulate a range of emotions and opinions that traditional text might fail to capture. However, in the process of data preprocessing for sentiment classification, emojis are often removed, leading to the potential loss of sentiment information. Recognising this gap, this study aims to develop a sentiment classifier for online reviews that incorporates emoji features. In doing so, this study seeks to enhance the accuracy of SA to better serve the proposed SMA framework. Moreover, the field lacks a transparent framework for conducting SMA. Unclear processes in implementing frameworks and a lack of detailed documentation make it difficult for other researchers to reproduce the results of past studies accurately and may compromise scientific rigour. This lack of transparency extends to commercial tools, raising concerns about the validity and potential bias of their outputs. Therefore, transparent and standardised guidelines and best practices are needed to ensure consistency and comparability of results. Addressing these methodological challenges would improve the reliability and validity of SMA, making it a more robust tool for understanding the complexities of online discourse.

1.3 Research Aim, Questions, and Objectives

This research aims to contribute to the field of SMA by providing and validating a comprehensive analytics framework that integrates SA and network analysis, referred to as the dual framework. The framework will be designed to facilitate the identification of dominant themes or factors and their corresponding sentiments, key influencers, complex patterns of user interactions and information dissemination, and predictions that will contribute to an understanding of the complexities of social media discourse across industries and topics.

The main research question of this study is as follows:

How effective can the dual framework, based on SA and network analysis, be in capturing and analysing social media discourse for insights into social, political, and economic issues?

To realise the research purpose, the following sub-questions and objectives have been developed:

a) *How can SA and network analysis be integrated into the dual framework, and what are the key components of the proposed framework?*

Objective 1: Identify and outline the key steps involved in incorporating SA and network analysis into the dual framework (Chapter 5).

b) *How does the dual framework address the limitations of current SA techniques when dealing with the informal nature of social media language?*

Objective 2: Incorporate emoji features into the sentiment classification component of the dual framework to enhance its classification accuracy and reliability (Chapter 4).

c) *How does the framework identify key influencers, topics, and sentiment trends in social media discussions, and how do these elements together provide deeper insights into public opinion and emotional responses to various issues?*

Objective 3: Apply network analysis to user data to identify key influencers within social media networks and analyse how information spreads and how public opinion is shaped (Chapters 3 & 5).

Objective 4: Apply network analysis and SA to textual data to identify and analyse prominent topics and sentiment trends in social media discussions (Chapters 3 & 5).

d) *How can the framework be utilised to understand the relationship between online user engagement and economic outcomes?*

Objective 5: Apply the framework to specific cases, namely the United Kingdom (UK)'s cost of living crisis and movie box office evaluation, to assess its robustness, effectiveness, and applicability in different contexts (Chapters 6, 7, & 8).

These two case studies are chosen because the intensity and significance associated with them make them an ideal testing ground for the proposed dual-framework. Additionally, these cases provide rich and diverse data due to the extensive discussion and debate they generated on social media platforms. Rooted in real-world and topical issues, the cases not only assess the robustness and generalisability of the proposed methodology but also allow for drawing conclusions that are directly relevant to society and business.

1.4 Methodology Overview

This study aims to address the gaps identified in Section 1.3. Utilising user-level and word-level network analysis, along with SA based on ML algorithms, the main aim is to develop a robust analytics framework for interpreting social media data to gain deep insights into social, political, and economic issues.

The first step in network analysis involves gathering data relevant to the research topics from social media platforms. This data is then cleaned and pre-processed to prepare for further analysis. Following this, entity analysis is conducted as a preliminary step to identify and categorise key text entities, such as hashtags, mentions, and emojis. Their weighted frequencies are calculated, taking into account the influence of each user. Subsequent, user-level analysis constructs networks, where each user is a node, with interactions like retweets and replies, are represented as links between users. The structural properties of these networks are evaluated using metrics such as power-law distribution, clustering coefficient, and diameter. Key influencers are identified using metrics such as outdegree, indegree, outward closeness centrality, betweenness centrality, and Katz Eigenvector centrality. Community detection algorithms then cluster the network into several groups of closely connected nodes. At the tweet level, semantic network analysis is conducted to generate visual representations of word co-occurrence patterns in tweets. Latent topics are then identified from the co-occurrence patterns using cluster analysis. Subsequently, tweets are assigned to each user community from the user network analysis or each word community from the semantic network analysis. A rule-based approach is followed to assign the tweet to its corresponding community. Finally, content analysis is conducted on each word cluster to identify topics.

The SA component employs advanced NLP techniques to classify emotions and opinions in social media posts as positive, neutral, or negative. A sentiment classifier is developed that incorporates emoji features to enhance accuracy. A weighted sentiment score is calculated for different user or topic communities, taking into account sentiment polarity and the number of tweets to reflect users' sentiment intensity and engagement. The dual framework leverages network and SA to explore the interplay between network structure and emotional tone. This integration aids in understanding how sentiments spread through networks, how key influencers impact public opinion, and how the emotional tone of discussions evolves over time.

This research evaluates the dual framework through specific cases in different domains, namely the UK's cost of living crisis and movie box office performance evaluation, to demonstrate its comprehensiveness, accuracy, robustness, and practical utility in real-world scenarios. By addressing the limitations of current SMA frameworks, the proposed dual framework supports better-informed decision-making across various domains, from businesses and governments to social activism and cultural analysis.

1.5 Expected Outcomes and Contributions

The proposed dual-framework aims to advance the theoretical understanding of SMA by addressing several existing gaps. Firstly, by integrating sentiment and network analysis, the framework provides a more holistic view of social media discourse. It captures key influencers and information dissemination patterns, and also offers an in-depth look at the most discussed topics, people's sentiments, and how these sentiments evolve over time. This integration provides a nuanced understanding of social media interactions that has primarily remained underexplored in current research. Secondly, the framework incorporates an emoji feature-incorporated sentiment classifier based on advanced DL techniques. This innovation improves the accuracy and depth of SA, particularly in handling the varied and contextual meanings of emojis.

On a practical level, the dual-framework's application to real-world case studies, such as the UK's cost of living crisis and movie box office predictions, is expected to demonstrate its utility in various contexts. Firstly, its utility is evident in governmental applications. Governments can use the proposed framework to gain insights into public perceptions and discussions of policies, norms, and laws. By identifying key influencing factors and analysing the key aspects of regulations that generate the most discussion, as well as the public's thoughts, in a timely and accurate manner, government departments can target their strategies and implement policy improvements efficiently. The utility of the dual-framework extends beyond government applications and is invaluable for understanding broader societal issues. For example, social activists and organisations can use the tool to assess public sentiment on challenges such as climate change and human rights. With a deeper understanding, they can more effectively tailor their campaigns to resonate with the concerns and passions of the masses.

The proposed analytics framework offers a new opportunity in an increasingly competitive business landscape. Both established giants and startups can use this tool to investigate consumer preferences and brand sentiment. The framework supports business innovation by identifying unmet needs and changing preferences among the target population, guiding product development, and ensuring greater market resonance. In addition, it can be used to monitor competitors and dissect the sentiment associated with them, providing valuable data for market positioning and differentiation strategies, thus aiding companies in competitive analysis. The framework can also analyse the economic performance of companies based on social media metrics, informing their business decisions to improve customer engagement and drive better market performance.

Risk management is often a top concern for stakeholders, and this is another area where the framework proves its usefulness. By identifying public concerns and monitoring sentiment, stakeholders can proactively identify brewing PR crises and take preventive measures before issues escalate. This application is especially useful during periods of social unrest or sudden crises. Decision makers, with aggregated public sentiment, can formulate timely and targeted responses to avoid any escalation or misunderstanding.

This thesis also aims to contribute to the improvement of methodological norms in the field of SMA. By emphasising methodological transparency and developing standardised guidelines and best practices, the framework will enhance the reliability and validity of social media research. The clear and replicable process detailed in this study will allow other scholars to learn from and utilise it in their research. Furthermore, the framework promotes the use of open-source tools and platforms to increase the transparency and accessibility of social media analyses.

1.6 Structure of the Thesis

This thesis is structured into several chapters, each addressing different aspects of research on social media data analytics, the proposed dual-framework, and its applications. Below is an outline of the chapters and their contents.

Chapter 2 reviews existing literature on social media data analysis, SA, and network analysis. It begins by discussing the significance of social media data in contemporary research and its applications across various fields. The chapter then introduces fundamental concepts and methodologies of SA, covering its processes, applications, and various approaches. Following this, the chapter explores network analysis and details key techniques and methods used to analyse social networks. It concludes by emphasising the need for a comprehensive framework for SMA, addressing current challenges, and proposing future directions for research. Chapter 2 provides an overview of relevant frameworks and methodologies at a conceptual level, setting the foundation for the more technical details covered in the subsequent chapters. Specifically, it focuses on the literature surrounding the frameworks used in social media analysis, while the technical aspects of the proposed dual framework, including its components and implementation, are explored in Chapters 3 and 4.

To clearly illustrate the design of the proposed dual-framework, this thesis divides the methodology into three chapters, each explaining a different component: network analysis; SA; and the integration and extension of these components.

Chapter 3 explores the use of network analysis to investigate connections and relationships within social media platforms. The analysis is divided into three main sections. The first section, Entity Analysis, identifies and categorises key components such as mentions, hashtags, and emojis to understand how posts relate to each other and why users use these entities. The second section, User Level Analysis, constructs networks where users are nodes and interactions like retweets, quotes, and replies are links. It focuses on metrics such as power-law distribution, clustering coefficient, and centrality measures to identify key influencers and community structures. The third section, Tweet Level Analysis, applies semantic network analysis to tweets to identify the themes and concepts discussed. It uses methods like word co-occurrence patterns and clustering to analyse the content and structure of discussions on specific events.

Chapter 4 focuses on SA, emphasising the incorporation of emoji features into a multi-view sentiment classifier. It begins by discussing the importance of considering emoji use when analysing the sentiment of online reviews on social media. The chapter details the experimental procedures, including the novel E-BiLSTM-CNN model, features and embeddings, and the evaluation metrics employed to assess the impact of emoji features on sentiment classification. The experimental results demonstrate the effectiveness of different emoji handling methods and the proposed model. Notably, Chapter 4 has been published as a standalone paper (Xu et al., 2024), further validating its contribution to SA research.

Chapter 5 integrates network analysis and SA into the dual-framework to provide a comprehensive understanding of social media discourse. It explains the rationale and methodology for combining these two analytical lenses, showing how this integration enhances the analysis. The chapter provdes guidance on applying the dual framework to social science issues with a case study on the UK's cost of living crisis, and to business contexts with a case study on predicting box office collections. Finally, the chapter discusses how the framework can be adapted for various applications, highlighting its versatility and practical significance.

After introducing the dual-framework and providing guidance for its implementation, Chapter 6 applies this approach to analyse the UK's cost of living crisis to test its effectiveness. The analysis focuses on public sentiment and discourse surrounding government support measures. Using entity analysis, network analysis, and SA, the study examines tweets from key periods related to the announcement and distribution of Cost of Living Payments. The findings reveal a range of public responses, from concern and criticism to calls for guidance and solidarity. SA highlights predominantly negative sentiments during the announcement and distribution periods, shifting to a mix of sentiments afterwards. Semantic network analysis identifies key topics, such as payment eligibility, energy bills, and support for low-income households. This chapter demonstrates the dual- framework's practical utility in analysing complex issues and provides actionable insights for policymakers. The results indicate the need for effective communication and targeted interventions to address public concerns and support vulnerable populations during the crisis.

Chapter 7 applies the dual framework to business contexts within the entertainment industry, specifically focusing on evaluating the box office success of the movie "Joker." The analysis examines the intertwined relationship between consumer engagement, sentiment, and business performance. Using the dual framework approach, the chapter analyses a comprehensive dataset comprising Twitter data and box office statistics to identify key influencers, dominant themes, and the changes in their sentiment trends over time. In addition, the chapter demonstrates how early social media buzz and sentiment can significantly impact box office performance. The case study on 'Joker' illustrates the effective use of integrating network and SA in evaluating business outcomes and provides actionable recommendations for industry stakeholders.

Chapter 8 evaluates the proposed dual framework in terms of comprehensiveness, accuracy, robustness, and practical utility. The framework's comprehensiveness is demonstrated by its ability to capture diverse data points and analyse multiple topics. Its accuracy is validated by comparing its results with government surveys and existing studies. The framework proves to be robust across different contexts and data structures, maintaining stability over time. Its practical utility is highlighted by its effectiveness in informing policymaking, business strategies, and crisis management. Challenges include data quality, language complexity, and computational demands, which need to be addressed by continually updating data management, community detection, and sentiment analysis techniques.

Finally, Chapter 9 summarises the thesis findings, evaluates the developed dual framework, and suggests future research directions. The framework, which integrates sentiment, user network, and semantic network analysis, was validated through case studies for its comprehensiveness, accuracy, robustness, and practical utility. It also highlights advancements in network and SA. Future research should focus on multi-modal data integration, real-time analytics, longitudinal studies, and applications across various sectors.

Chapter 2 Frameworks for Social Media Data Analysis, Sentiment Analysis, and Network Analysis

2.1 The Role and Importance of Social Media Data

The emergence and widespread use of social media have revolutionised the way information is shared and consumed, leading to a rich data source that significantly contributes to research across various disciplines (Zachlod et al., 2022). The analysis of social media data provides insights into societal phenomena and business opportunities, influencing areas ranging from political outcomes to public opinion (Dwivedi et al., 2021). SMA represents a novel and growing field within research, characterised by its interdisciplinary nature. It involves the development, adaptation, and extension of tools and methods to efficiently track, collect, and analyse vast amounts of structured and unstructured social media data. This data, in turn, is leveraged to extract meaningful patterns and insights (Fan & Gordon, 2014; Stieglitz et al., 2018).

The transformative impact of social media data is particularly evident in its real-time nature, offering an ongoing stream of information that reflects current events and public sentiment as they unfold. This aspect distinguishes social media from traditional data sources, which often suffer from time lags and may not accurately capture the immediacy of social dynamics (Liere-Netheler et al., 2019; Zachlod et al., 2022). Real-time data from social media platforms enable researchers and organisations to respond swiftly to emerging trends, crises, or shifts in public opinion, providing a strategic advantage in various domains. It facilitates the understanding of group behaviours, the dynamics of opinion, the analysis of collective sentiments, and the making of predictions (Belcastro et al., 2017; Crisci et al., 2018; Liere-Netheler et al., 2019).

In the context of SMA, social media platforms like Twitter, Facebook, and Instagram serve as rich data sources. These platforms capture a wide range of human activities and interactions, providing a comprehensive view of public opinion, trends, and behaviours. The data from these platforms are highly diverse, covering textual posts, images, videos, and metadata such as likes and shares. The immediacy and diversity of social media data enable researchers to analyse and understand public sentiment, track emerging trends, and forecast market changes in ways that were not possible with traditional data sources (Zachlod et al., 2022).

The scope of SMA extends beyond mere data analysis; it also involves the development of new methodologies and tools. As social media platforms evolve, so does the complexity of the data they generate. Researchers in SMA are continually challenged to develop innovative analytical techniques and tools that can handle this complexity, ranging from advanced algorithms for NLP to sophisticated data mining techniques for pattern recognition (De Andrade et al., 2021; Liere-Netheler et al., 2019; Wang et al., 2021).

The application of SMA spans various fields, illustrating its multidisciplinary nature. In marketing, SMA is used to gauge consumer sentiment and preferences, thereby shaping marketing strategies. In political science, it aids in understanding public opinion and electoral behaviours. In disaster management, real-time social media data can provide critical information for response coordination. Zachlod et al. (2022) highlight the broad applicability of SMA, illustrating its use in areas such as tourism, healthcare, and environmental monitoring. The versatility of SMA shows its potential to provide actionable insights across different domains. SA and content analysis are the most commonly used methods in these studies, highlighting the diversity and applicability of social media data in different domains.

The use of SMA in academic research, however, is not without challenges. As a relatively young field, SMA lacks consolidated methodologies and clear definitions, necessitating ongoing discussion and refinement within the academic community (Misirlis & Vlachopoulou, 2019). The diversity of approaches and definitions is evident across studies. Additionally, the ethical implications of using publicly available social media data, including privacy concerns and the need for consent, are subjects of ongoing debates within the academic community. Zachlod et al. (2022) emphasise the need for a more systematic approach to SMA, advocating for standardised guidelines and ethical frameworks to ensure the responsible and effective use of social media data in research.

In conclusion, the role and importance of social media data in contemporary research are pivotal. Its real-time, the diverse, and expansive nature offers unparalleled opportunities for in-depth understanding and analysis. However, the effective and ethical use of this data necessitates continuous methodological innovation and strict adherence to ethical standards. As the field of SMA continues to evolve, it promises to deepen our understanding of complex human behaviours and social trends.

2.2 Basics of SA and Network Analysis

2.2.1 SA

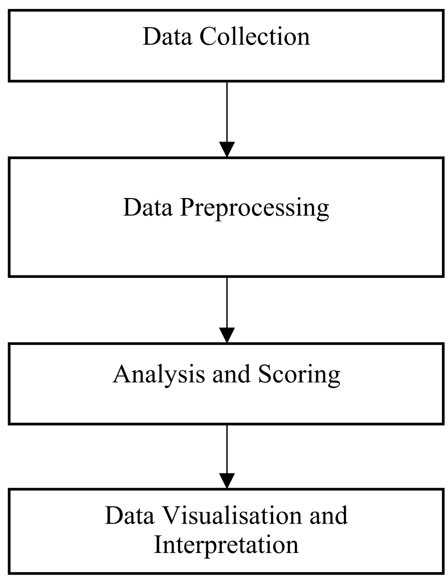
SA is defined as the technique used to automatically extract opinions, emotions, and sentiments from written language (Lombardo et al., 2019). The primary benefit of SA is its ability to effectively identify and classify the attitudes and sentiments (positive, negative, or neutral) of users in texts, thereby ascertaining their attitudes towards products, subjects, or services (Agüero-Torales et al., 2019; Salur & Aydin, 2020). In this section, the process of applying this technique, its applications, and the data utilised in existing studies are introduced.

2.2.1.1 The Process of SA

This subsection outlines the general process of SA. The specific steps scholars take to implement SA vary depending on the research objectives or application requirements. However, all of them follow a general process, as shown in Figure 1.

Figure 2

The General Process of SA (Xu et al., 2022)



The first step is data collection. Researchers focusing on SA in low-resource languages collect primary datasets from a variety of social media platforms, such as Twitter (. Ibrahim et al., 2022; Salur & Aydin, 2020), Facebook (Al-Bakri et al., 2021), Reddit (Yan et al., 2021), or TripAdvisor (Agüero-Torales et al., 2019). Low-resource languages are those with no or limited data resources available for ML algorithms (Chauhan et al., 2021). Researchers select datasets that meet their specific objectives using particular search terms. Alternatively, some researchers prefer to use secondary datasets, which are largely acknowledged and have played a significant role in several studies. They are often used to test the performance of models. The most used secondary datasets include Internet Movie Database (IMDb) (50,000 reviews) (Jnoub et al., 2020), Amazon

Product Review (2,000 reviews) (Chen et al., 2021; Khatoon et al., 2020), and the Yelp Dataset (Bilro et al., 2019).

The second step is data pre-processing. Initially, the data samples are cleaned through several procedures, including converting text from uppercase to lowercase, removing unnecessary and repetitive elements like multiple pronunciations, hashtags and URLs, and stop words, as well as correcting text (Gopi et al., 2020; Abd et al., 2021; Singla et al., 2022). Subsequently, tokenisation is conducted by extracting the words from the texts. In ML -based approaches, these tokens need to be encoded into integer values to facilitate processing (Hameed & Garcia-Zapirain, 2020; Rehman et al., 2019).

The third step is analysis and scoring. It involves employing different methods or models to process the dataset prepared in the previous step. Analysis approaches vary based on the level of details, including document-level (Choi et al., 2020), sentence-level (Mai & Le, 2021), phrase-level (Singla et al., 2022), aspect-level (Ansar et al., 2021), and emotion-level analysis (Yan et al., 2021). Technically, the methods of SA can be categorised into lexicon-based techniques (Hossen & Dev, 2021), machine-learning-based techniques (Budhi et al., 2021), and hybrid techniques (Dang et al., 2021), each addressing different aspects of SA.

The fourth step is data visualisation and interpretation. It allows researchers to present their findings through various types of visual formats. Different types of charts and graphs are used to convey insights, each expressing different information, such as word clouds showing the most frequently occurring words (Ibrahim et al., 2022), heatmap analysis of type of aspects (Chang et al., 2019), as well as a histogram plot (Martin et al., 2018), visual effect map (Zheng & Zheng, 2019) and confusion matrix (Salur & Aydin, 2020) presenting the performance of the classifiers.

2.2.1.2 Application of SA in Different Areas

Applications of SA have covered a wide range of areas, including healthcare, movie, products, travel, and politics, providing numerous benefits to businesses, governments, and individual users.

First of all, SA is a promising tool for governments and authorities to monitor online public opinions for improved risk management and response, especially in the case of emergencies or major events. The COVID-19 pandemic, for example, has been affecting the lives of people around the world for more than five years now and has been mentioned on a large scale on social media. Posts, comments and tweets about the coronavirus have increased dramatically in a short space of time, reflecting people's thoughts and views about the pandemic (Ibrahim et al., 2022). A number of studies have applied SA to understand public opinions about COVID-19 (Ibrahim et al., 2022; Rahman & Islam, 2022; Basiri et al., 2021; Es-Sabery et al., 2021; Yan et al., 2021; Chandra & Krishna, 2021). Additionally, recent research indicates that social media has become a major source of false information, particularly during the global pandemic crisis. For governments and public health authorities, learning about the information circulating among the public, as well as public opinions and sentiments through SA, is very useful in clarifying rumours in a timely manner to appease the community, develop appropriate strategies and take timely action (Alamsyah et al., 2018a).

Secondly, the application of SA in business has been extensively researched. For businesses, SA helps determine how customers perceive their products, services, and even the business by analysing social media data. Moreover, online reviews with ratings and textual information on a variety of aspects provide potential customers with vital information about the user experience of a product or service. Numerous businesses have begun to see the value of SA and user ratings to improve existing goods and develop new ones (Jain et al., 2021). Kausar et al. (2020) proposed a sentiment polarity categorisation technique for online product reviews with five sentiment classes: strongly negative, negative, neutral, positive, and strongly positive, and three polarity features: verb, adverb, and adjective. Rehman et al. (2019) proposed a hybrid Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) model to improve the performance of SA on movie reviews. Dashtipour et al. (2021) set their research target on movie reviews written in Persian, which is the official language of Iran and Afghanistan. They compared the performance of shallow learning algorithms and DL algorithms, and the results demonstrated that the stacked-Bidirectional Long Short-Term Memory (BiLSTM) model, which is a DL method that processes sequential data bidirectionally to capture richer contextual information, outperformed all other methods. Martin et al. (2018) constructed eleven different deep-learning models to classify the sentiments of online tourists' comments that potential new tourists use to plan their trips. They collected their data from the websites of Booking[1] and TripAdvisor[2] and all the eleven models achieved an accuracy exceeding 87%. Analysing sentiments from online posts or comments can

[1] http://booking.com
[2] http://tripadvisor.com

also be employed to assess companies. Agüero-Torales et al. (2019) developed integrated software for the large-scale analysis of social media data regarding the restaurants in the Granada Province of Spain. Based on SA, the restaurants can learn what customers think about their products and services and how they can improve their image, products, and services.

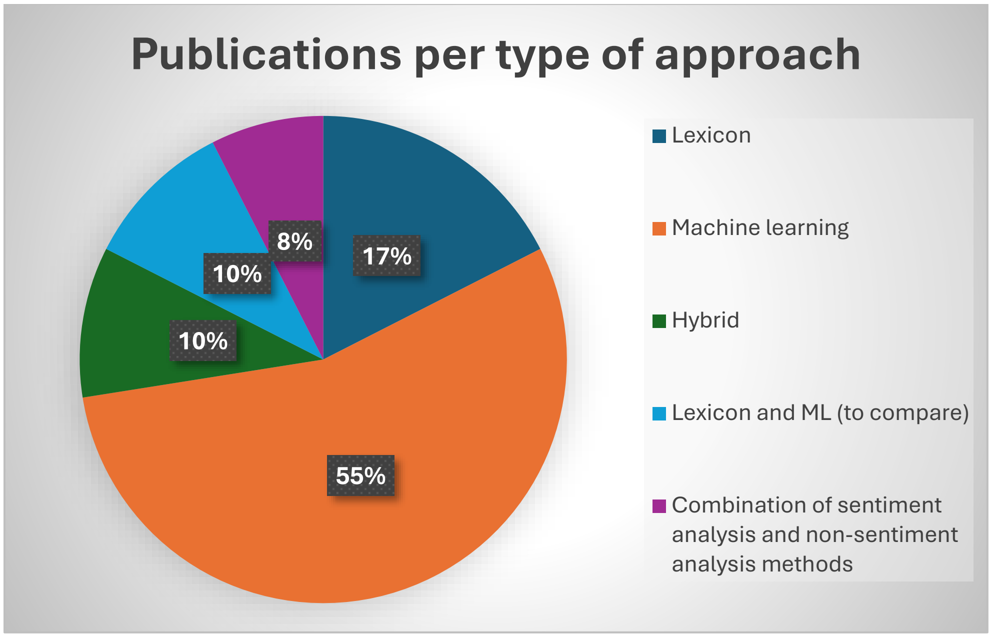
Thirdly, individuals can also benefit from SA techniques to receive personalised services. In recent years, SA has been employed to improve the performance of recommendation systems for different services or products. Dang et al. (2021) suggest approaches to improve the performance of recommender systems for streaming services by using SA to better understand user preferences. They tested and evaluated two different combinations of LSTM and CNN, LSTM-CNN and CNN-LSTM, on the Multimodal Album Reviews Dataset (MARD) and Amazon movie reviews. The baseline they used was a version of the recommendation system that does not include SA and genres. The results show that their models outperformed the baseline in predicting ratings and the evaluating of the top recommendation lists. Wang et al. (2018) also integrated SA into their mobile movie recommender system and tested it on movie datasets in Chinese. Jain et al. (2021) proposed a service recommendation system based on a multi-label ensemble classifier that predicts consumer recommendations in tourism. They collected online airline review data from an online platform and developed an ensemble classifier to evaluate the sentiments of the users.

2.2.1.3 Taxonomy of SA

In this section, all the publications reviewed in this thesis are classified into five categories according to the methods used for social media data analysis: lexicon-based approaches; ML approaches; hybrid approaches that integrate the previous two categories; comparative approaches (Lexicon and ML); and approaches that combine the SA with other analysis methods such as regression and SNA.

Figure 3

Number of Publications Per Type of Approach



A. Lexicon-Based Approaches

According to Figure 3, 17% of publications adopted lexicon-based approaches, 10% integrated the lexicon-based approaches and ML approaches, and 10% of them compared these two types of approaches. Lexicon-based approaches were the initial methods employed for SA and include two types: dictionary-based approach and corpus-based approach. Dictionary-based sentiment classification relies on predefined dictionaries, such as WordNet and SentiWordNet (Baccianella et al., 2010). However, corpus-based SA is performed based on a statistical analysis of the documents' contents, rather than predefined dictionaries (Dang et al., 2020).

Bilro et al. (2019) applied text mining and both corpus and dictionary-based SA to identify the sentimental drivers of online customer engagement by investigating related concepts in online customer reviews (involvement, emotional states, experience, and brand advocacy). They created their customer engagement dictionary based on the Yelp dataset and then extended it based on WordNet 2.1. Fifty-nine topics were identified by MeaningCloud, and ten of them were selected for further investigation. Their sentiment results indicated that the cognitive processing dimension of engagement and hedonic experience might significantly influence consumers' review endeavours. Additionally, customers appear to be more interested in favourably promoting a company/brand than negatively.

In Grljevic et al.'s (2020) study, the lexicon-based SA was applied to the area of higher education. They generated their HiEd-Sent corpus from a Serbian website containing the countries' teaching staff profiles. The spelling and grammar errors in the corpus were corrected using an online tool, Hascheck, and the ones omitted by the tool were manually corrected. To build sentiment dictionaries, a hierarchical annotation procedure for the aspects, sentiment polarity and intensity was conducted by four independent annotators, and the interrater agreement was evaluated. Five dictionaries that contain positive sentiment expressions, negative sentiment expressions, intensifiers, neutralisers and inverters were developed based on the HiEd-Sent corpus. To carry out the sentiment detection, they used both a dictionary-based approach and a ML approach. Each sentence was first pre-processed and converted to tokens in the dictionary-based SA. Then, the tokens were matched with words or phrases from the dictionaries and assigned corresponding labels and sentiment scores. Finally, the sentiment score of each sentence was computed by cumulating the scores of all tokens in the sentence, which determines its polarity. The authors analysed the performance of various combinations of dictionaries at the document and sentence classification levels and found that the combination of the five dictionaries together achieved the best result.

Abd et al. (2021) employed a phrase-level SA using the corpus-based approach and tested their model on the IMDb dataset. Based on the training set, they built their sentiment dictionary by separating the lexicon into positive and negative words. In order to achieve the best result for their model, they conducted four experiments by building different sentiment dictionaries of 25,000, 30,000, 34,000, and 40,000 review terms and used them to classify the test set. On The IMDb dataset, although the second experiment achieved the best accuracy result of 76.585%, the variance between the four experiments was not significant, around 76%.

B. ML-Based Approaches

A number of ML approaches have been utilised to classify people's sentiments. Different from lexicon-based approaches, SA, based on ML, trains the models with sentimental features in the text to enable them to detect sentiments automatically. According to Figure 3, 75% of included publications employed ML approaches (55% used only ML approaches, 10% used hybrid approaches, and 10% compared the two types of approaches).

K-Nearest Neighbours (KNN) is a simple ML approach, but it has an issue with noise features, leading to poor performance. In order to improve the performance of KNN in SA, Daeli and

Adiwijaya (2020) employed information gain to conduct feature selection and evaluate its influence on the performance of KNN as well as other conventional machine learning (CML) models, namely Naïve Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF). On a secondary movie dataset, named the polarity dataset v2.0 with 2000 movie reviews, KNN, with the help of information gain feature selection, became the best performing method with 96.8% accuracy while the optimum K was 3.

Al-Bakri et al. (2021) employed CML algorithms to evaluate Iraqi e-tourism firms based on sentiments extracted from Iraqi dialect reviews on Facebook. The algorithms included KNN, NB, and Rough Set Theory (RST), and their performances were evaluated through a confusion matrix. The results show that the best classifier was RST, with an accuracy value of nearly 95%. In the work of Kastrati et al. (2021) who studied the public's views expressed on Facebook about the COVID-19 in low-resource languages, the third group of experiments is to analyse the performance of SVM, Decision Tree (DT), RF, and NB models in the health domain. Their results showed that RF outperformed all the CML classifier models, both in terms of count occurrence known as term frequency (TF) and in terms of term frequency-inverse document frequency (TF-IDF) as feature representations.

In recent years, DL models have performed excellently in SA. Particularly, the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) and their different combinations have been studied by several scholars. Rehman et al. (2019) proposed a hybrid CNN-LSTM model to classify the IMDb dataset and Amazon movie reviews. The results showed that their model improved the f-measure score by 4-8% when compared to CNN and LSTM individually. El-Affendi et al. (2021) tested another combination of the CNN and LSTM models. They compared the models' performances with other models', namely KNN, NN, CNN, LSTM, and CNN-LSTM. The results showed that the proposed model outperformed other models with an overall accuracy greater than 97%. As Rehman et al. (2019) and El-Affendi et al. (2021) both used the IMDb dataset and used the accuracy and F-measure to evaluate their models, their performance models can be compared. In terms of the CNN-LSTM model, the one from El-Affendi et al. (F-measure: 92%; Accuracy: 93.8%) was better than that of Rehman et al. (F-measure: 88%; Accuracy: 91%).

BiLSTM is designed to capture the semantics in both directions, compensating for the inability of LSTM to encode information from back to front. Salur & Aydin (2020) and Ghorbani et al. (2020) tested models with the BiLSTM layer on Turkish tweets and the IMDb dataset, respectively, and both of their results showed that the BiLSTM layer can help sentiment classifiers achieve better performance. However, the models with BiLSTM may not always outperform. For example, in the work by Kastrati et al. (2021), the first group of experiments compared the performance of the CNN, BiLSTM, and the hybrid CNN-BiLSTM for SA in the health domain. Unlike other scholars, their results showed that the 1D CNN achieved the best performance in classifying the dataset they collected, outperforming the hybrid CNN-BiLSTM.

To improve the performance of DL models, several scholars have attempted to apply the Attention Mechanism to extract high-level feature vectors. Zheng & Zheng (2019) proposed a bidirectional recurrent convolutional neural network attention-based (BRCAN) model. Their evaluation results indicate that the attention mechanism improved the accuracy of all the DL models, and the BRCAN model achieved the best accuracy of 96.32%. In the work by Kastrati et al. (2021), the first group of experiments also tested the role of the attention mechanism in improving the performance of CNN, BiLSTM, and the hybrid CNN-BiLSTM models. The difference between the hybrid models in these two papers is the order of the CNN and BiLSTM layers. Their results also showed the effectiveness of the attention mechanism. However, in their study, the Bi-LSTM model with an attention mechanism achieved the best performance.

According to Devlin et al. (2019), Bidirectional Encoder Representations from Transformers (BERT) is an attention-based architecture that shows significant performance on a variety of NLP tasks, including language inference, question answering, text classification, etc. The design of BERT co-regulates the left and right contexts in all layers, overcoming the unidirectional nature of the standard language model that limits the architectures available for pre-training. Kastrati et al. (2021) tested the performance of contextualised word embeddings and the Multilingual BERT (mBERT) classifier in their work. The mBERT encoder layer contains 12 successive transformer layers trained on Wikipedia pages. The performance of the Multilingual BERT classifier was also very competitive against the best model.

C. Hybrid Approaches

Among the 40 papers, 10% adopted hybrid methods that integrate the lexicon-based and ML - based approaches. Zainuddin et al. (2018) conducted a finer-grained hybrid SA on Twitter at the aspect level. The Association Rule Mining (ARM) and Stanford Dependency Parser (SDP) methods were first used to identify aspects in their model. Then, the dictionary-based method was employed to detect sentiment words in the identified aspects to identify significant ones. Three feature selection approaches, namely Principal Component Analysis (PCA), Random Projection

(RP), and Latent Semantic Analysis (LSA), were then conducted, respectively, to eliminate redundant and irrelevant features. After these steps of feature selection, the most relevant features were used to train the SVM classifier and conduct sentiment classification. The authors tested the hybrid models and other baseline models on three different Twitter datasets, representing different domains. The hybrid model achieved an accuracy of over 70%.

Gopi et al. (2020) used the dictionary-based approach to conduct opinion mining and assigned sentiment scores of -5 to +5 to tweets using the WordNet lexicon. Their proposed model was built based on the existing SVM with Radial Basis Function (RBF) classifier. According to the authors, the existing system could not accurately classify neutral opinions. Therefore, they intended to improve it by changing the gamma value and soft margin to achieve perfect scoring for neutral sentences as well. Their results indicate that the proposed model outperformed the existing SVM-RBF classifier and other models, achieving an accuracy of 98.8%.

Dashtipour et al. (2020) integrated the rule-based approach and deep neural networks to construct a hybrid SA framework for the Persian language. By using the PerSent lexicon, the framework first detected the polarity of reviews based on symbolic dependency relations. Then, the unclassified reviews from the rule-based approach were fed into the DL classifiers to conduct the polarity detection. The DL classifiers the authors used were CNN and LSTM. The two datasets they used were product reviews and hotel reviews, while the PerSent lexicon is built on product reviews. In terms of f-measure and accuracy, both the hybrid CNN and hybrid LSTM models outperformed the rule-based approach as well as other classifiers. However, the DL classifiers improved the performance of the rule-based approach more significantly on the hotel review dataset than on the product review dataset. Shrivastava & Kumar (2020) proposed an unsupervised sentiment classifier based on a lexicon-based approach, fuzzy entropy, and clustering technique. In each review, they identified the adjectives or adverbs as unigrams through part-of-speech tagging and computed their sentiment scores and polarity scores based on the SentiWordNet lexicon (Zainuddin et al., 2018). After that, the phrases (bigrams and trigrams) were formed by using linguistic hedges, including concentrators, dilators, and negators. The sentiment scores and polarity scores of the phrases were computed by predetermined rules depending on their linguistic hedges. Based on the fuzzy entropy, the authors then applied the k-means clustering technique to identify the key phrases used to determine the sentiment of reviews by computing and adding up their fuzzy products.

D. Combined with Other Analytic Approaches

In this section, the studies that combine SA with other analytic approaches are presented. According to Figure 3, they account for 8 percent of publications. Lombardo et al. (2019) applied SA and SNA techniques to support groups on Facebook for Italian patients with Hidradenitis Suppurativa. They studied how the mood of these individuals was affected by various social network factors, such as friendships and interactions within the group, over the years of observation. The dataset they used was collected from Facebook, consisting of 50000 posts and comments published from 2009 to 2017, which were manually annotated. They hierarchically classified the posts or comments, and the sentiments were finally classified as love, joy, surprise, sadness, fear, and anger. This study also constructed an interaction network that focused on the connections between review authors and repliers, and a social network that focused on users and their friendships. The results indicate a significant correlation between the degree of a node and the prevalence of positive emotions, suggesting a possible positive effect of establishing stable social connections within support groups.

In their study Jaidka et al. (2019) applied methods of SNA and SA to predict the results of the general elections in Pakistan (2013), Malaysia (2013), and India (2014). Their method correctly predicted the election results in Pakistan and India but incorrectly predicted the election results in Malaysia. According to the authors, a combination of several methods performs better than independent methods. Twitter posts closer to the time of the election were found to be more meaningful for election prediction.

Ricard et al. (2018) employed an integrated method of SA and an elastic-net regularised linear regression model to detect depression in social media content. Through SA of Instagram post captions and comments, several features were extracted and input into the regression model as part of the variables. These features included sentiment scores regarding happiness, arousal, and dominance, as well as emoji sentiment scores. With the intention of improving the accuracy of the prediction model for monthly vehicle sales, Pai and Liu (2018) combined the SA with statistical analysis models, namely multivariate regression and time series forecasting models. The sentiment scores obtained from the SA on the social media comments was considered as an input in the statistical model. The findings confirmed that the integration of sentiment scores improved forecasting accuracy.

2.2.1.4. Dataset Features for SA

This section first presents the languages of the datasets of reviews, comments, or posts for the reviewed papers included in this study. The languages of the datasets vary. As shown in Figure 4, SA has been applied to 11 languages: Albanian, Arabic, English, Hindi, Malayalam, Italian, Iraqi, Persian, Serbian, and Turkish. Among the studies investigated by this research, 72% use datasets for SA in English. Research on SA in English has yielded significant achievements, advancing not only to adapt the state-of-the-art theories in the fields of lexicon approaches (Agüero-Torales et al., 2019; Khatoon et al., 2020; Abd et al., 2021) and ML approaches (Ricard et al., 2018; Chang et al., 2019; Dang et al., 2021) but also at the application level, including different domains: movies (Rehman et al., 2019; Priyadarshini & Cotton, 2021), health (Es-Sabery et al., 2021), tourism (Jain et al., 2021), products (Priyadarshini & Cotton, 2021), and elections (Jaidka et al., 2019). Although SA research for datasets in English has been extensive, the application domain may not use English as the major language (Alamoodi et al., 2021). For example, in the work of Jaidka et al. (2019), English tweets that expressed people's opinions on the general elections in Pakistan (2013), Malaysia (2013), and India (2014) were collected to predict the election outcomes based on SA and SNA. The hybrid model successfully predicted the election results in Pakistan and India, but not in Malaysia. A potential reason is that only 23% of the tweets were written in English for the Malaysian election. The authors generated nearly 1.1 million tweets to predict the election in Malaysia (2013), and they removed a significant percentage of Malay tweets (Jaidka et al., 2019), possibly leading to bias in the classification results. Further research can be conducted on the construction of Malay lexicons and the use of effective ML classifiers.

In addition to English, SA studies on other languages are increasing, such as Chinese (Zheng & Zheng, 2019), Albanian (Kastrati et al., 2021), Arabic (El-Affendi et al., 2021), Hindi (Shrivastava & Kumar, 2020), Turkish (Salur & Aydin, 2020), Iraqi (Al-Bakri et al., 2021), etc. Due to the unavailability of suitable lexicons, scholars who study SA of non-English texts often prefer to build their own dictionaries, unlike those studying SA of English texts (Wang et al., 2018; Grljevic et al., 2020; Al-Bakri et al., 2021). However, the usefulness of a model based on a self-built dictionary may not be ideal due to a variety of factors in the self-built process. One potential reason for this is the source of the data. With the development of mobile technology, there is a wide range of platforms for social networking. Therefore, one lexicon-based dataset from one or a few social media platforms may not be comprehensive. On the other hand, although larger corpora have been shown to improve the accuracy of classifiers (Rice and Zorn, 2021), acquiring such corpora requires a great deal of time and effort.

Among the studies included in this thesis, 54% employed primary datasets, which were manually collected from various social media platforms, and 46% used secondary datasets that have been studied by other authors. In the work of Khatoon et al. (2020), to construct a domain-independent automatic labelling system, aside from the secondary dataset of movie reviews (IMDb) and product reviews (Amazon Product Review), they also collected reviews on businesses from Twitter. The domains of the datasets consist of tourism, health, movies, products, books, companies, education, and crime. The most popular primary datasets are IMDb and Amazon product reviews, especially in studies where some authors design novel sentiment classifiers and use them to test the performance of the models constructed (Chen et al., 2021; Khatoon et al., 2020; Priyadarshini & Cotton, 2021; Abd et al., 2021; Vashishtha & Susan, 2021). In addition, as shown in Figure 5, only 18.33% of publications used datasets with fewer than 10,000 samples, and 7.13% of datasets contained more than 1 million samples. The taxonomy of SA in social media is shown in

Table 1
Taxonomy of SA in social media

Author	Study language	Dataset _name	Dataset _volume	Domain	Approach Type	Algorithm	Result
Chen et al. (2021)	English	IMDB	2000	Movie	Hybrid	SentiWordNet/TF-IDF/word2vec/BERT + PCA/CHI/MI/CFRT + SVM	Bert-CFRT (Accuracy:0.758)
		Amazon product review	2000	Product			BERT-CHI (Accuracy: 0.744)
Agüero-Torales et al., (2019)	English	TripAdvisor	33594	Tourism	Lexicon	Dictionary-based approach	-
Lombardo et al. (2019)	Italian	Facebook	50000	Health	with other non-SA methods	Naive Bayes, Degree centrality (Social network analysis)	hierarchical classifier (Accuracy: 0.490)

Kastrati et al. (2021)	Albanian	Facebook	10742	Health	ML	DNN/CNN/BiLSTM+Attention, BERT, SVM, NB, DT, RF	BiLSTM+Attention (F-score: 0.721)
Khatoon et al. (2020)	English	Amazon product review	1000	Product	Lexicon and ML	SVM, ME, FBS, SO-CAL, DIALS	DIALS (F-score: 0.926)
		IMDb	1000	Movie			DIALS (F-score: 0.926)
		Tweets_business	1000	Business			DIALS (F-score: 0.922)
Zheng & Zheng (2019)	Chinese	Yelp Reviews full	150000	Movie	ML	BiLSTM-CNN-attention(BRCAN), SVM, BOW,NB, CNN, RNN, LSTM	Att-CNN (Accuracy: 0.683)
		Yelp Reviews Polarity	300000				BRCAN (Accuracy: 0.968)
		Douban Movie full	12500				BRCAN (Accuracy: 0.751)
		Douban Movie Poliarity	100000				BRCAN (Accuracy: 0.963)
Rehman et al., (2019)	English	IMDb	40000	Movie	ML	CNN, LSTM, CNN-LSTM	CNN-LSTM (F-score: 0.880)
		Amazon Movie Review	2000				CNN-LSTM (F-score: 0.860)
Es-Sabery et al. (2021)	English	sentiment140	1600000	Health	ML	TF-IDF/FastText/word embedding (Word2Vec, GloVe)/Bag-Of-Words/N-grams+ ID3 Decision Tree + Chi-square/Gain Ratio/Information gain/Gini index	FastText+ID3+information gain (Accuracy: 0.865)
		COVID-19_Sentiments	637978				FastText+ID3+information gain (Accuracy: 0.888)
Jain et al. (2021)	English	online airline reviews	165682	Tourism	ML	KNN, SVM, MLP, Logistic Regression (LR), RF,Ensemble +	Ensemble+RAkELo partitioning (Accuracy: 0.827)

						RAkELo/Louvain partitioning	
El-Affendi et al. (2021)	Arabic	34 public datasets	275491	multiple domains	ML	LSTM-CNN-3 Embedding Channels (MPAN)	Tertiary classification case (Accuracy: 0.943); Binary classification case (Accuracy: 0.956)
Basiri et al. (2021)	English	Tweets	1056049.00	Health	ML	CNN, BiGRU, fastText, NBSVM, DistilBERT, and the proposed fusion model.	the proposed fusion model (Accuracy: 0.858; F-score: 0.858)
Salur & Aydin (2020)	Turkish	Tweets	17289	Product	ML	LSTM, GRU, BiLSTM, CNN	CNN-BiLSTM (Accuracy: 0.821)
Priyadarshini & Cotton (2021)	English	Amazon product review	2880000	Product	ML	KNN, NN, CNN, LSTM, CNN-LSTM, LSTM-CNN, LSTM-CNN-GRID SEARCH	LSTM-CNN-GS (Accuracy: 0.964; F-score: 0.981)
		IMDB	50000	Movie			LSTM-CNN-GS (Accuracy: 0.978; F-score: 0.972)
Shrivastava & Kumar (2020)	Hindi	website	8604	Movie	ML	SVM, NB, KNN, DT, CNN, LSTM, GA-GRU	GA-GRU model (Accuracy: 0.880)
Wang et al. (2018)	Chinese	Douban Movie 1st	6179857	Movie	Lexicon	Corpus-based Approach	The recommendation model with lexicon SA (F-score: 0.771)
Singla et al. (2022)	English	sentiment140	1048576	multiple domains	ML	NB, SVM, LR, CNN, BERT, LSTM, LSTM-CNN	LSTM-CNN (Accuracy: 0.856; F-score: 0.877)
Abd et al. (2021)	English	IMDB	50000	Movie	Lexicon	Corpus-based Approach	Four experiments by building dictionaries with different sizes (Average Accuracy: 0.760)

Yan et al. (2021)	English	Reddit	45303	Health	ML	RF	predict joy (RMSE: 0.083); sadness (RMSE: 0.068); anger (RMSE: 0.074); fear (RMSE: 0.079)
Ghorbani et al. (2020)	English	Movie Reviews (MR) dataset	2000	Movie	ML	CNN-BiLSTM-CNN	CNN-BiLSTM-CNN (Accuracy: 0.890)
Chandra & Krishna (2021)	English	Senwave COVID-19 sentiment dataset	10000	Health	ML	LSTM, BiLSTM, BERT	BERT (F1 macro: 0.530; F1 micro: 0.587)
F. Ibrahim et al. (2022)	English	HTC smartphone	22977	Product	Lexicon	HTSM, rCRP, HASM, SSA, HUSTM	HTSM outperforms in terms of execution time
		COVID-19_Sentiments	33175	Health			
S. Kumar et al. (2020)	English	Facebook	900	Book	Lexicon and ML	Valence Aware Dictionary and sEntiment Reasoner (VADER), NB, ME, SVM,LSTM, CNN	CNN (Accuracy _without gender info: 0.770; Accuracy _female: 0.800; Accuracy _male: 0.700)
Bilro et al. (2019)	English	Yelp Dataset	15000	business	Lexicon	Corpus-based Approach	-
Rahman & Islam (2022)	English	Tweets	12000	Health	ML	Decision Tree (DT), SVM, LR, Bagging Classifier, Stacking Classifier	Stacking Classifier (F-score: 0.835)
Ricard et al. (2018)	English	Instagram	749	Health	Lexicon	Dictionary-based approach	-
Vashishtha & Susan (2021)	English	Movie Reviews (MR) dataset	2000	Movie	Lexicon	SentiWordNet + unigram/bigram/trigram +	Proposed system with all n-grams (Accuracy:

						fuzzy techniques + k-means clustering	0.700; F-score: 0.701)
		IMDB	50000				Proposed system with all n-grams (Accuracy: 0.693; F-score: 0.691)
Zainuddin et al. (2018)	English	Hate Crime Twitter Sentiment (HCTS) dataset	1078	hate crimes	Hybrid	SentiwordNet lexicon + PCALSA/RP + SVM/NB/RF/ Extreme learning machine+ n gram	Sentiwordnet+PCA+SVM with POS Tags+Unigram features (Accuracy: 0.716; F-score: 0.647)
		Stanford Twitter Sentiment (STS) dataset	353	multiple domains			Sentiwordnet+PCA+SVM with POS Tags (Accuracy: 0.766; F-score: 0.760)
		Sanders Twitter Corpus (STC) dataset	1091	business			Sentiwordnet+PCA+RF+POS Tags+Unigram (Accuracy: 0.742; F-score: 0.740)
Grljevic et al. (2020)	Serbian	'Oceni Profesora'	3863	Education	Hybrid	Corpus-based Approach, corpus-NB/SVM/kNN	document level_positive: dictionary-based (F-score: 0.898); document level_negative: dictionary-based (F-score: 0.889) ; sentence level_positive: dictionary-based (F-score: 0.861); sentence level_negative: SVM (F-score: 0.861)
Jaidka et al. (2019)	English	Tweets	3400000	Political	with other non-SA methods	SentiStrength lexicon, NB, Social network analysis	NB

Pai & Liu (2018)	English	Tweets	6000000	Product	with other non-SA methods	SentiStrength lexicon, regression	-
Dashtipour et al. (2021)	Persian	Persian movie review (websites)	2010	Movie	Hybrid	LR, SVM, and multilayer perceptron (MLP) classifiers, CNN, LSTM, BiLSTM	Stacked-BiLSTM (Accuracy: 0.956; F-score: 0.960)
		Persian hotel review (websites)	-	Tourism			2D-CNN (Accuracy: 0.898; F-score: 0.890)
Daeli & Adiwijaya (2020)	English	Polarity dataset v2.0	2000	Movie	ML	KNN, NB, SVM, RF	KNN_k=3 + information gain (Accuracy: 0.968)
Thomas & Latha (2021)	Malayalam	social media platforms	10000	multiple domains	ML	RNN-LSTM	RNN-LSTM (Accuracy: 0.815)
Chang et al. (2019)	English	TripAdvisor	634277	Hotel	ML	NB, SVR, SVM, LST, sentiment sensitive tree (SST)+convolution tree kernel (CTK) classification	
Al-Bakri et al. (2021)	Iraqi	Facebook	14200	Tourism	ML	Rough Set Theory (RST), NB (NB), KNN	SST+CTK (Accuracy: 0.893; F-score: 0.935)
Martin et al. (2018)	English	Booking & TripAdvisor	12425	Tourism	Lexicon and ML	Corpus-based Approach, CNN, LSTM	embedding-LSTM (Accuracy: 0.892, training time:10,630); CNN-LSTM:(Accuracy: 0.883, training time:1602)
C. N. Dang et al. (2021)	English	Multimodal Album Reviews Dataset (MARD)	263525	Music	ML	DNN, LSTM, CNN	hybrid models
		Amazon Movie Review	203967	Movie			hybrid models

Kausar et al. (2020)	English	Office product reviews	30842	multiple domains	Lexicon and ML	Sentiword Net, NB, DT, RF, SVM, gradient boosting, Seq2Seq	DT, RF, SVM, gradient boosting classifier with Comparative adverbs (F-score: 0.960)
		Musical DVD reviews					
Jnoub et al. (2020)	English	IMDB	50000	Movie	ML	Proposed-CNN, Proposed SNN, SVM, KNN, NB, RF	Proposed SNN (Accuracy: 0.870; F-score: 0.870)
		Movie Reviews (Cornel)	10000	Movie			Proposed SNN (Accuracy: 0.820; F-score: 0.820)
		Amazon product review	1000	Product			Proposed SNN (Accuracy: 0.740; F-score: 0.740)
Ibrahim et al. (2019)	English	IMDb	-	Movie	ML	LSTM-User Movie attention	LSTM-User Movie attention (Accuracy: 0.533)
		yelp13	-				LSTM-User Movie attention (Accuracy: 0.650)
		yelp14	-				LSTM-User Movie attention (Accuracy: 0.667)

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Figure 4

Publications Per Type of Review Language

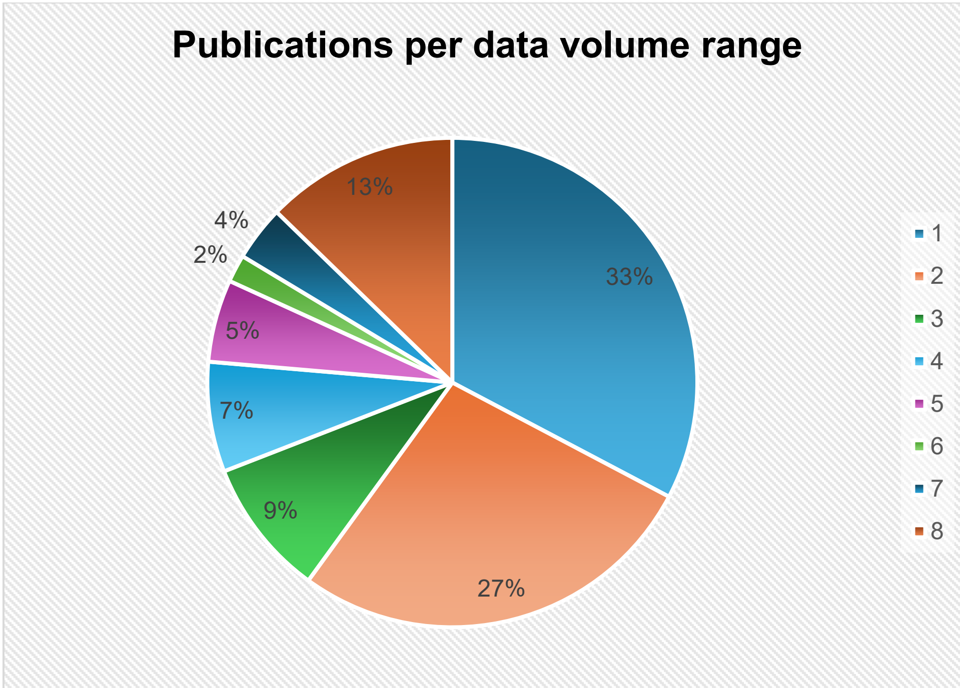


Figure 5

The Number of Publications Per Data Volume Range

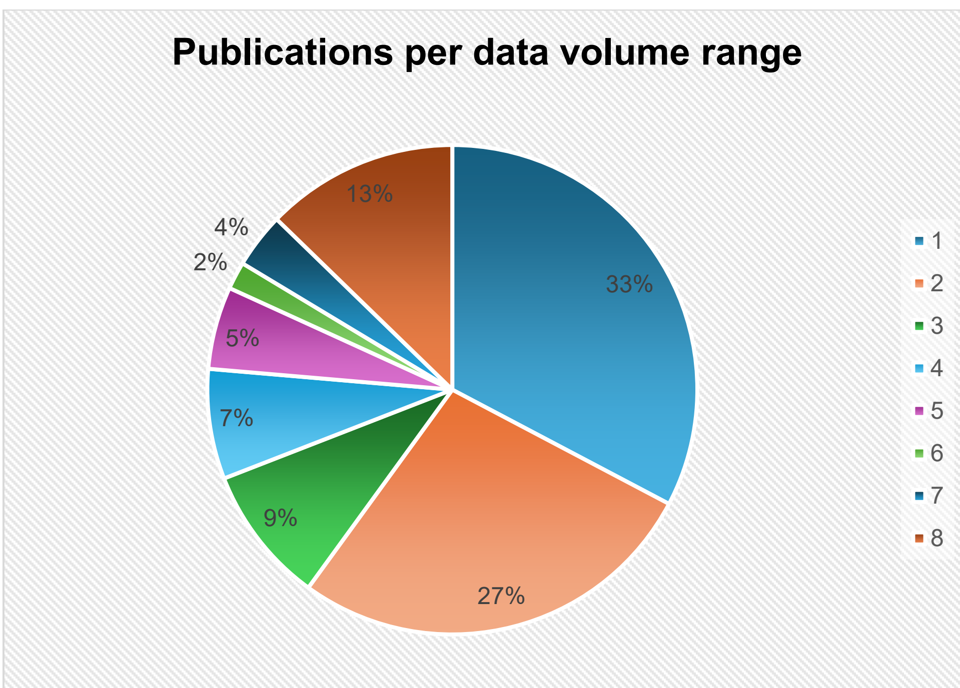


Table 1
Taxonomy of SA in social media

Author	Study language	Dataset _name	Dataset _volume	Domain	Approach Type	Algorithm	Result
Chen et al. (2021)	English	IMDB	2000	Movie	Hybrid	SentiWordNet/TF-IDF/word2vec/BERT + PCA/CHI/MI/CFRT + SVM	Bert-CFRT (Accuracy:0.758)
		Amazon product review	2000	Product			BERT-CHI (Accuracy: 0.744)
Agüero-Torales et al., (2019)	English	TripAdvisor	33594	Tourism	Lexicon	Dictionary-based approach	-
Lombardo et al. (2019)	Italian	Facebook	50000	Health	with other non-SA methods	Naive Bayes, Degree centrality (Social network analysis)	hierarchical classifier (Accuracy: 0.490)
Kastrati et al. (2021)	Albanian	Facebook	10742	Health	ML	DNN/CNN/BiLSTM+Attention, BERT, SVM, NB, DT, RF	BiLSTM+Attention (F-score: 0.721)
Khatoon et al. (2020)	English	Amazon product review	1000	Product	Lexicon and ML	SVM, ME, FBS, SO-CAL, DIALS	DIALS (F-score: 0.926)
		IMDb	1000	Movie			DIALS (F-score: 0.926)
		Tweets_business	1000	Business			DIALS (F-score: 0.922)
Zheng & Zheng (2019)	Chinese	Yelp Reviews full	150000	Movie	ML	BiLSTM-CNN-attention(BRCAN), SVM, BOW,NB, CNN, RNN, LSTM	Att-CNN (Accuracy: 0.683)
		Yelp Reviews Polarity	300000				BRCAN (Accuracy: 0.968)
		Douban Movie full	12500				BRCAN (Accuracy: 0.751)
		Douban Movie Poliarity	100000				BRCAN (Accuracy: 0.963)
	English	IMDb	40000	Movie	ML	CNN, LSTM, CNN-LSTM	CNN-LSTM (F-score: 0.880)

Rehman et al., (2019)		Amazon Movie Review	2000				CNN-LSTM (F-score: 0.860)
Es-Sabery et al. (2021)	English	sentiment140	1600000	Health	ML	TF-IDF/FastText /word embedding (Word2Vec, GloVe)/Bag-Of-Words/N-grams+ ID3 Decision Tree + Chi-square/Gain Ratio/Information gain/Gini index	FastText+ID3+information gain (Accuracy: 0.865)
		COVID-19_Sentiments	637978				FastText+ID3+information gain (Accuracy: 0.888)
Jain et al. (2021)	English	online airline reviews	165682	Tourism	ML	KNN, SVM, MLP, Logistic Regression (LR), RF,Ensemble + RAkELo/Louvain partitioning	Ensemble+RAkELo partitioning (Accuracy: 0.827)
El-Affendi et al. (2021)	Arabic	34 public datasets	275491	multiple domains	ML	LSTM-CNN-3 Embedding Channels (MPAN)	Tertiary classification case (Accuracy: 0.943); Binary classification case (Accuracy: 0.956)
Basiri et al. (2021)	English	Tweets	1056049.00	Health	ML	CNN, BiGRU, fastText, NBSVM, DistilBERT, and the proposed fusion model.	the proposed fusion model (Accuracy: 0.858; F-score: 0.858)
Salur & Aydin (2020)	Turkish	Tweets	17289	Product	ML	LSTM, GRU, BiLSTM, CNN	CNN-BiLSTM (Accuracy: 0.821)
Priyadarshini & Cotton (2021)	English	Amazon product review	2880000	Product	ML	KNN, NN, CNN, LSTM, CNN-LSTM, LSTM-CNN, LSTM-CNN-	LSTM-CNN-GS (Accuracy: 0.964; F-score: 0.981)
		IMDB	50000	Movie			LSTM-CNN-GS (Accuracy:

						GRID SEARCH	0.978; F-score: 0.972)
Shrivastava & Kumar (2020)	Hindi	website	8604	Movie	ML	SVM, NB, KNN, DT, CNN, LSTM, GA-GRU	GA-GRU model (Accuracy: 0.880)
Wang et al. (2018)	Chinese	Douban Movie 1st	6179857	Movie	Lexicon	Corpus-based Approach	The recommendation model with lexicon SA (F-score: 0.771)
Singla et al. (2022)	English	sentiment140	1048576	multiple domains	ML	NB, SVM, LR, CNN, BERT, LSTM, LSTM-CNN	LSTM-CNN (Accuracy: 0.856; F-score: 0.877)
Abd et al. (2021)	English	IMDB	50000	Movie	Lexicon	Corpus-based Approach	Four experiments by building dictionaries with different sizes (Average Accuracy: 0.760)
Yan et al. (2021)	English	Reddit	45303	Health	ML	RF	predict joy (RMSE: 0.083); sadness (RMSE: 0.068); anger (RMSE: 0.074); fear (RMSE: 0.079)
Ghorbani et al. (2020)	English	Movie Reviews (MR) dataset	2000	Movie	ML	CNN-BiLSTM-CNN	CNN-BiLSTM-CNN (Accuracy: 0.890)
Chandra & Krishna (2021)	English	Senwave COVID-19 sentiment dataset	10000	Health	ML	LSTM, BiLSTM, BERT	BERT (F1 macro: 0.530; F1 micro: 0.587)
F. Ibrahim et al. (2022)	English	HTC smartphone	22977	Product	Lexicon	HTSM, rCRP, HASM, SSA, HUSTM	HTSM outperforms in terms of execution time
		COVID-19_Sentiments	33175	Health			
S. Kumar et al. (2020)	English	Facebook	900	Book	Lexicon and ML	Valence Aware Dictionary and	CNN (Accuracy _without gender info: 0.770; Accuracy

						sEntiment Reasoner (VADER), NB, ME, SVM,LSTM, CNN	_female: 0.800; Accuracy _male: 0.700)
Bilro et al. (2019)	English	Yelp Dataset	15000	business	Lexicon	Corpus-based Approach	-
Rahman & Islam (2022)	English	Tweets	12000	Health	ML	Decision Tree (DT), SVM, LR, Bagging Classifier, Stacking Classifier	Stacking Classifier (F-score: 0.835)
Ricard et al. (2018)	English	Instagram	749	Health	Lexicon	Dictionary-based approach	-
Vashishtha & Susan (2021)	English	Movie Reviews (MR) dataset	2000	Movie	Lexicon	SentiWordNet + unigram/bigram/trigram + fuzzy techniques + k-means clustering	Proposed system with all n-grams (Accuracy: 0.700; F-score: 0.701)
		IMDB	50000				Proposed system with all n-grams (Accuracy: 0.693; F-score: 0.691)
Zainuddin et al. (2018)	English	Hate Crime Twitter Sentiment (HCTS) dataset	1078	hate crimes	Hybrid	SentiwordNet lexicon + PCALSA/RP + SVM/NB/RF/Extreme learning machine+ n gram	Sentiwordnet+PCA+SVM with POS Tags+Unigram features (Accuracy: 0.716; F-score: 0.647)
		Stanford Twitter Sentiment (STS) dataset	353	multiple domains			Sentiwordnet+PCA+SVM with POS Tags (Accuracy: 0.766; F-score: 0.760)
		Sanders Twitter Corpus (STC) dataset	1091	business			Sentiwordnet+PCA+RF+POS Tags+Unigram (Accuracy: 0.742; F-score: 0.740)

Grljevic et al. (2020)	Serbian	'Oceni Profesora'	3863	Education	Hybrid	Corpus-based Approach, corpus-NB/SVM/kNN	document level_positive: dictionary-based (F-score: 0.898); document level_negative: dictionary-based (F-score: 0.889) ; sentence level_positive: dictionary-based (F-score: 0.861); sentence level_negative: SVM (F-score: 0.861)
Jaidka et al. (2019)	English	Tweets	3400000	Political	with other non-SA methods	SentiStrength lexicon, NB, Social network analysis	NB
Pai & Liu (2018)	English	Tweets	6000000	Product	with other non-SA methods	SentiStrength lexicon, regression	-
Dashtipour et al. (2021)	Persian	Persian movie review (websites)	2010	Movie	Hybrid	LR, SVM, and multilayer perceptron (MLP) classifiers, CNN, LSTM, BiLSTM	Stacked-BiLSTM (Accuracy: 0.956; F-score: 0.960)
		Persian hotel review (websites)	-	Tourism			2D-CNN (Accuracy: 0.898; F-score: 0.890)
Daeli & Adiwijaya (2020)	English	Polarity dataset v2.0	2000	Movie	ML	KNN, NB, SVM, RF	KNN_k=3 + information gain (Accuracy: 0.968)
Thomas & Latha (2021)	Malayalam	social media platforms	10000	multiple domains	ML	RNN-LSTM	RNN-LSTM (Accuracy: 0.815)
Chang et al. (2019)	English	TripAdvisor	634277	Hotel	ML	NB, SVR, SVM, LST, sentiment sensitive tree (SST)+convolution tree kernel (CTK) classification	

Al-Bakri et al. (2021)	Iraqi	Facebook	14200	Tourism	ML	Rough Set Theory (RST), NB (NB), KNN	SST+CTK (Accuracy: 0.893; F-score: 0.935)
Martin et al. (2018)	English	Booking & TripAdvisor	12425	Tourism	Lexicon and ML	Corpus-based Approach, CNN, LSTM	embedding-LSTM (Accuracy: 0.892, training time:10,630); CNN-LSTM:(Accuracy : 0.883, training time:1602)
C. N. Dang et al. (2021)	English	Multimodal Album Reviews Dataset (MARD)	263525	Music	ML	DNN, LSTM, CNN	hybrid models
		Amazon Movie Review	203967	Movie			hybrid models
Kausar et al. (2020)	English	Office product reviews	30842	multiple domains	Lexicon and ML	Sentiword Net, NB, DT, RF, SVM, gradient boosting, Seq2Seq	DT, RF, SVM, gradient boosting classifier with Comparative adverbs (F-score: 0.960)
		Musical DVD reviews					
Jnoub et al. (2020)	English	IMDB	50000	Movie	ML	Proposed-CNN, Proposed SNN, SVM, KNN, NB, RF	Proposed SNN (Accuracy: 0.870; F-score: 0.870)
		Movie Reviews (Cornel)	10000	Movie			Proposed SNN (Accuracy: 0.820; F-score: 0.820)
		Amazon product review	1000	Product			Proposed SNN (Accuracy: 0.740; F-score: 0.740)
Ibrahim et al. (2019)	English	IMDb	-	Movie	ML	LSTM-User Movie attention	LSTM-User Movie attention (Accuracy: 0.533)
		yelp13	-				LSTM-User Movie attention (Accuracy: 0.650)
		yelp14	-				LSTM-User Movie attention

							(Accuracy: 0.667)

Source: *(Xu et al., 2022)*

2.2.2 Network Analysis

2.2.2.1 Introduction to Social Network Analysis

The term 'social network' was first used in a study by anthropologist John A. Barnes, who examined the connections among individuals in Norway. Since then, the concept has evolved and expanded across various fields, including sociology, economics, computer science, and education (Saqr et al., 2020). A social network comprises actors and their relationships. These networks can be represented graphically, with nodes representing the actors and links depicting the relationships (Can & Alatas, 2019). The famous 1977 karate club network graph, showing 34 individuals and their interrelations, exemplifies this (Girvan & Newman, 2002). Today, with the proliferation of online social networks (OSNs), these structures have grown to encompass millions of nodes, covering a wide array of relationships and interactions. In addition, these nodes can represent not only individuals, but also any systems related to each other, such as institutions, words, and groups.

SNA has become a critical tool for analysing and extracting new insights in various fields due to their vast size and complexity. The primary objective of SNA is to understand the patterns and contents of relationships within these networks, focusing more on the relations themselves than the individual entities (Tabassum et al., 2018). Applications of SNA are diverse and influential. For instance, in the realm of social movements, SNA was leveraged to understand social movements and capture the nuanced dynamics of online activism (Xiong et al., 2019; S. Singh et al., 2020). In the business sector, Wang et al. (2020) used SNA to predict e-book purchasing behaviours on ReadDouban, a prominent Chinese online sharing platform. Moreover, in the field of public policy and governance, SNA can assess the impact of governmental roles on policy and public engagement (Eom et al., 2018). The utility of SNA extends beyond social entities to include data networks composed of various objects like words, images, products, and governments, illustrating its versatility and widespread applicability in contemporary research and industry.

2.2.2.2 Analytical Techniques

A. Ego Network Analysis

Ego Network Analysis focuses on the study of individual actors (referred to as "egos") and their immediate relational environment in a social network. This type of analysis provides a microscopic view of the larger network, concentrating on the personal networks of individual nodes and their direct connections, known as "alters" (Crossley et al., 2015). Ego networks are instrumental in understanding how individuals leverage their social capital, and how information flows to and from them within the network, and the influence these interactions have on their behaviours, opinions, and social roles. An ego network can be evaluated by the following aspects:

- Number of Components: This refers to the count of distinct social circles or clusters within an ego's network. It helps in identifying how diverse or compartmentalised an individual's social interactions are (Crossley et al., 2015; Tabassum et al., 2018).
- Effective Size and Efficiency: The effective size of an ego network measures the number of alters with whom the ego has unique relationships, discounting those connected to each other. It reflects the diversity and reach of an individual's network (Burt, 1992; Everett & Borgatti, 2020). Network efficiency in the context of an ego network assesses how effectively the ego maintains its relationships, considering the network's size and redundancy among connections. Efficiency is calculated by dividing the effective size of an ego network by its total number of alters. It represents a normalised version of an ego network's effective size, and its value ranges from 0 to 1 (Tabassum et al., 2018).
- Constraint: This measures the degree to which an ego's connections are concentrated among a few alters. High constraint suggests a lack of diversity in the ego's network, potentially limiting access to new information or resources (Burt, 1992; Everett & Borgatti, 2020).
- Krackhardt's E/I Ratio: Developed by David Krackhardt, this ratio evaluates the balance between internal (I) and external (E) ties in an ego's network. It is calculated by subtracting the number of internal ties within a group from the number of external ties outside the group and then dividing this difference by the total number of ties (Gonzalez-Brambila et al., 2013). This index is used to assess how outwardly or inwardly focused an individual's network interactions are.

Ego network analysis is widely applied across various fields to understand individual behaviour within a network context. In business, it helps in identifying key factors that influence consumer decision-making (Hoffmann et al., 2020). In organisational studies, it helps analyse employees' collaboration and communication patterns (Yang et al., 2021). In the realm of social movements, Xiong et al. (2019) showcased the power of ego network analysis in dissecting the #MeToo movement on Twitter. They constructed a feminism-centric network, using ego network analysis to unravel the centrality and interconnectedness of specific terms within the feminist discourse. Ego network analysis offers a detailed perspective from the point of view of individual actors within a larger network, emphasising the importance of direct relationships and their impact on all aspects of social life. This type of analysis is essential for revealing the complexity of social interactions at the individual level and understanding how these micro-level interactions coalesce to form larger network phenomena.

B. Link Analysis

Link analysis is one of the SNA methods that studies the connections between nodes in a network. It can reveal direct interactions between entities and also uncover indirect relationships that help shape the overall network structure. This approach is essential for understanding how information flows through a network and for identifying the most influential and authoritative nodes or groups (Camacho et al., 2020; Tabassum et al., 2018).

Hubs and authorities are fundamental concepts in link analysis, distinguishing between two types of influential nodes in a network. Hubs are nodes that feature numerous links to other nodes, and a good hub is one that points to many authoritative nodes. On the other hand, authorities are nodes that are frequently linked by hubs, with a page deemed as a high-quality authority if it is linked by numerous good hubs. This distinction is crucial in networks where the flow of information or influence is a primary concern, like in web page networks or citation networks. The most commonly used algorithms to identify these two types of nodes are Google PageRank, conceptualised by Brin and Page (1998) and Hyperlink-Induced Topic Search (HITS) by Kleinberg (1999). PageRank is the backbone of Google's search technology. It assigns a numerical weight to each element of a hyperlinked set of documents, like the World Wide Web, to quantify its relative significance within the set. PageRank works on the principle that a webpage derives importance if important pages link to it. The algorithm determines this importance through the number and quality of links to a page. The HITS algorithm, developed by Jon Kleinberg, iteratively computes a hub and authority score for pages based on the quality and number of incoming and outgoing links. In SNA, both methods allow the determination of the most influential individuals or organisations within a network.

Link prediction is another area of link analysis that predicts new link formations or dissolutions in the network. Link prediction techniques anticipate future changes in network structure by analysing existing connections. This helps in understanding the evolving social networks and applications such as friend recommendation systems on social media platforms (Daud et al., 2020). Moreover, link analysis can also be used in network robustness and vulnerability analysis. This method estimates the robustness of a network against failure or attack by analysing the links and their respective strengths; hence, it can identify the key links or nodes whose removal would essentially disrupt the network (Díaz Ferreyra et al., 2022). Link analysis provides a powerful set of tools to understand and interpret the complex network of relationships in social networks.

C. Community Detection

Community detection in SNA refers to the process of identifying clusters in a network where nodes are more densely connected to each other than to nodes outside the cluster. These clusters often represent groups with common interests, behaviours, or roles. This technique helps in understanding the structure and organisation of large networks, as it can reveal the natural division of a network based on the strength and frequency of interactions between nodes (Jin et al., 2021). It also helps in understanding social dynamics and provides insights into how information or influence spreads within the network. It is particularly useful in large-scale networks where the complexity of relationships makes it difficult to identify latent patterns.

Hierarchical clustering, the Girvan-Newman algorithm, and modularity optimisation are the most commonly used methods in community detection. Hierarchical clustering creates clusters based on the distance or similarity between nodes. It can be either aggregative, where small clusters are merged into larger clusters, or divisive, where large clusters are split into smaller clusters. It is used to analyse the cluster structure of nested layers in a network (Govender & Sivakumar, 2020). The Girvan-Newman algorithm (2002) is a representative method in hierarchical clustering. This algorithm detects communities by progressively removing edges from the original network. It focuses on edges that are most likely to be between communities (i.e., edges with high 'betweenness centrality'). The Girvan-Newman algorithm is particularly effective in networks where community structures are not immediately apparent (Madhulika et al., 2023). Modularity optimisation involves measuring the strength of division of a network into communities. High modularity indicates a strong division with dense connections within communities and sparse connections between them.

Community detection has a wide range of applications. For instance, Suitner et al. (2022) utilised community detection to group hashtags into topics in the context of online climate action on Twitter.

Loukianov et al. (2023) applied network analysis with a focus on thematic clusters to interpret the connotations of 'good life' on Instagram. In the study by Singh et al. (2020), community detection was employed to understand user influence and trust in the context of the Momo Challenge. Milani et al. (2020) used it to classify actors into anti-vaccine and pro-vaccine communities and analyse their interaction patterns on Twitter.

D. Evolving Network Analysis

While traditional SNA often assumes a static network structure, evolving network analysis in SNA recognises and analyses the temporal changes in networks (Yang & Pei, 2020). This approach examines how nodes and connections emerge, evolve, and dissolve over time, providing insights into the dynamic processes that shape social networks. Temporal networks are evolving networks where the timing of interactions is crucial. Analysis of these networks involves studying patterns of connections based not only on their existence but also on their duration and timing. This method is essential for understanding networks where the timing and sequence of interactions significantly impact the network's behaviour, such as in communication networks or transaction networks.

Evolving network analysis has diverse applications and is vital in areas such as epidemiology, for tracking the spread (Gongora-Svartzman & Ramirez-Marquez, 2022) and recovery of diseases (Yeo et al., 2022); in telecommunications, for understanding changing communication patterns; and in social media, for observing the evolution of online discourses (Suitner et al., 2022); and in academia, for providing a macro overview of trending topics using bibliometric analysis (Zhang et al., 2022; Kim et al., 2021). These applications involve various techniques to track and analyse changes in network structure over time, including studying the formation of new links, the dissolution of existing ones, the emergence of new nodes, and the disappearance of old ones. In addition, statistical models and visualisations are often used to capture and understand these evolutionary patterns. Several models exist to explain how networks grow and evolve. These include the Barabási–Albert model (Albert & Barabási, 2002), which explains how networks evolve based on the principle of preferential attachment, leading to scale-free networks. Other models address growth patterns through random connections or based on specific nodal attributes. In summary, evolving network analysis represents a comprehensive and nuanced approach in SNA, enabling a deeper understanding of the dynamic nature of social interactions and the ability to predict how networks will change and evolve over time.

2.2.2.3 Data in Social Network Analysis

A. Types of Data

In SNA, understanding the types of data used is essential for comprehending the structure and function of social networks. The primary categories of data in SNA are relational and attribute data. Relational data provides insight into who is connected to whom and the nature of these connections within a network, which refers to directed relationship or undirected relationship (Tabassum et al., 2018). This type of data can be further categorised into dyadic data, which involves pairs of nodes and their interactions, crucial for analysing direct relationships in a network. Another form is adjacency data, often represented in matrix form, showing which nodes are adjacent to each other and offering a comprehensive view of the network's structure.

In contrast, attribute data adds context to the network's structure by providing information about the nodes themselves (Diviák, 2022), such as demographic information, behavioural information and psychographic data. Demographic information includes age, gender, occupation, and location, which helps in understanding the characteristics of nodes within the network. Behavioural data covers the actions of nodes, like purchasing history, online activity, or communication patterns, while psychographic data covers attitudes, interests, values, and lifestyles.

The types of data used in SNA are the basis for revealing the complexities of social networks. Relational data provides the structural framework, while attribute data adds depth and context. Combining these data types results in a more detailed analysis, allowing researchers to understand not just the network structure but also the characteristics and behaviours of its members in relation to their position within the network.

B. Data Representation

Data for SNA can be sourced from a variety of platforms, including social media sites, organisational databases, communication logs, and survey responses. The choice of data source significantly influences the scope of the network analysis. In SNA, the representation of data can affect the analysis process and the interpretation of results. Effective data representation helps in visualising complex network structures and applying various analytical techniques. The most common forms of data representation in SNA are graphs and matrices (Cerra Escobar & Villarreal Padilla, 2017).

In graph representation, entities in the network are represented as nodes or vertices, and the relationships between them are depicted as edges or links. This form of visualisation reveals the network's structure. Edges can be directed or undirected; directed edges indicate a one-way relationship, while undirected edges indicate a two-way relationship (Tan et al., 2021; Valeri & Baggio, 2021). For example, in a Twitter network, follows are directed edges, while mutual friendships on Facebook are undirected (Trolliet et al., 2021). Additionally, networks may feature weighted graphs, where edges have varying thicknesses or values to represent the strength or intensity of the connections (Bellingeri et al., 2020). Matrix representation is another vital form of data representation for social network analysis, and the two principal methods are adjacency matrix and incidence matrix. The adjacency matrix is a square matrix used to represent a finite graph. The elements of the matrix indicate whether pairs of vertices are adjacent or not in the graph (Ahdan & Setiawansyah, 2021). In an unweighted graph, the values are binary (0 or 1), while in a weighted graph, the matrix contains the weights of the edges. The incidence matrix, on the other hand, details the relationship between nodes and edges, useful in networks where edges have unique attributes or in the analysis of bipartite graphs (Tudisco & Higham, 2021).

Various software and tools, such as Gephi, UCINET, and NetworkX, are available for representing social network data (Rani & Shokeen, 2021). Gephi is renowned for its robust visual and network analysis features. As an open-source, standalone software, it excels in handling large datasets and offers enhanced data representation through "Plugin Alchemy AP." Gephi supports a variety of input file formats and integrates data from multiple SNA tools, facilitating user-friendly network graph creation. Its main drawback is the occasional slow response time for basic tasks (Majeed et al., 2020). UCINET is a menu-driven software, primarily used for cultural domain analysis and SNA. It operates on a standalone basis, with data predominantly represented in matrix form. UCINET is adept at handling smaller networks and offers versatility in input and output formats. Its Netdraw tool for network visualisation provides multiple layout options and adjustable node properties for in-depth network analysis (Majeed et al., 2020). NetworkX is a Python-based package, well-suited for creating, analysing, and exploring complex networks, especially large real-world graphs. It supports a variety of functions like computing centrality measures, clustering, and drawing networks in 2D and 3D. In NetworkX, nodes can be diverse objects, and edges can carry weights, offering flexibility in graph construction and analysis (Rani & Shokeen, 2021). These tools provide functionalities for creating different types of graphs and matrices and conducting various forms of analysis. The choice of data representation method in SNA is not merely a means of visualisation but a foundational aspect of network analysis, significantly impacting the insights derived from the data and influencing both the analysis process and the interpretation of social networks.

C. Data Sources and Pre-processing

The effectiveness of SNA largely depends on the quality and relevance of the data used. The sources and methods of data acquisition are diverse, each providing unique insights into the dynamics of social networks. A deep understanding of these data sources and collection methods is vital for conducting robust and precise network analysis, as it directly influences the scope and accuracy of the findings.

Firstly, social media platforms serve as a rich source of data, offering a real-time snapshot of public opinion and social interactions. Twitter data, for instance, has been used to study diverse topics ranging from public health discussions to social movements. This data is particularly valuable for capturing organic, user-generated content that reflects current trends, sentiments, and behavioural patterns within large populations (Milani et al., 2020; Jastania et al., 2020). Similarly, e-commerce sites serve as another vital data source, particularly for consumer behaviour analysis. They provide a wealth of information on user preferences, purchasing behaviours, and interaction patterns. This type of data is instrumental in understanding how digital communities form around products or topics and how consumer choices evolve in online marketplaces (Wang, Wang, Chai, et al., 2020). On the other hand, institutional data, derived from public documents, reports, or internal databases, offers a structured and often formal perspective on various interactions. This data is crucial for studies focusing on organisational behaviour, such as industry-university collaborations (Huggins et al., 2020), and other formalised network structures. It provides a foundation for examining structured relationships and formal communication patterns within and between institutions. Surveys and questionnaires represent a more direct approach to data collection, allowing researchers to gather specific information directly related to their study objectives. This method is especially useful for collecting nuanced data that may not be readily available through other sources, such as personal opinions, experiences, or detailed demographic information (Han et al., 2020; Zarate et al., 2022).

Additionally, publicly available datasets and repositories are invaluable for broad-scale studies, especially those focusing on historical events or large-scale public reactions. The utility of these data sources is not limited to the immediate availability. They provide a standardisation resource and can be used as a benchmark for new analytical methods or theories, allowing researchers to validate their findings across different contexts or datasets. Moreover, these datasets are often subjected to some degree of pre-processing, such as anonymisation or cleaning, which can speed up the research process (Yeo et al., 2022).

Each data source has its own strengths and limitations. Social media data is inherently broad and real-time, making it ideal for capturing the pulse of public sentiment. However, this type of data often presents challenges such as being voluminous, incomplete, or inconsistent. Sophisticated tools and techniques are required to effectively process and analyse such large datasets. Additionally, access to social media data can be difficult due to privacy concerns and proprietary restrictions.

Institutional data is reliable and structured, but it may lack the spontaneity and diversity of user-generated content. On the other hand, surveys and questionnaires can provide specific and targeted insights but may suffer from sample size and response bias. This can lead to challenges in ensuring that data is representative, as the collected data might not fully reflect the range of views or behaviours within the wider population. Public datasets have broad coverage but may not fully represent all demographics or behaviours, potentially introducing bias into the research findings. Therefore, the choice of data source in SNA is driven by the research question at hand and the nature of the social phenomena under investigation. Whether through social media, institutional data, surveys, or public datasets, each approach provides a unique lens through which to analyse the complex tapestry of social networks.

Once suitable datasets are collected, they will be pre-processed for the following analysis. Data pre-processing in SNA is an essential process for effective analysis. It transforms raw data into a structured format that can be processed through different network analysis techniques to ensure the validity and reliability of the study's findings. This task encompasses data selection, cleaning, and organisation. It is particularly crucial when dealing with large volumes of data.

The initial step often involves selecting data that is pertinent to the research question. For instance, when analysing online discussions on specific topics, researchers may filter tweets or posts based on keywords, hashtags, or language criteria. This targeted selection is essential for filtering out the most relevant data for the study (Hung et al., 2020; Jastania et al., 2020). For studies focusing on SA or thematic exploration, this stage might also involve refining the data to contextually appropriate words, removing extraneous elements like connector words or usernames used as hashtags, and even standardising different expressions of the same word (Xiong et al., 2019).

Organising the data effectively is another critical aspect of pre-processing. It structures the data in a way that facilitates analysis, such as organising tweets by date for a time-series analysis or categorising posts based on sentiment (Wang et al., 2020; Featherstone et al., 2020). For studies examining interactions or relationships within networks, this step might include constructing adjacency matrices or sociograms. In the context of studies that involve ML or complex statistical analyses, pre-processing also entails preparing the data in a format that can be easily ingested by analytical tools. This could mean converting text data into numerical values, encoding categorical data, or creating features that represent key aspects of the network being studied (Ahmed et al., 2020; Pascual-Ferrá et al., 2022).

2.2.2.4 Node and Network-Level Analysis

A. Node-Level Statistical Measures

In SNA, node-level statistical measures provide valuable insights into the roles and significance of individual nodes within the network. These measures help in understanding the behaviour of social systems that generate such networks. At the node level, various centrality measures are used to understand the position of a node within the overall network structure, thereby identifying key players or 'focal points' in the network. The most commonly used measures in the existing studies are introduced as follows.

The *degree* of a node is a basic indicator of its direct adjacency and participation in the network. It is calculated as the number of edges connected to the node or the number of neighbours of the node. This measure is evaluated using the adjacency matrix or by counting the neighbours of a node. For nodes in directed networks, they can be evaluated from perspectives of in-degree and out-degree, reflecting support and influence respectively (Tabassum et al., 2018).

Betweenness centrality quantifies the extent to which a node lies on the shortest paths between other nodes in the network. High betweenness indicates that the node plays a critical role in connecting different parts of the network, acting as a gatekeeper or bridge. They control the flow of information between network communities (Tabassum et al., 2018). *Closeness centrality* measures how quickly a node can reach other nodes in the network and indicates the node's reachability or accessibility within the network. It is defined as the average length of the shortest paths from the node to all other nodes. *Eigenvector centrality* assigns a relative score to a node based on its connectivity to other nodes that are also well-connected. It operates on the principle that a node's importance is a function of the importance of its neighbour. Eigenvector centrality became widely recognised when it was applied to the Google PageRank algorithm (Tabassum et al., 2018).

Local Clustering Coefficient quantifies how close a node’s neighbours are to forming a clique (complete graph). It measures the likelihood that the friends (neighbours) of a node are also friends with each other. The local clustering coefficient is particularly useful for understanding the transitivity of relationships in the network (Tabassum et al., 2018).

These node-level measures reveal the relative importance and influence of individual actors within the network. They not only highlight the most central nodes but also provide a deeper understanding of the network's overall structure and connectivity, which are crucial for analysing social networks and interpreting the latent social phenomena.

B. Network-Level Statistical Measures

Compared to node-level measures, network-level statistical measures evaluate the overall structure and dynamics of networks. Rooted in fundamental concepts such as paths, geodesic distances, and eccentricity, these measures provide insights into the network's connectivity, reachability, and cohesiveness. The most commonly used measures in the existing studies are introduced below.

A *path* in a network is a sequence of nodes connected by edges, with unique start and end vertices. The *geodesic distance*, or the shortest path between two nodes is key in network analysis. It represents the minimal number of steps required to connect any two nodes in the network, while *eccentricity* is the greatest geodesic distance from a given vertex to any other in the network. *Average geodesic distance* represents the average of the shortest paths between all pairs of nodes in the network. It indicates the average separation between nodes and can be used to assess the efficiency of information flow within the network. In networks with multiple components, the harmonic mean of the geodesic distances is often used to account for infinite distances in disconnected node pairs.

The *diameter* of a network refers to the maximum eccentricity among all vertices, and it is the farthest distance between any two nodes in the network (Han et al., 2020; Pascual-Ferrá et al., 2022). Conversely, the *radius* is the minimum eccentricity and represents the shortest distance to the farthest node. These measures indicate the network's extent and how spread out the nodes are. Real-world networks often show changing diameters over time, sometimes even shrinking contrary to expectations.

Average degree of a network is the mean degree across all vertices, representing the average number of connections per node. It is a straightforward measure of the network's overall connectivity.

In directed networks, *reciprocity* measures the likelihood of mutual connections between pairs of nodes. It is calculated as the ratio of the number of mutual connections to the total number of connections. High reciprocity indicates a tendency towards bidirectional relationships in the network (Pascual-Ferrá et al., 2022).

Density provides a measure of how well connected the network is. It is calculated as the proportion of actual edges relative to the maximum possible number of edges in the network. Density values range from 0 (no connections) to 1 (fully connected network), with higher values indicating denser networks (Han et al., 2020; Pascual-Ferrá et al., 2022).

Global clustering coefficient assesses the degree to which nodes in a network tend to cluster together (Carattini et al., 2023). High global clustering coefficients are typical of small-world networks and indicate that there is a strong tendency to form tightly knit groups or cliques.

These network-level statistical measures can provide a comprehensive analysis of the structural features of social networks. They provide an understanding of the overall layout, connectivity, and communal aspects of networks.

2.2.2.5 Content-Based Analysis in Social Networks

A. User Profiling

Content-based social network analysis primarily focuses on the interaction content between nodes in an online social network (OSN) to extract topics or opinions. An integral part of this approach involves user profiling, which concerns understanding the nodes, or users themselves. User profiling in OSNs is established by analysing behavioural patterns, correlations, and activities of users, using aggregated data from various techniques like clustering, behavioural analysis, content analysis, and even face detection (Camacho et al., 2020). User profiling necessitates data related to the user's online activities within the OSN. These activities could be influenced by personal interests or external factors. Several studies have contributed to the methods and applications of user profiling.

In the study by De França et al. (2018) during the Brazilian impeachment process in 2016, they emphasised the role of user profiling in understanding the impact of significant events on different user groups in social networks. By segmenting users into categories such as popular, activists, and observers, the study provides insights into the real interests of citizens, showcasing how user profiling can offer detailed analyses of events in social networks. Devi & Pattabiraman (2019) highlight the need for accurate user profiling in the context of big data and social media networks. Their study proposes a user profiling approach that groups user intelligence, which is crucial for personalised marketing and advertising strategies. The focus on narrative tags on Twitter and accurate profiling on Yelp for restaurant suggestions exemplifies the practical applications of user profiling in enhancing user experience.

Kaushal et al. (2019) and Gilbert et al.'s (2023) research highlights the challenge of user profiling across multiple OSNs. To address this, Kaushal et al. (2019) introduce five methods: Advanced Search Operator, Social Aggregator, Cross-Platform Sharing, Self-Disclosure, and Friend Finding Feature. These methods, applied to a large dataset, demonstrate the effectiveness of cross-platform user profiling in gathering comprehensive information. Gilbert et al. (2023) explore the application of social network analysis (SNA) in politics and other fields, emphasising the importance of detecting fake profiles and understanding user behaviour. The MapMe solution mentioned in the study is instrumental in identifying similar users across multiple platforms, highlighting the versatility of user profiling.

Rashmi & Kodabagi's (2020) research proposes a graph-based methodology for connecting user profiles based on attribute similarity, tested on the LinkedIn dataset. This approach addresses the challenges of analysing unstructured data in social networks, proving essential for applications like link prediction, criminology, public health, and recommendation systems. Tamil Selvi et al.'s (2022) work underlines the importance of egocentric network analysis in social networks. This approach focuses on individual users, their groups, or communities, considering factors like the size, structure, and composition of their ego networks. The study reveals that, although the means of communication and maintaining social relationships are evolving with online social networks, the way individuals organise their social networks seems to remain unchanged. This consistency suggests that the basic structure of social networks, and thus user profiling, may be more static than previously thought.

These studies highlight the multifaceted nature of user profiling in SNA, underscoring its importance in understanding the roles, influence, and behaviours of individuals within social networks. By analysing content and interaction patterns, researchers can extract valuable insights into user characteristics, preferences, and social dynamics.

B. Topic Extraction

Topic extraction is a pivotal technique in SNA, used for uncovering abstract themes or subjects within a collection of documents. This process is instrumental in various applications, including text auto-categorisation, SA, and enhancing the depth of SNA. The methods employed for topic extraction are diverse and sophisticated, ranging from mixtures of unigrams and latent semantic indexing to Latent Dirichlet Allocation (LDA) and knowledge-driven approaches. These techniques are especially potent in gleaning user interests from the vast and complex data landscapes of OSNs (Albalawi et al., 2020; Jaffali et al., 2020; Khanam et al., 2023).

Innovations in this field have been dynamic and impactful. Recent studies like those by Hung et al. (2020) and Ahmed et al. (2020) have applied topic extraction to analyse discussions and sentiments on Twitter related to COVID-19, revealing dominant themes and sentiment trends. Hung et al., (2020) utilised NLP and ML, specifically LDA, for topic modelling. Ahmed et al. (2020) utilised SNA to dissect the 5G COVID-19 conspiracy theory on Twitter, employing NodeXL for data retrieval and network graph layout, along with cluster analysis for understanding the spread of misinformation. Curiskis et al. (2020) evaluated various document clustering and topic modelling techniques on Twitter and Reddit, focusing on overcoming the challenges of short and noisy text typical in OSNs. The study benchmarked different feature representations derived from term-frequency inverse-document-frequency (TF-IDF) matrices and word embedding models, combined with various clustering methods. A key finding was that clustering techniques applied to neural embedding feature representations yielded the best performance. Bibliometric network analysis was used in the evolution of the field of innovation systems (Dahesh et al., 2020) and interactive digital marketing (Krishen et al., 2021) to identify major topics in the corresponding domain. They employed a range of analyses including word co-occurrence, co-citation, and bibliographic coupling analyses to categorise historical and contemporary views and identify emerging research trends.

Garcia and Berton (2021) explored Twitter content related to COVID-19 from Brazil and the United States (US) using topic detection and SA. One of the primary methods used was the LDA, which represents topics as probability distributions over words in a dictionary. However, recognising the limitations of traditional topic models with short texts, they utilised the collapsed Gibbs Sampling algorithm for the Dirichlet Multinomial Mixture (GSDMM). This approach was better adapted to the short texts typical of Twitter, simplifying the inference process by assuming that each document is influenced by a single topic. The study involved adjusting probability distributions to maximise the likelihood of producing the document set, using Collapsed Gibbs Sampling for this purpose. Mohawesh et al. (2023) developed a semantic graph-based topic modelling framework for multilingual fake news detection. Their framework began by integrating a pre-trained XLM-ROBERTa language model with neural topic modelling to extract contextual information and global linguistic features. This integration enabled the creation of multi-typed heterogeneous text graphs. These graphs were instrumental in elucidating various interactions between document and word nodes, thereby providing a detailed understanding of the textual data. By focusing on the semantic aspects of the text, the framework enhanced the accuracy and effectiveness of fake news detection across different languages, making it a significant contribution to the field of text classification and misinformation studies. Noekhah et al. (2020) proposed an innovative graph-based model for opinion spam detection, particularly in the e-commerce sector. Recognising the rising need to combat the negative impact of such spam on e-commerce reputations, their model, named "Multi-iterative Graph-based Opinion Spam Detection" (MGSD), addressed the limitations of existing spam detection techniques. This algorithm took into account a diverse set of factors to update the spamicity score of entities, enhancing the model's accuracy and applicability. The model employed a combination of feature fusion techniques and ML algorithms, selecting a higher number of existing weighted features and novel proposed features from various categories.

Topic extraction in SNA has evolved into a multifaceted discipline, leveraging complex algorithms and models to mine and understand user interests and topics within OSNs. These advancements have not only enriched the understanding of individual and community behaviour in online networks but have also provided tools for deeper analysis and interpretation of social interactions and trends.

C. Classification Analysis Using ML Algorithms

Content-based analysis in social networks has increasingly utilised ML algorithms for classification, especially in SA. This approach is crucial for deciphering vast streams of data and extracting meaningful insights, particularly during significant global events, as demonstrated in several studies.

In their analysis of COVID-19 discussions on Twitter, alongside social network analysis, Hung et al. (2020) applied ML to categorise over 900,000 tweets into various sentiments and themes. They found a significant spread of positive sentiments and prevailing themes, such as healthcare, emotional support, and psychological stress. Their work also included a geographical analysis, revealing differing sentiment trends across various states in the US Garcia and Berton (2021) extended this approach to a comparative analysis of COVID-19 related tweets from Brazil and the US. By employing topic detection and SA on millions of tweets, their study provided insights into how public discourse evolved over time in response to pandemic news, highlighting differences in public reactions and information dissemination between the two countries. In the context of natural disasters, Yeo et al. (2022) analysed social media communications related to the 2016 Southern Louisiana Flood. By examining sentiment data, they tracked changes in public reactions to long-term recovery efforts. Their study revealed the dynamics of participant numbers, dominant voices, and sentiments in digital communication during the disaster recovery process.

Milani et al.'s (2020) research on the visual vaccine debate on Twitter offered a different perspective. Focusing on how vaccine-related images were shared, their study investigated the influence and distribution of these images to understand the formation of communities and networks around vaccination debates. Their classification analysis was comprehensive, incorporating various Twitter elements to identify potential gatekeepers of vaccination information.

Wang et al.'s (2020) study on e-book adoption behaviours on an online sharing platform constructed a multi-relational network to identify factors impacting user product adoption behaviour. They developed a predictive model using ML methods, considering various feature sets to predict consumer behaviour. Their approach highlights the role of network features in understanding user preferences in a digital marketplace. Finally, they utilised International Business Machines Corporation (IBM) Watson Natural Language Understanding for SA. Featherstone et al. (2020) examined childhood vaccine discussions on Twitter and classified tweets from influential users. Their analysis provided insights into the distribution of vaccine information and the polarisation within pro- and anti-vaccine communities.

In summary, classification analysis in the field of SNA has evolved into a sophisticated tool that not only understands the sentiment or other characteristics of a group, but also provides actionable insights in a variety of domains. Its integration with other analytics helps in understanding the nuances of online interactions.

These advances in topic extraction and classification analysis by SNA highlight the depth and diversity of content-based analytics in understanding and interpreting complex social network dynamics.

2.2.2.6 Applications of Social Network Analysis

SNA has been adopted to analyse social media data to inform a variety of issues across different domains.

Xiong et al. (2019) examined how social movement organisations (SMOs) used words and hashtags on Twitter to participate in the #MeToo movement, specifically addressing issues of sexual violence and assault. The uniqueness of their method is that they constructed a feminism-centric network via ego-network analysis to measure the centrality of words within the broader #MeToo and feminist discourse. Word frequencies and normalised-degree centrality were calculated to determine the centrality and interconnectedness of each term. Thematic analysis was also applied to extract deeper insights from the semantic network, revealing multiple facets and perspectives of the #MeToo movement on Twitter. However, the methodology behind the thematic analysis remains unspecified. Manual text analysis, especially within expansive social media datasets, is notably challenging. The analytical framework might benefit from the inclusion of cluster algorithms or ML techniques to enhance its efficiency. In the work of Suitner et al. (2022), they utilised network analysis on hashtags to explore the connection between digital activism and the psychological processes related to social drives in the context of online climate action. They constructed bipartite networks linking tweets to hashtags and then projected the networks onto hashtags to obtain the hashtag network. They used community detection to group hashtags into topics, identifying 16 communities, with the most relevant ones being climate action, nature, and recycling. Loukianov et al. (2023) investigated the impact of hashtag use on Instagram in interpreting the connotations of the 'good life.' Similar to Suitner et al. (2022), they employed network analysis on the hashtags rather than users to explore narrative patterns. Utilising degree centrality, they assessed the visibility and recognisability of different themes. They found that highly connected connections did not follow consistent patterns, leading to high visibility but lower recognisability. Smaller thematic clusters with few tags had lower visibility in the discourse field could increase visibility by establishing strong relationships with particular clusters. Despite identifying connectivity patterns, their reliance on manual categorisation echoes the methodological limitations seen in Xiong et al.'s (2019) study, which again raises the potential for subjectivity and inefficiency. The need for objective and scalable analysis methods, like cluster analysis or graph neural network analysis, is a shared limitation within this group of studies.

Singh et al. (2020) employed network analysis and content analysis to study the nature of the Momo Challenge, a cyberbullying phenomenon prevalent on social media platforms. By analysing 18,000 tweets, they assessed user connections and identified the primary platform contributing to the Momo Challenge narrative. Network metrics like degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, and clustering coefficient were used to understand user influence and trust. Content analysis, as another key method, highlighted linguistic preferences, popular hashtags, and sentiment concerning the event. However, the study's focus leaned heavily towards frequency and not on the deeper relationships among these aspects. Despite this multi-faceted approach, the study's reliance on frequency metrics and lexicon-based SA could lead to an oversimplified understanding of complex sentiments and overlook the subtleties of evolving language and context-specific connotations. This limitation is echoed in the work of Milani et al. (2020), who investigated vaccine perceptions on Twitter through SNA. The study classified actors and sentiments into anti-vaccine and pro-vaccine communities. Through network analysis at the user level, they identified gatekeepers by betweenness centrality and hubs by in-degree centrality for each community. A qualitative review of images from these key players showed the anti-vaccine community frequently shared images questioning vaccine safety and promoting conspiracy theories, with a well-connected network. In contrast, the pro-vaccine community had more openness and largely consisted of official accounts, primarily emphasising vaccine efficacy. While Milani et al.'s analytical framework sheds light on the integral role of images in vaccine information propagation patterns, there would have been potential for enhanced depth if interactions or relationships between words or hashtags were analysed. Furthermore, their approach to actor and sentiment classification was rule-based, demanding extensive efforts to delineate rules. Both studies contribute to the application of network analysis to social media phenomena but have encountered similar obstacles in terms of potentially underestimating the complexity of language and the relationships that drive online discourse. This provides a common space for future research to refine content analysis methods and integrate more advanced tools to discern and explain subtle dynamics in social media networks.

Jastania et al. (2020) utilised a social network analytical framework on Twitter to investigate the topic of women driving cars in Saudi Arabia. The study focuses on identifying influencers and leading distributors of news on Twitter within this domain by creating four different networks: retweet, mention, co-mention, and hashtag networks. Specifically, the retweet and mention networks identified influential individuals and news sources, while the co-mention network was instrumental in detecting significant individuals closely associated with the discussions. The top users in the co-mention network were identified as influencers, whereas those in the retweet and mention networks were considered leading distributors of news. Even though a hashtag network was developed for the subject, the study did not sufficiently utilise semantic network analysis to comprehensively unpack public perspectives on the issue of women driving in Saudi Arabia.

Wang et al. (2020) employed social network analysis and machine learning to study user adoption behaviours and predict e-book purchases on ReadDouban, a prominent Chinese online sharing platform. The results indicated that user activity and book popularity influenced purchasing decision more than genuine preferences. To predict user purchases of user-generated e-books, the authors also trained a binary classifier using machine learning methods, with the RF algorithm outperforming others. They used four feature sets, namely book and user identity features, and combined them with network features. The study also found that network features contributed the most to the accuracy of the model, indicating the importance of considering multi-relational network extraction in identifying user adoption behaviour on the sharing platform. Wang, Wang, & Liu (2020) also applied network analysis to the business domain. Different from the previous study by Wang et al. (2020) on predicting customer purchase behaviour, they present a framework for determining customer-focused product features. This approach combined entity analysis for feature extraction, dependency parsing, and the TF-IDF algorithm to refine accuracy, and network analysis to identify the most demanding features. Using degree centrality as a principal metric, they applied this framework to electric drills, revealing that customers prioritise battery durability and are sensitive to price. This work proves that network analysis can also be used to help businesses understand the product features that matter most to their customers, improving the product design and marketing. Nonetheless, the study's reliance on degree centrality might overshadow other pivotal network metrics, such as betweenness centrality, closeness centrality, or eigenvector centrality, potentially skewing the outcomes. Integrating a deep learning-based SA could further enrich the insights, providing a more nuanced understanding of customer perceptions concerning the identified product features.

Network analysis has consistently proven its capacity to offer valuable insights across a diverse range of domains. In the work of Han et al. (2020), network analysis was applied to the education domain by analysing how different types of relationships (task interdependence, trust, friendship, and awareness of expertise) influence knowledge sharing among management students in a business school setting. Their study utilised network level metrics, namely the number of nodes, edges, network density, diameter, and degree centralisation. Their findings suggest that friendship relationships had less of an impact on knowledge sharing than other relationships. LR was also conducted to validate their network analysis results. Eom et al. (2018) explored the roles of mayors and public officials on social media, focusing on the Twitter network of Seoul's civil administration services. They analysed network structures, emphasising Mayor Park's role as a bridging hub and the repercussions of his absence. Through SNA, they pinpointed thematic networks using the Clauset, Newman, and Moore algorithms to delineate network structure and clustering. The study assessed the network's stability by measuring its disruption when key bridging hubs, characterised by notable betweenness and in-degree centrality, were removed. This research demonstrates the value of network analysis in comprehending governmental roles concerning policy and programmes. However, it primarily focuses on government actors and overlooks the citizen's perspective. Integrating semantic network analyses could provide a more holistic perspective, capturing the key concerns and sentiments of citizens.

In addition to its application to social, commercial, and political issues, network analysis can also be employed for risk management. Díaz Ferreyra et al. (2022) explored the role of homophily and information diffusion in community detection for access-control decisions in OSNs. The study utilises simulation models to analyse the performance of various community detection approaches and investigates the impact of removing gatekeeper nodes as a strategy to counteract unwanted data dissemination to protect information security. Park et al. (2019) employed network analysis to evaluate information exchanges within Disney World's online community during Hurricane Irma. By analysing data from the Walt Disney World (WDW) Facebook fan page, they established two distinct member networks for the periods before and during the hurricane. Through degree and betweenness centrality measures, influential Facebook members were identified. Additionally, a word-level network analysis revealed a noticeable prominence of hurricane-related terms (e.g., evacuation, damage), while entertainment-centric words weakened in connection. This indicates a community focus shift from entertainment to crisis-related information. However, the study's depth in semantic network analysis was limited. The reliance on degree centrality merely highlighted frequently mentioned words, potentially missing out on phrases or combinations of words. Moreover, the rule that the authors classified the topics is not clear. An improvement can be made by using clustering analysis and advanced machine learning algorithms.

Ahmed et al. (2020) utilised network and content analysis, similar to Singh et al. (2020), but focused on COVID-19 related topics. Their research aimed to identify the origins of the #FilmYourHospital conspiracy theory, analyse the ratio of automated to organic accounts, and derive lessons to mitigate the spread of such conspiracy theories in the future. SNA was performed to depict the structure, with nodes clustered using the Clauset-Newman-Moore algorithm, uncovering six distinct network shapes. Through content analysis, they explored videos and hashtags, identifying broadcasting groups and dissemination routes of the conspiracy. Although the user network analysis was proficient, other aspects like hashtags and bots, were confined to frequency analysis. Moreover, not all tweets including #FilmYourHospital support this conspiracy. An improvement to the analytical framework could involve classifying the collected tweets into support, neutral, and non-support categories based on SA, followed by sifting out the supportive tweets and then applying the authors' methods.

The COVID-19 pandemic has raised a great deal of discussion on social media platforms. Pascual-Ferrá et al. (2022) studied three pivotal COVID-19 communication events on Twitter, analysing their network topology using metrics such as diameter, density, reciprocity, centralisation, and modularity. They also pinpointed influential users based on mentions, activity, and retweets. The findings indicated that personal comments on the racialisation and politicisation of the virus engaged more users than official World Health Organisation (WHO) announcements. This poses a challenge for public health officials in conveying risk effectively on Twitter. While influential user analysis is insightful, more insights could be obtained by applying the network analysis on the tweets to identify the specific aspects and corresponding perceptions with the help of machine learning algorithms.

2.3 Need for a Comprehensive SMA Framework

In the digital era, social media platforms have become one of the keys to shaping our world. Twitter, Instagram, and Facebook are not only platforms to interact socially, they have become significant sources of data about public views and feelings. This user-generated content, encompassing comments, posts, likes, and shares, offers valuable information to understand and, in turn, influence the dynamics in social, political, and economic spheres. However, extracting actionable insights from this vast pool of unstructured data poses a major challenge. Consequently, it is crucial to develop a comprehensive framework for analysing social media data using advanced AI and data science techniques.

The field of SNA offers a variety of approaches for understanding the complex network of interactions on social media. For example, user-level network analysis aims to highlight influential participants and delineate the structure of connections and information dissemination within a network. Commonly used metrics in this field include inter-degree centrality, intra-degree centrality, and the general degree centrality, which are crucial for identifying hubs, gatekeepers, and important nodes in the network. Meanwhile, semantic and tag network analyses have been studied mainly around words, tags, and images. These approaches typically combine entity frequency analysis with centrality measures. Ego network analysis and thematic analysis have also found notable applications in some academic activities, both aiming to uncover dominant themes and discourse structures.

SA, on the other hand, is a sophisticated branch of NLP that provides a perspective on public sentiment and perceptions. It involves extracting opinions, emotions, and sentiments from text, aiding in categorising public attitudes about a myriad of topics. Analysis methods range from rule-based and lexicon-based approaches to DL techniques.

However, certain limitations are apparent in the current SMA frameworks. A major issue is the over-reliance on entity frequency analyses, which, although informative, might fall short in exposing implicit relationships and connections. The narrative is often steered by count-based measures, such as frequency and degree centrality, potentially sidelining the intricate relationships and interactions in the network. Moreover, the field seems to bear the weight of a substantial dependence on manual and rule-based classifications. These methodologies, while foundational, can be laborious and might introduce biases. The dynamic and evolving nature of social media language and discourse might not always find resonance with these static techniques. In addition, the rise of emojis, for instance, represents a unique challenge. These graphical symbols, while expressive, complicate traditional text analysis methods due to their varied and contextual meanings. Additionally, there appears to be a tunnel vision in certain studies, emphasising specific network elements, such as users or hashtags. This narrow lens might eclipse a comprehensive understanding of the network. Some analyses seem to be anchored in discerning user influence, potentially sidelining the semantic and thematic layers that can be investigated by semantic network analysis and NLP techniques. In addition, in studies that combine network analysis and SA, the focus is mostly on user sentiment, ignoring the depth of this sentiment, i.e., how users perceive different aspects of the target being discussed and how these sentiments change over time. Therefore, there is a need to systematise these two approaches into a more comprehensive framework for social media data analysis. Another concern is the nebulous methodological clarity in some research undertakings. The steps, especially in thematic and SA, are not always delineated with precision, instigating doubts about the study's replicability and analytical depth. Therefore, another significant challenge in social media data analysis is methodological transparency. Often, studies in this domain lack a clear, traceable process, leaving questions about data extraction, cleaning, and analysis. This lack of clarity not only impedes scientific rigour but also hinders the replication of studies, an essential aspect of scientific progress.

The practical application of SMA frameworks is often compromised by the opacity of commercial tools. While these tools are user-friendly, their lack of transparency in analysis methods can lead to questions about validity and bias. This issue is exacerbated in regions with stringent privacy laws, where data accessibility becomes a hurdle, further limiting research scope and applicability.

While current SNA applications have greatly contributed to our understanding of different domains, there are still clear opportunities for improvement. By utilising advanced tools and maintaining a balanced focus on users and content, future research can explore the multifaceted nature of online interactions in greater depth.

In order to address these limitations, this study proposes a comprehensive framework that integrates advanced SA techniques with network analysis. The aim of the framework is not only to increase efficiency and reduce bias but also to apply to diverse domains. Moreover, instead of limiting the analysis to one main metric, the framework combines various metrics to gain a more nuanced understanding. As for SA, moving beyond traditional dictionary-based approaches, this framework leverages DL algorithms to provide deeper insights, especially when analysing huge datasets such as social media platforms. An emoji feature incorporated sentiment classifier is specifically developed, trained, and tested for the proposed SMA framework. It aims to provide a more nuanced and accurate interpretation of social media data. Finally, the framework integrates semantic content analysis and user interaction to provide a broader view of digital conversations, revealing the content and mechanisms of information flow.

Methodological transparency is essential to the practical application of the proposed framework. It emphasises a clear and replicable process that details every step from data extraction to analysis. This approach ensures that the research can be reviewed and replicated, trusted, and confirmed by the scientific community. Furthermore, the framework promotes the use of open-source tools and platforms for analysis to ensure transparency and accessibility.

The potential uses for such an application of the framework are immense. In governmental applications, it can be used to aid timely policymaking based on the public's attitude towards laws, regulations, and public norms. In business applications, it offers a way of understanding consumer sentiments to support market research and brand management. In addition, social activists and cultural analysts can use it to measure public sentiment about issues such as climate change and human rights in order to tailor their campaigns and initiatives accordingly. In periods of social unrest or crisis, the framework's ability to quickly analyse public sentiment becomes invaluable. Decision makers can formulate responses that are timely and nuanced, potentially preventing escalation and fostering understanding.

To sum up, the proposed comprehensive framework addresses the current gaps in SMA. By integrating advanced SA with network analysis and emphasising methodological transparency and ethical considerations, it sets a new standard in the field. The framework not only enhances the understanding of social media discourse but also paves the way for more informed and effective decision-making across various sectors. The ever-evolving landscape of social media demands continuous innovation in data analysis techniques. This framework, therefore, represents not just a solution to current challenges but also a flexible foundation for future advancements in SMA. As the digital world grows and changes, the framework will adapt and evolve, ensuring its relevance and efficacy in a rapidly changing social media environment.

Chapter 3 Network Analysis in Social Media

The network analysis method helps to explore the connections and relationships between entities within a complex system such as a social media platform. It maps the interactions between users and the content of their interactions, revealing the system's underlying structure and dynamics (Camacho et al., 2020). In the context of Twitter, this analysis helps reveal both visible and hidden patterns of communication, collaboration, and influence among users and content. Network analysis is a key component of the proposed dual-framework . This part of the analysis will be subdivided into three sections: entity analysis, which provides an initial review of the entities within the text; user-level analysis, which focuses on interactions between individual users; and tweet-level analysis, which emphasises the semantic relationships within tweets. The detailed steps that make up the network analysis module of the dual-framework are presented in the following sections.

3.1 Entity Analysis

Entity analysis refers to the process of identifying and categorising key components within a text, often focusing on named entities such as people, places, organisations (Nasar et al., 2021), and special symbols. In the context of social media, this analysis extends to elements like mentions, hashtags, and emojis (Sharma et al., 2021), which often carry significant meaning. To gain a basic understanding of the research topic, entity analysis will be conducted first. Hashtags, mentions, and emojis will be extracted from the text and analysed separately. Their absolute frequency, weighted frequency, and relative value will be calculated. Absolute frequency measures how many times each entity appears in the entire corpus. Weighted frequency considers an additional numeric attribute associated with each document (e.g., views, retweets) and weights each entity's occurrence by this value. In this thesis, the number of retweets is used as the weight, and the weighted frequency is the sum of retweets associated with each appearance of the entity. Relative value refers to the average weight per occurrence of the entity, calculated as weighted frequency divided by absolute frequency. The most 10 popular entities, as measured by weighted frequency, will be analysed to understand how posts are related to each other and why social media users use these entities.

3.2 User Level Analysis

The next step is to construct the user networks, where each user is represented by a node, and a link between two users is created when they retweet, quote, or reply to one another (Gongora-Svartzman & Ramirez-Marquez, 2022). To better reflect the influence of a user in the network, the number of users interacting with each other in the above ways will be used as the weight of the edges. In addition, the networks will be visualised by using the node's degree centrality as their size and the weighted value of the number of user interactions, like count and impression count of the tweets, and the number of followers of the users as the width of the edges. Although the number of retweets, quotes, and replies are included in the public metrics for each tweet, they are not taken into account as these relationships have been considered during the construction of the networks. After network construction, specific metrics will be calculated to evaluate both the structure of the overall network and the relative position of individual nodes within it. In order to evaluate the structural properties of the networks, the size of the networks, power-law distribution, clustering coefficient, density and the diameter of the network will be evaluated, and they are introduced below:

- Network Size: In this study, the size of a user network will be evaluated from the perspectives of the number of nodes and edges in the network.
- Power-Law Distribution: A power-law distribution is a functional relationship between two quantities, where a relative change in one leads to a proportional relative change in the other (Jo et al., 2021). In network analysis, it usually describes the degree distribution of nodes, i.e., a large number of nodes with few connections and a small number of nodes with many connections. Networks with power-law distributions are often referred to as "scale-free networks", in which hubs or nodes with high connectivity dominate the network structure. This is a common pattern in many real-world networks such as social networks and the Internet.
- Clustering Coefficient: It provides a quantification of how tightly knit the neighbours of a node are with one another. This provides an understanding of the local cohesion or local clustering of the network. In short, if a node has two connected neighbours, the clustering coefficient measures the probability that the neighbours are linked to each other. High clustering coefficients show that the neighbours of a node tend to cluster together, while low clustering coefficients denote a lack of connection among the neighbours. The clustering coefficient is often used to understand the social aspects of network structures, such as the tendency for friends of friends to become friends themselves.

- Density: It is calculated by dividing the number of connections a participant may have by all possible connections a participant may have. The metric provides information related to the level of cohesion or integration among the participants in a network.
- Diameter: The diameter of a network is the longest shortest path between any two nodes in the network. In other words, it represents the greatest distance between any pair of nodes, where the distance is measured by counting edges along the shortest path connecting them. The diameter gives one a sense of the "spread" of the network or the "reach." A low diameter indicates that information or influence can spread quickly to the furthest reaches, while a large diameter may suggest a more disconnected or sparse network. For instance, understanding the diameter of a network may be very important in applications regarding information dissemination when the very aim is to reach as many nodes as possible in as short a time as possible.

In this study, the metrics used to identify the key influencers include outdegree, indegree, outward closeness centrality, betweenness centrality for nodes, and Katz Eigenvector centrality. The degree centrality is measured by outdegree and indegree because this user network is directed, with the outgoing links representing a referenced or mentioned relationship, while the incoming links represent the referencing or mentioning relationship. Distinguishing the links can help us identify who is playing the key influential roles and who is spreading the information in the network. A summary of these metrics is below:

- Outdegree: This metric calculates the number of links emanating from a given node towards other nodes in the network (Xiao et al., 2022). This parameter measures how many times the user is referred to or mentioned by others in their tweets. Large outdegree values imply that the user has a big impact and has the potential to influence the course of conversation by affecting others.
- Indegree: Indegree measures the number of incoming links to a particular node from other interconnected nodes in the network. This metric indicates the degree to which a user references or mentions other users in their content. A high indegree may signal a user's prominence in disseminating information and opinions across a broad audience.
- Outward Closeness Centrality: This measure calculates the average shortest path from a given node to all other reachable nodes in the network through outgoing links (Karim et al., 2022). It serves as a reflection of a user's capability to efficiently propagate information and viewpoints to other network members. High outward closeness centrality values are indicative of a user's vital role in the rapid and effective spread of information.
- Betweenness Centrality for Node: It is a measure of how much a given node lies on the shortest path that connects other nodes in the network (Burt, 2000). This metric elucidates a user's function

as a mediator or broker of information, facilitating the flow of ideas and communication among different network constituents. High betweenness centrality values underline a user's importance in bridging various network segments and enhancing connectivity and interaction (Pournajar et al., 2022).

- Katz Eigenvector Centrality: This assesses a node's influence by considering its connections to other influential nodes within the network (Bloch et al., 2023). This metric reveals the extent to which a user engages with other prominent network members, emphasising the interconnected nature of influence. Users possessing high Katz Eigenvector Centrality tend to contribute to the dissemination of information and opinions among other influential network participants.

The third step is community detection, where the network is clustered into several groups using clustering algorithms. This step can also indicate the structure of the networks. By analysing the network of connections between users, the most influential users, the communities that emerge within the network, and the types of interactions between users can be identified.

3.3 Tweet Level Analysis

The network analysis will then be applied to the tweet level to identify the aspects of a specific event people are talking about on social media. Semantic network analysis is used to visualise the co-occurrence patterns of words in the tweets (Park et al., 2019). In the semantic network, nodes represent words and links represent the co-occurrence of word pairs. In the course of conducting this analysis, retweets and quotes will be selectively removed from the dataset to preclude the duplication of information and mitigate potential bias in the analysis (Li & Su, 2020). This is because retweets and quotes often contain the same or similar text to the original tweet, and they can artificially inflate the importance of certain nodes in the network. The exclusion of retweets and quotes serves to ensure that the semantic network analysis faithfully represents the distinctive perspectives and viewpoints of individual users. By concentrating exclusively on original tweets, this approach facilitates the identification of principal themes and concepts that are the focus of user discussions, as well as an understanding of their interconnections. Furthermore, search terms were also removed from the final networks, as predominant words are highly likely to link all the other words together into a single group, which may distort the results. Therefore, further cleaning of the dataset for the semantic network analysis can help ensure that the analysis accurately reflects the unique perspectives and opinions of individual users (Loukianov et al., 2023).

The analysis centred on the co-occurrence of vocabulary words, forming the basis for the construction of the semantic network. In the semantic network, the nodes will represent word pairs and the links represent the co-occurrence of word pairs (n-grams). The size of the word label indicates how frequently the word occurred, and the thickness of each link represents the weight or number of co-occurrences between two words. To enhance clarity and focus in visualising the network, the top 100 words, as ranked by degree centrality in each corpus, were retained. By analysing the central position of each word in the corresponding semantic network through degree centrality metrics, the most mentioned concepts will be identified to provide an overview of the aspects of a specific event.

After that, clustering analysis will be used to extract latent topics from the co-occurrence patterns identified in the semantic network analysis. In this analysis, node embeddings are employed rather than TF-IDF or word embeddings due to its versatile applicability across various network types, without confinement to a particular algorithm or underlying assumption. In contrast to clustering algorithms such as greedy, Louvain, and walktrap methods, node embedding possesses the ability to capture intricate relationships and the structural complexities of the social network. This enables a more sophisticated clustering analysis, whereas other algorithms may be heavily influenced by the selected similarity measure and the sequential assignment of nodes to clusters; factors that could substantially affect the final clustering outcomes. For the execution of the final clustering, KNN, hierarchical clustering, and spectral clustering will be explored and assessed. Jaccard scores will be used to indicate the stability of the clustering results and determine the final clustering method. A higher score signifies more consistent results and thereby indicates a more reliable method.

After the cluster analysis, the next step is to assign tweets to each user community from user network analysis or each word community from semantic network analysis. The approach this study follows is a rule-based approach. It iterates over each tweet and checks if any keyword from a community is present in the tweet. If a keyword is found, this approach increments the score for the corresponding community. Finally, it assigns the tweet to the community with the highest score. The content analysis is then conducted on each cluster of words, which are grouped and named into a topic. By conducting cluster analysis on the semantic network based on the textual data, a more comprehensive analysis of the structure and content of the tweets on the given event can be provided.

An innovation in this study's network analysis lies in the use of co-occurrence patterns to construct the semantic network. While methods based on individual words captures broad associations between words, it often lacks the contextual specificity needed to understand the nuanced relationships within social media discourse. By filtering out less significant word associations, this study ensures that the edges are informed by the more contextually relevant relationships. Consequently, the network reflects not just the presence of words, but their meaningful pairings, resulting in a more focused and contextually rich analysis. In addition, by using degree centrality based on the co-occurrence patterns, the top words will be those that appear in the most significant pairings, ensuring that the identified themes are highly pertinent and thematic. Another innovative aspect of this study is the use of node embedding for clustering analysis. Node embedding techniques enable the transformation of nodes into continuous vector spaces, capturing the intricate relationships and structural complexities of the network that simpler clustering algorithms may overlook. These designs collectively aim to improve the usefulness of the network analysis part of the framework by identifying and understanding the key elements and thematic structures within social media discourse.

Chapter 4 SA in Social Media: Emoji Feature-Incorporated Multi-view Sentiment Classification

4.1 SA of Online Reviews

SA can be a useful tool for businesses to monitor and analyse eWOM. For businesses, SA helps them identify areas for improvement, measure brand reputation, track the effectiveness of marketing campaigns, and identify brand advocates by analysing social media data.

Based on a dictionary-based approach, Agüero-Torales et al. (2019) created an integrated software program to perform SA on social media data about restaurants in the Granada province of Spain. This software is intended to assist restaurants in comprehending what consumers think about their products, services, or brand and how to enhance their image, products, and services. Also applied to the tourism industry, Al-Bakri et al. (2021) collected 14,200 Facebook comments on 71 Iraqi tourism companies and categorised their sentiments as positive, negative, or neutral. They created an evaluation rule based on the sentiments and utilised supervised machine learning methods like Rough Set Theory, NB, and KNN to analyse these companies. Rehman et al. (2019) introduced a hybrid model that combines Convolutional Neural Network (CNN) and LSTM to enhance the accuracy of SA on movie reviews. They used IMDb and Amazon movie review datasets to train and test their model, which demonstrated higher accuracy than other models. In the work of Wang et al. (2021), they considered that many current DL models for SA fail to consider the importance of individual sentences in the text. While some approaches have been taken to calculate sentence-level attention, these methods are often overly complex and inefficient. To address this problem, the authors propose a new approach called the sentence-to-sentence attention network (S2SAN) using multi-head self-attention. The study reports on several experiments that demonstrate the superiority of the S2SAN model over other state-of-the-art models, including CNN, Recurrent Neural Network (RNN), and LSTM models.

Analysing online reviews is difficult and time-consuming, as the textual data is often unstructured. Compared to supervised methods, unsupervised SA offers more flexibility and adaptability, as well as lower costs (Wang et al., 2021). In a recent study, Srinivas & Ramachandiran (2023) employed unsupervised text analytics to better understand airlines' services and their competitors from online customer reviews. They used topic modelling algorithms, SA methods, and collocation analysis to automatically and efficiently extract information about airline-specific strengths and weaknesses from online customer reviews.

4.1.1 Emojis in Twitter SA

Multiview data is a type of data that describes objects or phenomena through different feature sets or perspectives, such as combining text and image or web page and clickthrough data. These data are increasingly available in real-world applications and can be used in conjunction with machine learning to yield more significant results compared to single-view representation learning (Zhang et al., 2022). For example, tweets are a form of multi-view data that combines textual and visual elements like emojis, making them valuable for SA. There are two types of facial expressions, namely emoticons and emojis. Emoticons are made up of ASCII and are the predecessor to emojis, which are in image form. According to the Oxford Dictionary, emoticons are facial expressions made up of various combinations of keyboard characters (Oxford English Dictionary, 2023a), such as smiles (:)), while emojis are small digital images or icons used to express ideas or emotions (Oxford English Dictionary, 2023b), such as 😊. A growing body of work has shown interest in considering emoji features as a way to enhance SA on such data, particularly on social media platforms.

Emojis can alter the sentiment polarity of posts or tweets through subtle interactions with text. A study by Lou et al. (2020) investigated how the emotional polarity of posts on social networking platforms was affected by emojis. They found in the data that the polarity of 4,044 posts altered owing to emojis, representing 40.27% of all posts.

Hankamer & Liedtka (2016) were the first researchers to take emojis into consideration in SA studies after the widespread use of emojis on Twitter. Due to the lack of labelled tweet datasets that contain emojis, they collected the data themselves. Each sample in the dataset contains emojis and is labelled by VADER (Hutto & Gilbert, 2014), a lexicon-based approach. They used two methods to handle the emojis. The first method calculates the average “emoji score” per tweet according to the occurrence information collated by Kralj Novak et al. (2015). This method was also employed in the study by Bansal & Srivastava (2019) for the prediction of vote shares in the 2017 Uttar Pradesh legislative elections and was proven to decrease the prediction error of the lexicon-based approach significantly. They took the number of positive occurrences of each emoji, subtracted the number of negative occurrences, and then divided it by the total number of occurrences. The second method in the study of Hankamer & Liedtka (2016) is called “emoji substitution.” They replaced each emoji with its alias (which is a word or several words) and averaged the GloVe embeddings of the alias to obtain an emoji embedding. In their case, the Shallow Neural Network performs better when adding an emoji score dimension, while the RNN significantly gains performance when using both emoji handling methods. Similar to Hankamer &

Liedtka (2016), Singh et al. (2019) also used “emoji substitution” on the Twitter classification problem, although in their case, it is called the “emoji description strategy”. Moreover, they also tried the direct use of pre-trained emoji embeddings (EE), called the “emoji embedding strategy”. The embeddings obtained by these two methods were learned by the BiLSTM model with an attention mechanism, respectively, and applied to the two classification tasks, i.e., irony detection and topic-based SA. They compared the results and concluded that replacing emojis with their textual descriptions is more effective than using EE.

Bansal & Srivastava (2019) integrated the method of adding emoji scores to lexicon-based approaches in their study of election prediction. They computed the overall sentiment of a tweet by adding up the sentiments of words provided by lexicon-based classifiers and the sentiment scores of emojis in each tweet. Then, they defined the vote share for each election party based on the overall score. To evaluate the effectiveness of the emoji scores, they evaluated their lexicon-based approaches by comparing their predicted vote share for each party to the true shares using mean absolute error (MAE). The results show that for most lexicons, combining emoji sentiments reduces MAE, and the VADER lexicon performs the best (Hutto & Gilbert, 2014). However, the effect of this improvement is only more than 1%, which may relate to the low number of emojis (1.45%) discovered in the data.

Liu et al. (2021) presented two other ways of dealing with emojis in the text. Firstly, they defined two types of words to represent emojis in their study. One is an emotion word, a word that directly indicates an emotion (e.g., 😊 happy), and the other is an emoji tag word, a word that describes an emoji (e.g., 😊 smiling face). One of their methods is to convert all emojis into corresponding sentiment words instead of the tag words, as they considered tag words to be ambiguous and could affect the sentiment recognition of the SA algorithm. However, they compared the changes in algorithm performance and found that emoji tags’ ambiguity did not show a negative effect on sentiment detection. They also considered the sentimental coherence between plain text and emojis. According to Liu et al. (2021), the results show that in posts where the emoji sentiment is inconsistent with the sentiment of the text tend to compromise the performance of the SA algorithm. However, the dataset of this experiment only includes consistent samples. Therefore, the results may require further investigation.

In contrast to Liu et al. (2021), Lou et al. (2020) used the SkipGram mode of word2vec to train Chinese words and emojis simultaneously to obtain embedding representations. They trained the embeddings of words and emojis in a corpus of 3.5 million posts with a total vocabulary of 252,267.

They proposed a deep learning model (EA-Bi-LSTM) to test the effectiveness of emoji embedding. Their model uses Bi-LSTM to read the text in both directions and then aggregated these informative word representations to create sentence representations using an attention mechanism. Their model proved to be the best performer, greatly outperforming all baseline models. Moreover, their experiments showed that both emojis and text performed an essential role in the sentiment recognition of microblog posts. While emojis had a stronger effect on the sentiment polarity of posts than text, the DL models that used both features performed better. However, all models performed extremely poorly in classifying neutral emotions.

To sum up, following a survey of the SA literature related to emojis processing, this study identifies the following types of emoji processing:

1) Replacing an emoji with the corresponding descriptive words
2) Replacing an emoji with the corresponding emotion words
3) Adding an emoji score as an additional feature
4) Transforming emojis into EE using the pre-trained EE
5) Manually annotating the sentiment consistency of the emoji with the plain text and using “sentiment consistency” as an additional feature
6) Building one's own corpus and simultaneously training words and EE
7) Employing BERT tokeniser with Transformer encoder

When using social media platforms like Twitter, people tend to express themselves in an effortless and quick way (de Barros et al., 2021), which is one of the reasons why the use of emojis is becoming increasingly popular. In SA, the emoji processing approaches discussed above provide useful sentiment information for identifying the sentiments expressed by users through short texts, greatly improving the performance of sentiment classifiers.

4.1.2 Explainable AI and its Role in SA

Explainable Artificial Intelligence (XAI), which focuses on enhancing the interpretability and transparency of AI models, has been used in a wide range of domains and has significantly influenced SA, futures price series prediction, and even professional athlete scouting (Ghosh et al., 2022; Haque et al., 2023; Janssens, 2022). Recent advancements in this domain have further highlighted its value.

The study by Ghosh et al. (2022) focuses on the vitality of XAI in decoding the decision-making process of complex AI models. Their use of ensemble feature selection in combination with advanced AI-based predictive modelling illustrated the role of various explanatory features in predicting futures price series, thus exemplifying the power of XAI. Meanwhile, Chowdhury et al. (2021) investigated the interpretability of Bi-directional Long Short-Term Memory (LSTM) networks, a type of RNN known for its complexity, in SA. Applying the Local Interpretable Model-Diagnostics Explanation (LIME) framework, they successfully decrypted important features and their interactions during prediction.

Advances in XAI in particular have enriched the general field of SA. This trend is evident in the works of Miron et al. (2023) and Dewi et al. (2022). Miron et al. (2023) proposed a sampling method to boost the performance of LIME for Aspect-Based Sentiment Classification (ABSC), thus offering a better understanding of the complex decision-making processes. Dewi et al. (2022) took a similar route by employing the SHapley Additive exPlanations (SHAP) method to explain a BERT model's decision-making in SA of movie reviews, providing intuitive and meaningful explanations.

Expanding upon the traditional utilisation of XAI, Moreira et al. (2021) and Lampridis et al. (2020) designed novel frameworks, LINDA-BN and xspells, respectively. These tools exemplify the great potential of XAI by elucidating the fundamentals behind prediction, either through local post hoc interpretation or by generating synthetic sentences. This notion is further reiterated by Yang et al.'s (2023) study, where XAI was integrated with SA, topic modelling, and Extreme Gradient Boosting (XGBoost) to predict customer ratings from online reviews. This integrated approach demystifies complex predictive patterns, highlights the key factors that influence predictions, and demonstrates XAI's ability to derive valuable information from unstructured data.

In contrast to these technical approaches, Kim et al. (2020) and Kim et al. (2023) highlighted the critical aspect of user preferences in the development of XAI systems. Their findings emphasised that local explanations, visualisations, and transparency can lead to a more intuitive AI decision support system, thereby fostering user trust and acceptance. These studies showed the broad applicability and importance of XAI and affirmed the indispensable role of explainability in the proposed model.

4.1.3 Gaps and Limitations of the Existing Studies

Upon a thorough review of existing literature, it is evident that while SA accuracy improves with expressive data processing, it also substantially complicates the data handling process. For example, it may not be practical to use the manually annotated sentiment consistency of an emoji with plain text (Liu et al., 2021) as an additional sentiment feature, as this feature is not an attribute value present in the text provided by the social media network. In addition, some approaches require the separation of text and expressions in order to process them separately and then merge them (Hankamer & Liedtka, 2016; Bansal & Srivastava, 2019), and some require the construction of their own corpus (Liu et al., 2021).

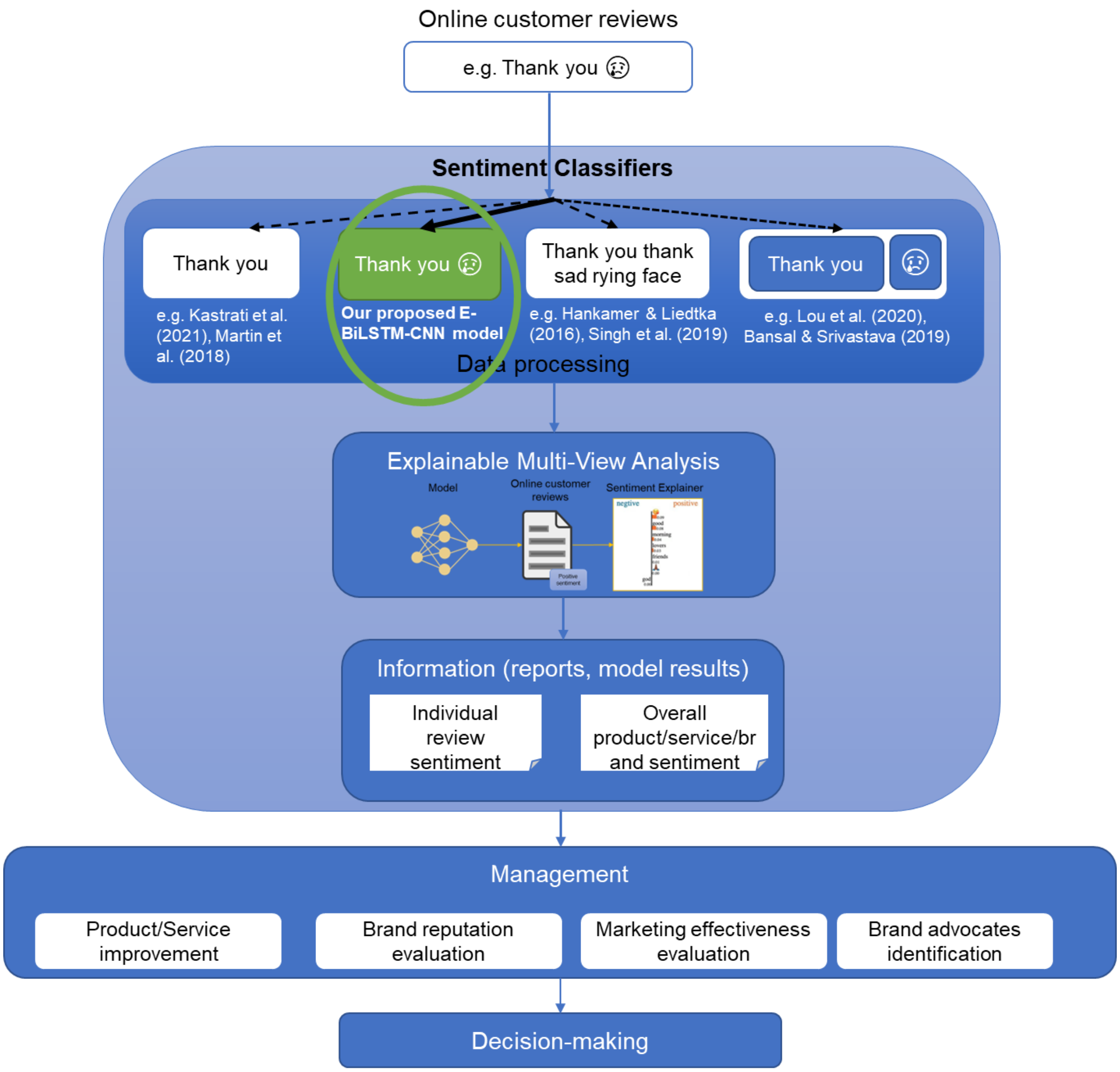
Another notable gap in the current research is the unrealistic usage of datasets, where all samples contain emojis. This significantly deviates from real-life scenarios, leading to an overemphasis on the impact of emojis in SA. In the context of these limitations, this study proposes an emoji-incorporated DL sentiment classifier that minimises the need for such exhaustive preprocessing. This study strategically aims to handle emojis in a practical manner by treating them as part of the input data without the need for separate processing. This approach substantially simplifies the data processing and makes the model more applicable to real-world data. Furthermore, to create a more representative study, this research employs a dataset with a realistic percentage of emojis, contrary to the often inflated representation in existing works. The present study believes this enhances the external validity of the proposed model.

In addition, while most existing studies on multi-view SA overlook the importance of transparency, this study adopts XAI techniques to improve model transparency. This feature adds significant value by enabling users to understand the rationale behind the model's predictions, thus building trust and facilitating better decision-making.

Figure 6 illustrates the explainable proposed emoji-incorporated sentiment classifier as an intelligent high-stakes business analytical tool and compares the proposed classifier with other major approaches to highlight its advantages. Emojis have the potential to alter the entire meaning of a review. For example, the review "Thank you 😢" presented in the system shows that the emoji 😢 (sad crying face) implies that the customer may not be satisfied and has a negative sentiment. Without this emoji, the sentiment would be positive, expressing gratitude. Therefore, the classifiers used by Kastrati et al. (2021) and Martin et al. (2018) may fail to identify such sentiments, resulting in missing or misleading information for businesses. In addition, compared to classifiers used in studies such as Singh et al. (2019) and Lou et al. (2020), the online reviews imported to the proposed classifier do not require further processing of emojis, such as replacing emojis with text or separating emojis from text for transformation into scores or embeddings individually. In addition, in order to increase the transparency of the proposed system, it employs a LIME-based interpretable technique to visualise the factors or features on which the system's outputs are based, so as to maximise the ancillary functions of the system. Overall, the proposed classifier aims to provide a more efficient and accurate SA of online reviews, which can help decision makers with product/service improvement, brand reputation evaluation, marketing effectiveness evaluation, and identifying brand advocates.

Figure 6

The Proposed Explainable High-stakes Business Analytical System



4.2 Methodology and Experiments

4.2.1 Experimental Procedure

While aiming to assess the effects of handling emojis on the effectiveness of different classifiers and the effectiveness of the proposed model, this study first divides the review dataset into a training set (80%) and a test set (20%). Four types of experiments will be carried out. The first type is to train sentiment classifiers with data removing all emojis. The second type is to perform only one type of emoji processing method before training. The third type is to perform any two of the emoji processing methods, and the last one is to perform all three methods. All these experiments will be conducted using each classifier described in section 4.2.2. This study trained the classifiers using the training set and evaluated them on the test set to determine their ability to learn emoji features.

To be specific, the purpose of the experiments is to address four research questions as follows:

1) Does the consideration of emojis as features facilitate sentiment recognition of online reviews by sentiment analysers?
   Rigorous contrast experiments were carried out to provide an answer to this question. To determine the effect of emojis on sentiment classification, this study compared the classifiers' performance for tweets with emoji features and text-only tweets.
2) Which of the methods proposed in this study for transforming emojis into features, emoji replacement, adding emoji scores and creating EE is the best for each algorithm?
   This study put forward three methods to handle emojis and compare their impact on emotion recognition in their individual and combined forms, respectively. A detailed description of the three processing methods for handling emojis is provided in section 4.2.3.
3) Does the emoji processing approach presented in this study outperform the others?
   This study proposed a new method to handle emojis in the text by creating EE alongside word embeddings, which is presented in section 4.2.2.2. The effectiveness of the new method E-BiLSTM-CNN is compared with the other classifiers.
4) Does the model, E-BiLSTM-CNN, outperform other sentiment classifiers when execution time is considered?
   To answer this question, after exploring the performance of each algorithm with various emoji treatments and their combinations, this study extracted the performance data of the best classifiers for each algorithm and compared them. In addition, this study evaluates these classifiers by performing a weighted average of their performance in terms of F1-score and execution time.

4.2.2 Models

4.2.2.1 Baseline Models

This study uses three classical machine learning algorithms as baseline models, namely Bernoulli NB, SVM, and LR. All these algorithms will be employed and tested in each experiment, and their performance will be evaluated against each other and against the proposed model to address the research questions. This study denotes: *Algorithm (T)* as the implementation of a selected algorithm in texts after removing emojis' *Algorithm (D)* as the implementation in tweets with emojis converted into their descriptions; *Algorithm (ES)* as the implementation in tweets with an additional feature of emojis score; *Algorithm (EB)* as the implementation in tweets with an additional feature of EE; *Algorithm (D+ES)* as the implementation in tweets with emojis replaced and emoji scores added; *Algorithm (D+EB)* as the implementation in tweets with emojis replaced and EE added; *Algorithm (ES+EB)* as the implementation in tweets with emoji scores and EE added; *Algorithm (D+ES+EB)* as the implementation in tweets with all three emoji handling methods applied. This study presents detailed information on the settings for each algorithm as follows.

Bernoulli Naïve Bayes (BernoulliNB): Multinomial Naive Bayes, Gaussian Naive Bayes, and Bernoulli Naive Bayes are three types of NB. By initially exploring their effectiveness in sentiment recognition, Bernoulli NB was finally chosen to conduct the experiments. This study denotes each experiment conducted by Bernoulli NB as *BernoulliNB (T), BernoulliNB (D), BernoulliNB (ES), BernoulliNB (EB), BernoulliNB (D+ES), BernoulliNB (D+EB), BernoulliNB (ES+EB)*, and *BernoulliNB (D+ES+EB)*.

SVM: SVM is a powerful algorithm that has been proven to be useful in SA (Chen et al., 2021). This research also tested its ability to learn emotional information from different emoji features. Each experiment conducted by SVM is named *SVM (T), SVM (D), SVM (ES), SVM (EB), SVM (D+ES), SVM (D+EB), SVM (ES+EB),* and *SVM (D+ES+EB).*

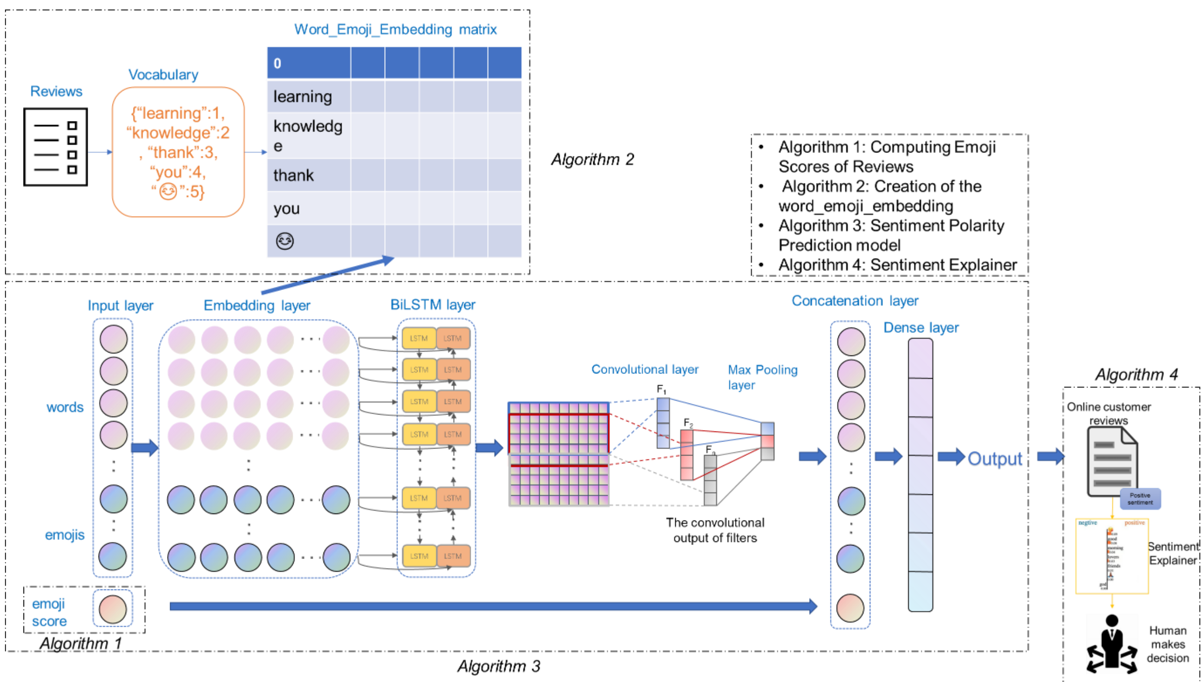
LR: LR is a widely employed algorithm that serves to solve the binary classification problem (Xiao et al., 2021; Książek et al., 2021). In this research, the performance of LR in identifying text sentiment is also evaluated and compared when using different emoji handling methods. The experiments are named *LR (T), LR (D), LR (ES), LR (EB), LR (D+ES), LR (D+EB), LR (ES+EB),* and *LR (D+ES+EB)*.

4.2.2.2 E-BiLSTM-CNN Model

While exploring the influence of emojis on SA from a multi-view perspective, this study presents an emoji-incorporated BiLSTM-CNN model (E-BiLSTM-CNN). To be specific, this model is built on a deep learning architecture that introduces emojis in tweets. It employs Bidirectional Long Short-Term Memory (BiLSTM) and CNN to extract key features from the text and learn their relationship with users' sentiments. As shown in Figure 7, the proposed model has eight layers: the input layer; the embedding layer; the BiLSTM layer; the CNN layer; the max pooling layer; the concatenation layer; the dense layer; and the output layer.

Figure 7

The Proposed Emoji-incorporated Deep Learning Model



Given an input Tweet T_i that consists of T elements s_t. Tweet T_i refers to a tweet containing text and emojis, and Elements s_t are components of a tweet, which include both words and emojis. Then, a tweet is described as **{**w_1, w_2, ..., w_a, e_1, e_2, ..., e_b**}**, where w_a refers to the word token (word components) and e_b refers to the emoji token (emoji components), and a+b = t ∈[1,T]. Another input is the normalised average "emoji score" of the tweet, es_i, and the calculation method is discussed in section 4.2.3. Each word or emoji token is transformed to a vector representation, x_t, through the embedding layer to be the input of the Bi-LSTM layer and CNN layer to obtain a tweet representation. The vector representation refers to the numerical representation of words and emojis in a high-dimensional space, and the tweet representation is the combined numerical encoding of an entire tweet, incorporating the vector representations of all its elements and capturing the overall content, context, and sentiment. The emoji score feature is then concatenated with the features that were derived from the CNN layer. Dropout layers and dropout rates are employed to prevent the issue of overfitting in neural networks. Finally, the output layer applies the SoftMax activation function to compute a probability distribution of the tweet's sentiment polarity. Each layer of this deep learning architecture is introduced in the following sections.

A. Word_Emoji Embedding Layer

The Word_Emoji Embedding Layer serves as an initial layer in the E-BiLSTM-CNN model. Given an input Tweet T_i with elements (words and emojis) e_t, $t \in [1,T]$, the element e_i is transformed to a real-valued vector x_t, through an embedding matrix W_e. The conversion equation is shown below:

$$x_t = W_e e_t \tag{1.}$$

$x_t \in R^d$, where d refers to the embeddings' dimension. Embedding matrix W_e refers to the matrix used to convert words and emojis into vector representations. The present study employed pre-trained word embeddings provided by GloVe and pre-trained EE provided by Emoji2Vec, creating the Word_Emoji embedding layer. The output from this layer is a set of vectors $x = \{x_1, x_2, \ldots, x_t\}$.

B. Bidirectional LSTM Layer

BiLSTM is a variant of RNN, which was proposed by Graves & Schmidhuber (2005). It was designed to address the drawbacks of the RNN model in terms of gradient explosion and disappearance. Many researchers have employed BiLSTM models for text classification tasks and achieved excellent performance (Zheng & Zheng, 2019). Abedin et al. (2021) constructed an exchange rate forecasting model based on BiLSTM and Bagging Ridge regression, which showed significant predictive performance and identified the currencies with the greatest impact on the US dollar. In this study, BiLSTM models are used in SA to learn the sentence representations, which are subsequently utilised as features for sentiment classification.

The LSTM model consists of several LSTM units that are employed to capture long-range dependencies in a sequence. Each unit has a memory cell and is controlled by three gates, namely input, forget and output gates, to enable the LSTM to store and access information over time (Lou et al., 2020; Efat et al., 2022).

First, by examining the input (x_t) and hidden state (h_{t-1}), values that hold information about the current input and previous hidden states, the forget gate (f_t) decides whether to maintain or discard the information from the preceding cell state (c_{t-1}). It uses a sigmoid function, which outputs a value of 0 or 1, helping to control the amount of information passed through. In the same way, the input gate (i_t) determines the amount of information to be updated in the hidden state (h_{t-1}) and input text (x_t). A new candidate value vector G_t, representing new information, is also created through the tanh activation function, which outputs values between -1 and 1 (Zheng & Zheng, 2019). The previous cell state c_{t-1} is updated with useful information retained by multiplying c_{t-1} and f_t, and new information from the new candidate value G_t by adding the product of i_t and G_t. The created cell state is represented by the value of c_t. The forget gate (f_t), input gate (i_t), new candidate value (G_t), and the created cell (c_t) are expressed as follows:

$$f_t = sigmoid\left(W_{fx}x_t + W_{fh}h_{t-1} + b_f\right) \tag{2.}$$

$$i_t = sigmoid\,(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \tag{3.}$$

$$G_t = \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c) \tag{4.}$$

$$c_t = c_{t-1} \odot f_t + i_t \odot G_t \tag{5.}$$

The output gate (o_t) is responsible for managing the information flow from the current cell state (c_t) to the hidden state (h_t). It decides which part of the cell state is to be output by evaluating the hidden state (h_{t-1}) and input (x_t). Then, the output gate (o_t)'s output is multiplied by the current cell state (c_t) dealt with by the tanh gate to determine the current hidden state.

$$o_t = sigmoid\,(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \tag{6.}$$

$$h_t = o_t \odot \tanh(c_t) \tag{7.}$$

In this study, the E-BiLSTM-CNN model uses a BiLSTM to read the text in both directions (Kamyab et al., 2021). The way the text is read allows it to capture more comprehensive context and dependencies compared to a standard LSTM. This results in improved performance, especially in tasks where the meaning of each word depends on both its preceding and succeeding words. BiLSTM contains a forward LSTM and a backward LSTM for reading text in the direction from x_1 to x_t and from x_t to x_1, respectively. The hidden state of the forward LSTM and backward LSTM are presented as $\overrightarrow{h_t}$ and $\overleftarrow{h_t}$. A word can then be represented by concatenating the two states as h_t.

$$\overrightarrow{h_t} = \text{LSTM}\left(x_t, \overrightarrow{h_{t-1}}\right) \tag{8.}$$

$$\overleftarrow{h_t} = \text{LSTM}\left(x_t, \overleftarrow{h_{t+1}}\right) \tag{9.}$$

$$h_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] \tag{10.}$$

In this way, the representation of the text as $[h_0, h_1, h_2, \ldots, h_T]$ is obtained and fed to a convolutional layer to extract important features.

C. Convolutional Layer

CNN is another type of neural network that is utilised to predict time series. They are biologically inspired variants of feed-forward neural networks. Because of their capacity to utilise spatially localised correlations in images, they are mainly employed for computer vision issues but can also be applied to time-series problems such as SA. In the CNN layer, the most significant higher-order features in the text are extracted (Khan & Niu, 2021). It first extracts local features over the matrix $h = [h_0, h_1, h_2, \ldots, h_T]$ output from the previous BiLSTM Layer. Each element h_t in the matrix corresponds to a word or emoji in the tweet. A group of k filters is applied, each for a window of *q* words, producing a new feature a_i from a window of vectors $h_{i:i+q-1}$. The filter can be thought of as a tool that slides over the matrix and picks out important patterns. The new feature a_i can be represented as follows:

$$a_i = f\left(F \circ h_{i:i+q-1} + b\right) \tag{11.}$$

where $F \in R^{l \times d}$ refers to the filter, b denotes the bias, and f refers to the activation function, which is ReLU in the present study. A feature map $c = [a_1, a_2, \ldots, a_{n-l+1}]$ is created by applying the filter to each window, resulting in k feature maps with k filters.

Only a few words and their combinations can provide relevant information about the meaning of a text in text classification tasks, while the max pooling layer allows for the discovery of the hidden semantic variables in the text (Rao & Yang, 2022). Therefore, after the convolutional operation, the max pooling operation is applied to feature maps to extract m = max{c}, which refers to the maximum value. It helps to focus on the most important features by keeping only the strongest signals. As a result, the output of the CNN layer is obtained by combining the maximum values from the pooling operation, which is $m = \{m_1, m_2 \ldots m_k\}$.

D. Concatenate Layer, Dense Layer, and Output Layer

The concatenate layer combines the features extracted by the CNN layer and the emoji score features into one layer, which is then passed on to the dense layer. In any neural network, a dense layer refers to a layer that is deeply linked to the previous layer (Wang et al., 2019). Each neuron in the dense layer is linked to each neuron in the previous layer. In this study, two dense layers will be employed. The reason for this is that convolutional layer's attempt to extract features in a distinguishable way, while fully connected layers attempt to categorise the features. According to Samala et al. (2017), there are more generic features in the early features of a CNN that are useful for many tasks. At the same time, subsequent layers of the CNN become progressively more specialised to the characteristics of the classes contained in the original dataset. As a result, increasing the number of dense layers might help in performing a better classification of the extracted features (Suzuki et al., 2016; He et al., 2020). Dropout is a commonly employed regularisation technique. It is employed to deal with the issue of overfitting. The dropout mechanism randomly drops some neurons to create a robust model, avoiding over-fitting. The dropout rate of 0.3 is employed in the proposed model.

The final layer of the model is the output layer. As this study addresses a binary sentiment classification task, binary cross-entropy is employed as the loss function. The equation of the binary cross entropy is presented as follows:

Binary cross entropy =

$$-\frac{1}{m}\sum_{i}^{m}(\mathrm{y_i} * \log(\mathrm{p}(\mathrm{y_i})) + (1 - \mathrm{y_i}) * \log(1 - \mathrm{p}(\mathrm{y_i}))) \qquad (12.)$$

where m denotes the total number of text samples, y_i refers to the actual labels, $p(y_i)$ refers to the probability of actual labels.

As with the baseline model, the deep learning model will be executed in all experiments and is named as *E-BiLSTM-CNN (T), E-BiLSTM-CNN (D), E-BiLSTM-CNN (ES), E-BiLSTM-CNN (EB), E-BiLSTM-CNN (D+ES), E-BiLSTM-CNN (D+EB), E-BiLSTM-CNN (ES+EB),* and *E-BiLSTM-CNN (D+ES+EB).*

To visualise the process, think of a simple tweet consisting of three words and two emojis, say, "I love summer ☀️ 😎". Here, 'I', 'love', and 'summer' are our word tokens, and '☀️' and '😎' are our emoji tokens. Each of these is passed through the Word_Emoji embedding layer. Here, it is converted into a vector using the embedding matrix, which is created using the GloVe and

Emoji2Vec embedding dictionaries. For each word and emoji token, the corresponding embedding vector is found in the relevant embedding dictionary. Now our tweet, "I love summer 🌞 😎", is represented as a sequence of vectors. Each word or emoji is now not just a numerical value, but a vector in high-dimensional space, containing rich information about its meaning. The tweet is then passed to a Bi-LSTM layer. This part looks at the tweet from start to end and also from end to start. It helps the computer remember the context of the words and emojis, understanding the tweet better. It is like reading a sentence forward and backwards to catch any hidden meanings. After that, the tweet is passed to a CNN layer. This layer picks out the key points from the tweet. For example, in "I love summer 🌞 😎", it may identify that "love" and the smiley face 😎 are important for understanding the sentiment. After the CNN layer highlights the key points, the max pooling layer selects the most important information from these highlights. The concatenate layer then combines the important features with an emoji score. The emoji score is a special number that represents the overall mood conveyed by the emojis in the tweet. Dense layers work like decision-makers. They synthesise all the information and start analysing it to categorise the sentiment of the tweet. Finally, the output layer decides the sentiment polarity of the tweet through the SoftMax activation function. It gives the probability of each sentiment and selects the one with the highest probability.

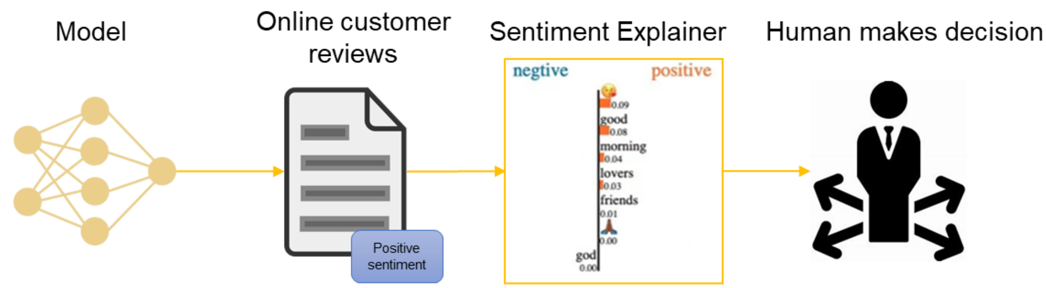
4.2.2.3 Explainable Multi-View SA

Explainable AI (XAI) is particularly important in the context of SA for high-stakes decision forecasting. While SA can provide valuable insights into customer attitudes and behaviours, it is essential to understand the reasoning behind these predictions. However, SA based on machine learning algorithms is one of the “black boxes” (Leung et al., 2021; Bussmann et al., 2021), which lacks transparency and interpretability (Zytek et al., 2021; Shin, 2021). As a result, decision-makers may be hesitant to act on its predictions. In addition, in high-stakes decision forecasting, the consequences of undetected incorrect predictions can be severe. For example, customer sentiment can have a significant impact on the success or failure of a product or service, and undetected inaccurate forecasting may lead to a decline in sales or even damage to the brand's reputation or waste resources on unnecessary product improvements or marketing campaigns.

Therefore, advanced AI models must be transparent and interpretable. In order to realise this aim, XAI methods offer explanations that make the functioning of AI comprehensible (Haque et al., 2023). This study will employ one of the most popular XAI methods, LIME, to visualise and explain the prediction results of the proposed multi-view SA model. This will support high-stakes decision-making related to marketing or customer preference forecasting. The algorithm of the sentiment explainer is shown in Algorithm A.4 in Appendix A, and the visualised process is shown in Figure 8.

Figure 8

Sentiment Explainer



4.2.3 Features and Embeddings

Both emojis and texts are employed as features. For all the algorithms, the words in each sentence are converted into 300-dimension word embeddings using Global Vectors for Word Representation (GloVe). It is an unsupervised learning algorithm that generates vector representations of words, which are trained over global word-word co-occurrence statistics (Pennington et al., 2014). As discussed in the literature review, emojis contain useful information that is related to the sentiment of a text. In this study, three methods were employed to handle the emojis, namely emoji replacement, adding emoji scores and adding EE. A detailed description of these methods is presented below:

Emoji replacement: This method employs the emoji package[3] to replace each emoji with its corresponding words or phrases. Then, the words or phrases become a part of the tweet and then are entered into the next step of word embedding.

[3] https://pypi.org/project/emoji/

Adding emoji scores: This approach computes the average “emoji score” of each tweet. Based on the calculation method provided by Hankamer & Liedtka (2016), an emoji score is calculated by taking the number of its positive occurrences, subtracting the number of its negative occurrences, and then dividing by the number of total occurrences (including neutral occurrences). As some tweets contain more than one emoji, for each tweet, this method takes the average score of the emoji appearing in the tweet and uses that score as an additional feature of the tweet. The pseudocode is shown in Algorithm A.1 in Appendix A. The occurrence information comes from the emoji sentiment lexicon provided by Kralj Novak et al. (2015)[4]. This lexicon contains occurrence information about 751 emoji characters.

$$\mathrm{es}_{\mathrm{e_b}} = (N(e_{b+}) - N(e_{b-}))/N(e_b) \tag{13.}$$

$$es_{\mathrm{i}} = (\sum_{1}^{b} \mathrm{es}_{\mathrm{e_b}})/b \tag{14.}$$

Creating emoji embeddings: Unlike emoji scores, this method applies an embedding method to emoji and generates emoji representations directly. This study used the emoji2vec embedding approach provided by Eisner et al. (2016), which includes 1662 emojis. This emoji embedding is pre-trained by the emoji's description in the Unicode emoji standard through the use of the Word2Vec embedding method. In the present study, the GloVe word embedding matrix was combined with the Emoji2Vec emoji embedding matrix to create a new Word_Emoji embedding (as described in Algorithm A.2 in Appendix A). Then, it was used as the weight in the model. As a result, the model is able to extract different emotional information from the tweets and then learn their relationship with users' sentiments (as discussed in Section 4.2.2 and outlined in Algorithm A.3 in Appendix A). In addition, this approach requires minimal preprocessing of the text as it does not require the removal of emojis or the calculation of emoji scores to add features.

[4] https://www.kaggle.com/datasets/thomasseleck/emoji-sentiment-data

4.2.4 Evaluation Metrics

Accuracy and F1-score are the two most frequently used performance evaluation metrics in published studies. Accuracy is useful because it helps us compute the number of correct predictions a model makes, but it does not take into account how the data is distributed. If most instances belong to the majority class, the accuracy score may be high even though it doesn't distinguish the classes very well. F1-Score accounts for both precision and sensitivity, and it compensates for uneven class distribution in the training dataset (Chicco & Jurman, 2020). In this study, the dataset is class balanced, the accuracy score and F1-score are therefore both suitable for evaluating the classifiers. The following equations are the formulas of the metrics:

$$\mathrm{Accuracy} = (\mathrm{TP} + TN)/(\mathrm{TP} + TN + \mathrm{FP} + \mathrm{FN}) \tag{15.}$$

$$F1 - Score = 2 * (Recall * Precision)/(Recall + Precision) \tag{16.}$$

$$Precision = TP/(TP + FP) \tag{17.}$$

$$Recall = TP/(TP + FN) \tag{18.}$$

where TP is True Positive, which refers to the sample size of positive labels correctly classified by the model. TN is true negatives and refers to the sample size of negative labels correctly classified by the model. FP is false positives and refers to the sample size of positive labels incorrectly classified by the model. FN is false negatives and refers to the sample size of negative labels incorrectly classified by the model. F1-Score is the weighted average of Recall and Precision.

As discussed in Section 2.2.1, many models in existing sentiment classification research have achieved high accuracy rates, F1-scores, or other statistical evaluation metrics. However, few studies have assessed these models from a practical perspective, such as execution time, which is critical for addressing real-world issues (Das et al., 2018). Therefore, the execution time is also employed as an evaluation metric in this study. In addition, this study will compute a comprehensive score based on the F1-score and execution time for each classifier to evaluate their overall performance.

$$Final\ score\ =\ 0.6 * \ F1 - score\ +\ 0.4\ *\ execution\ time \tag{19.}$$

4.3 Data

4.3.1 Data Collection

In recent years, a growing body of work has also examined the role of emojis in SA. While they proposed various methods to convert emojis to sentiment features, they ignored the issue of consistency between the dataset used and real-life datasets, for example, in terms of data distribution. This study argues that it is important that the distribution of the data used for training the model is as close as possible to that used for testing the model in real life, which is also reflected in the study (Hankamer & Liedtka, 2016; de Barros et al., 2021). Aiming to construct an ideal dataset that can simulate a realistic distribution of tweets containing emojis, this study investigated the ratio of tweets containing emojis to total tweets. Emojipedia (2022) reported that about 21.5% of tweets contained emojis at the end of 2021. Therefore, this study determined the ratio to be 20%. Based on this, this study constructed a Modern Tweet Dataset for the proposed study by the use of a Sentiment 140 Dataset and an Emoji Tweet Dataset.

The Sentiment 140 Dataset is composed of 1.6 million tweets provided by Go et al. (2009). This dataset is class balanced, with a 50/50 split between those labelled as positive and negative emotions. This study chose the Sentiment 140 Dataset because it is one of the most frequently used datasets in this domain, and its quality has been proven by many studies. In addition, it is less restricted to one specific domain compared to other datasets, covering various brands, products, or topics on Twitter. The Emoji Tweet Dataset is provided by Yan (2020). The dataset is also not limited to a specific domain. There are 16011 pieces of data in total, each containing emojis. This dataset's class is balanced, with 8010 entries classified as negative and 8001 entries as positive.

Based on the Sentiment 140 Dataset and the Emoji Tweet Dataset, this study constructed a Modern Tweet Dataset that contains a total of 80,000 tweets, with a 20% share of tweets containing emojis. This dataset is also balanced, with 40,000 samples labelled as positive and 40,000 samples as negative.

4.3.2 Basic Data Preprocessing

Data from social networking sites are often non-structured and contain noisy information that is irrelevant and inefficient, and they do not convey textual emotional meaning in the majority of cases (Priyadarshini & Cotton, 2021). Singla et al. (2022) claim that preprocessing is critical in identifying emotions or sentiments in non-uniform text input. To effectively conduct the classification tasks, a variety of data preprocessing techniques are required to convert text into an analysable and predictable form and to derive relevant information from massive data.

Since one of the research purposes is to assess how emojis affect the effectiveness of machine learning algorithms, this study will conduct a basic preprocessing of the data beforehand. The preprocessing techniques consist of changing capital letters to lower case, removing web links, mentions (@), hashtags and punctuation, reducing consecutive repeated letters in the vocabulary, changing contractions to their full forms, removing stop words, and finally, removing extra spaces from the text. It is worth noting that, unlike other studies, this study has only removed the hash symbols (#) of the topic labels, leaving the topics that were carried. While exploring the data, this study found some topics containing sentimental messages, such as #lovethis and #funbutwrong. Therefore, these topics remained in this study. In addition, stop words are a group of frequently used terms in all languages, not just English, and removing them from the text corpus enhances model performance and makes the model more robust. This study employed the list of stop words provided by the Natural Language Toolkit (NLTK) package to remove stop words from the data samples. According to HaCohen-Kerner et al. (2020), however, the removal of stop words may also alter the meaning of the sentences, which has an impact on the accuracy of the classifiers. Therefore, this study retained the negatives in the text, including 'but', 'no', 'nor', and 'not'. The finished text was processed by retaining the various emojis to conduct the following experiments. An example of a review before and after the preprocessing operation is shown in Figure 9:

Figure 9

A Review Example of Before and After the Preprocessing Operation

```
text = "I don't ❤️ flying @VirginAmerica. :D heyyyy ☺👍..&"
basic_preprocess_apply(text)
```

```
'not ❤️ flying laugh heyy ☺👍'
```

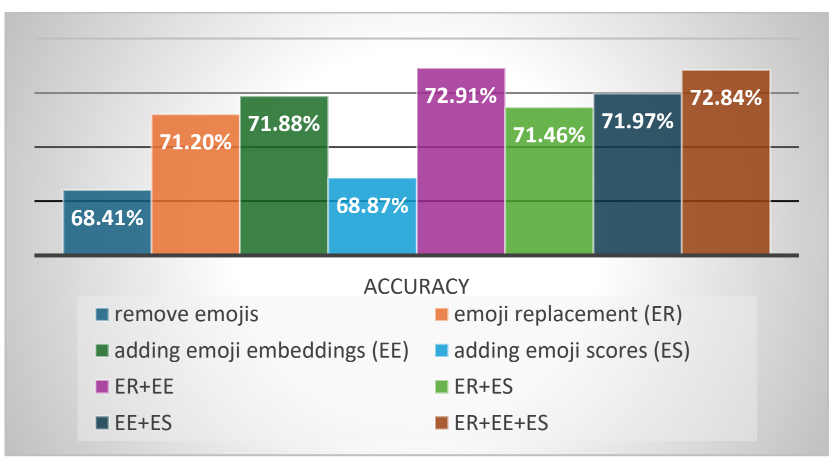
4.4 Experimental Results and Discussion

4.4.1 The Effect of Emoji Features on the Performance of Sentiment Classifiers

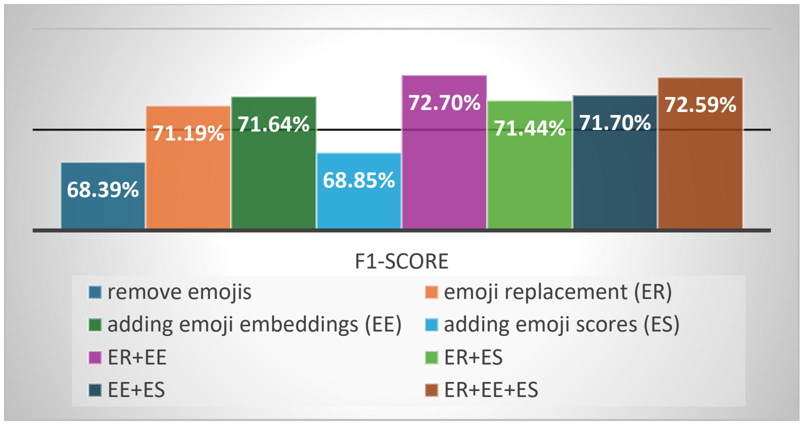
Firstly, this study evaluates the effectiveness of handling emojis on sentiment recognition of online reviews by sentiment analysers and the best handling method for each algorithm. Emoji_Less refers to using the method of removing emojis from the text, ER refers to emoji replacement, EE refers to creating emoji embeddings, and ES refers to adding emoji scores. The results are summarised in the following figures and tables. Figures 9 to 23 show the scores of the evaluation metrics for each method, namely accuracy, F1-score, and execution time. Their improvement or reduction in each metric compared to only considering word features in models and their rankings in each metric and the overall ranking are also listed in Tables 2 to 5. It is important to recognise that when using rank scores to evaluate classifiers, a potential limitation is that the relative positions of options (such as classifiers A and B) can be influenced by the inclusion of other options in the rankings. This means that adding or removing classifiers from the set could change the relative rankings of A and B, even if their individual performances remain the same. However, this limitation does not apply in this study, as the complete set of possible emoji-handling methods has been included in the analysis. Therefore, the relative rankings of the classifiers remain consistent, ensuring that the comparisons accurately reflect their performance in terms of accuracy, F1-score, and execution time.

Figure 10

Accuracy (a) and F1-score (b) of Different Classifiers Using NB



(a)



(b)

Figure 11

Execution Time of Different Classifiers Using NB

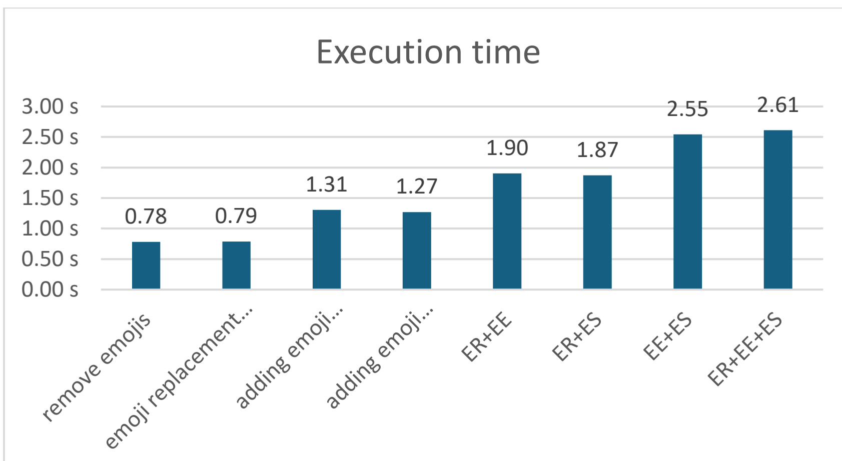


Table 2

Comparison and Rankings of Different Classifiers using NB

NB	*Variation in accuracy (%)*	*Accuracy_ranking*	*Variation in F1_score (%)*	*F1_score_ranking*	*Variation in Time(%)*	*Time_ranking*
remove emojis (EMOJI_LESS)	0.00%	8.00	0.00%	8.00	**0.00%**	**1.00**
emoji replacement (ER)	4.08%	6.00	4.09%	6.00	0.86%	2.00

adding emoji embeddings (EE)	5.07%	4.00	4.75%	4.00	66.71%	4.00
adding emoji scores (ES)	0.67%	7.00	0.67%	7.00	62.33%	3.00
ER+EE	**6.58%**	**1.00**	**6.30%**	**1.00**	143.17%	6.00
ER+ES	4.46%	5.00	4.46%	5.00	139.42%	5.00
EE+ES	5.20%	3.00	4.84%	3.00	225.08%	7.00
ER+EE+ES	6.48%	2.00	6.14%	2.00	233.28%	8.00

For Naive Bayes, handling emojis using any of the three approaches helped to increase the classifier’s performance in sentiment recognition (Figure 12 and Table 2). However, the effectiveness of the method, namely employing emoji scores as an additional feature, is not significant. According to Table 2, it only achieved an accuracy/F1-score 0.67% higher than when only word features were considered. From the perspectives of accuracy and F1-score, the best emoji handling method for NB is using both emoji replacement and adding emoji embedding methods (6.58% higher than EMOJI_LESS), while the method of removing emojis from the text takes the shortest execution time. In order to evaluate the classifiers' comprehensive performance, this study considers the ranking of each classifier in the F1-score and the execution time evaluation metric. The findings confirm that the smaller the rank score, the higher the ranking and the better the classifier performs. Stacked bars are employed to visualise this ranking for decision-makers to better understand the outcomes; the shorter the bar, the better the corresponding classifier performs. According to Figure 13, NB performs best when using both replacing emoji and adding emoji embedding methods, as it achieves the smallest ranking score.

Figure 14

The Comprehensive Ranking of Different Classifiers Using NB

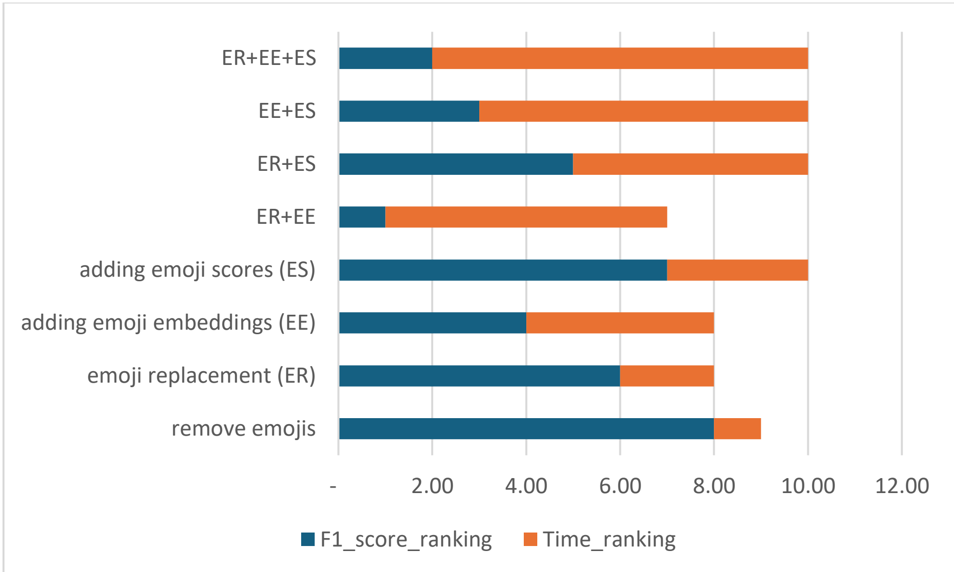
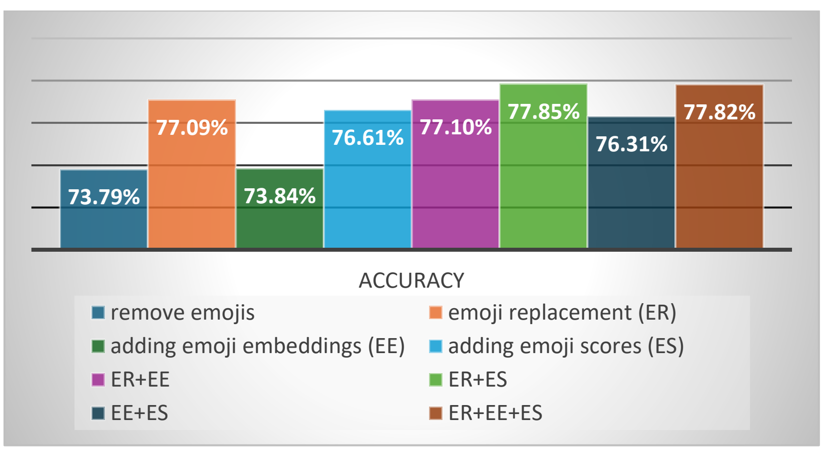
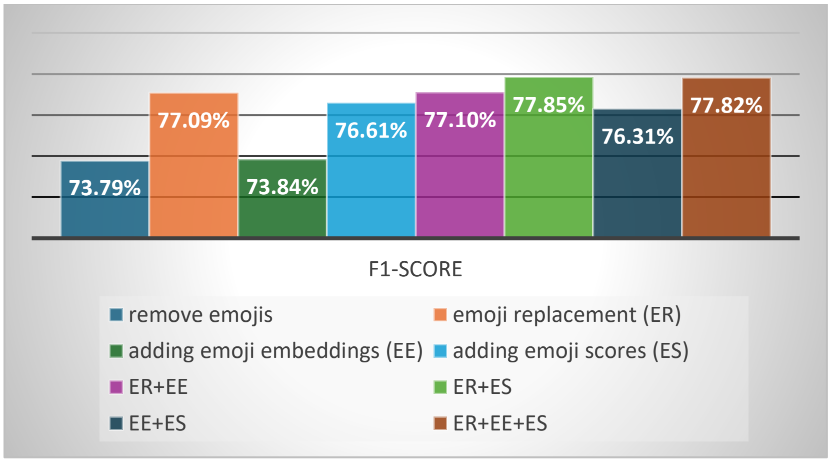


Figure 15

Accuracy (a) and F1-score (b) of Different Classifiers Using SVM



(a)



(b)

Figure 16

Execution Time of Different Classifiers Using SVM

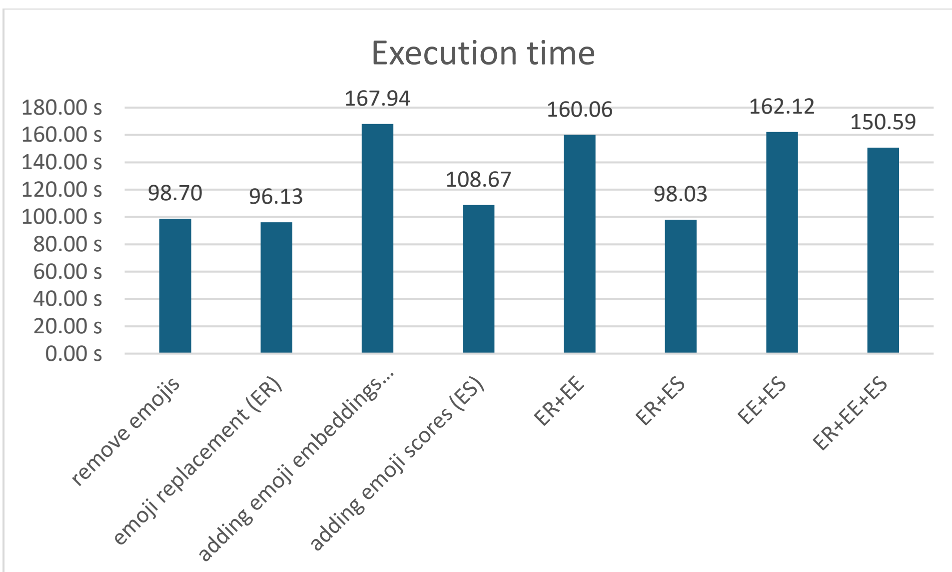


Table 3

Comparison and Rankings of Different Classifiers Using SVM

	Variation in accuracy (%)	*Accuracy_ranking*	*Variation in F1_score (%)*	*F1_score_ranking*	*Variation in Time(%)*	*Time_ranking*
remove emojis (EMOJI_LESS)	0.00%	8.00	0.00%	8.00	0.00%	3.00
emoji replacement (ER)	4.47%	4.00	4.47%	4.00	**-2.60%**	**1.00**
adding emoji embeddings (EE)	0.07%	7.00	0.07%	7.00	70.16%	8.00
adding emoji scores (ES)	3.82%	5.00	3.82%	5.00	10.11%	4.00
ER+EE	4.49%	3.00	4.49%	3.00	62.17%	6.00
ER+ES	**5.50%**	**1.00**	**5.50%**	**1.00**	-0.67%	2.00
EE+ES	3.42%	6.00	3.42%	6.00	64.26%	7.00
ER+EE+ES	5.46%	2.00	5.46%	2.00	52.58%	5.00

For SVM, handling emojis using the emoji embedding method slightly improved the classifier's performance by 0.07% accuracy compared to the Emoji_Less method, while replacing emojis with their description and adding an emoji score feature improved the performance of classifiers by 4.47% and 3.82%, respectively. From the perspectives of accuracy and F1-score, using emoji descriptions and emoji scores simultaneously could improve the classifier's overall performance in detecting the sentiment of tweets to a greater extent. From the perspective of execution time, the best handling method is the emoji replacement method alone. Suppose the performance of the classifiers in these two areas is considered together. In that case, the classifier employing SVM to conduct sentiment classification performs best when using the combination of emoji replacement and emoji scores.

Figure 17

The Comprehensive Ranking of Different Classifiers Using an SVM

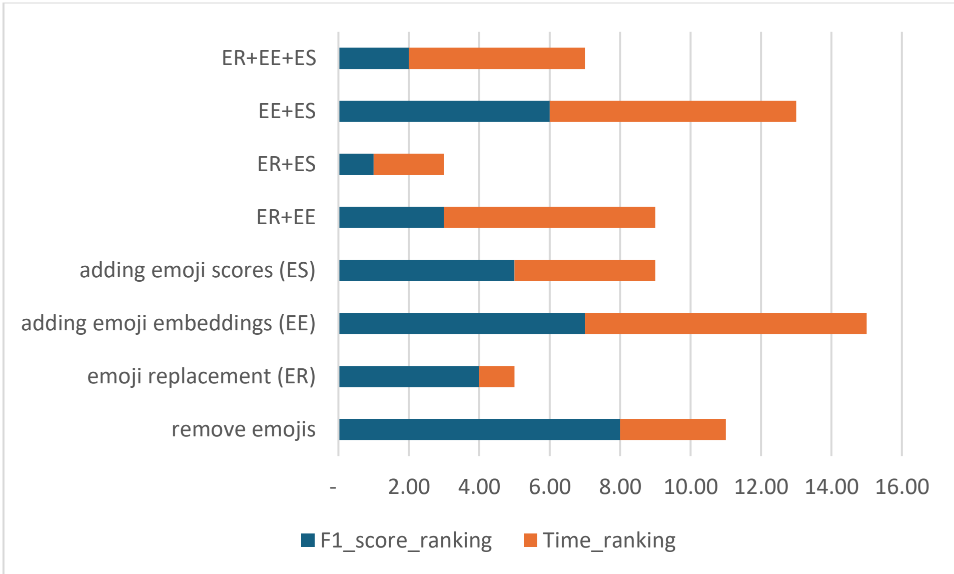
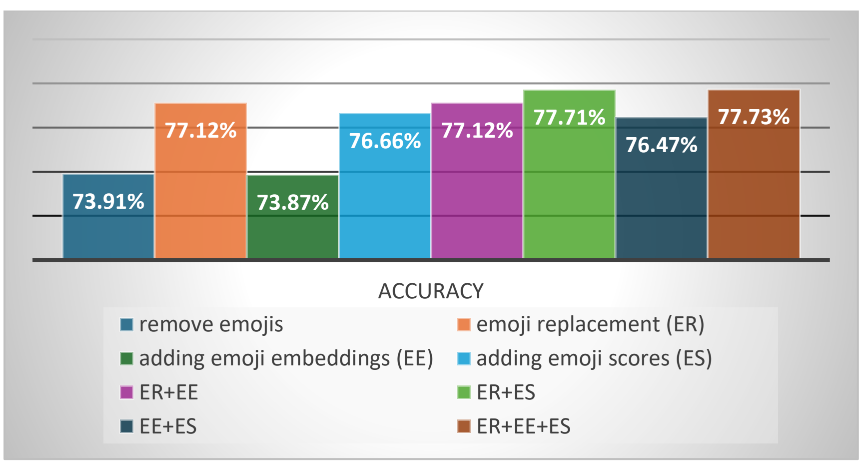
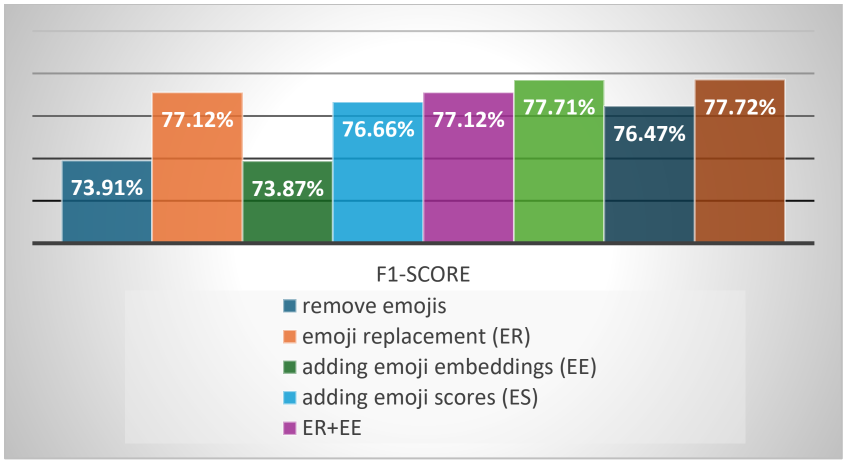


Figure 18

Accuracy (a) and F1-score (b) of Different Classifiers Using LR



(a)



(b)

Figure 19

Execution Time of Different Classifiers Using LR

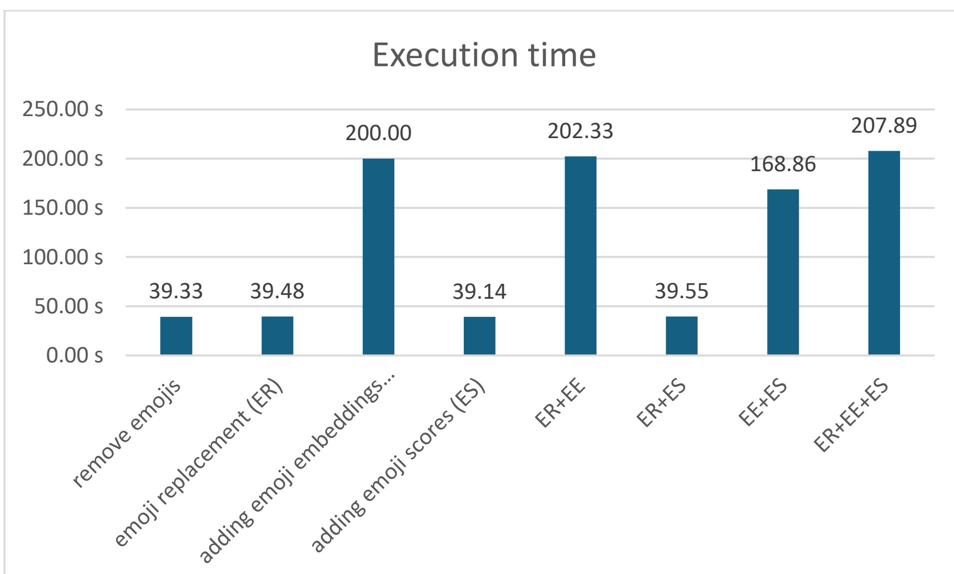


Table 4

Comparison and Rankings of Different Classifiers Using LR

	Variation in accuracy (%)	*Accuracy_ranking*	*Variation in F1_score (%)*	*F1_score_ranking*	*Variation in Time(%)*	*Time_ranking*
remove emojis (EMOJI_LESS)	0.00%	7.00	0.00%	7.00	0.00%	2.00
emoji replacement (ER)	4.34%	3.00	4.34%	3.00	**0.40%**	3.00
adding emoji embeddings (EE)	-0.05%	8.00	-0.05%	8.00	408.56%	6.00
adding emoji scores (ES)	3.72%	5.00	3.72%	5.00	**-0.48%**	**1.00**
ER+EE	4.34%	3.00	4.34%	3.00	414.48%	7.00
ER+ES	5.14%	2.00	5.14%	2.00	**0.57%**	4.00
EE+ES	3.46%	6.00	3.46%	6.00	329.38%	5.00
ER+EE+ES	**5.17%**	**1.00**	**5.15%**	**1.00**	428.62%	8.00

Regarding logistic regression, applying the emoji embedding method slightly deteriorates performance compared to just considering word features, while the methods of emoji replacement and adding emoji scores improved the performance of classifiers by 4.34% and 3.72%, respectively. The results are similar to those when SVM is used. It indicates that SVM and LR are not able to derive meaningful information from emoji embeddings. In terms of accuracy and F1-score, the best handling method is using all of the three methods together. From the perspective of execution time, the best handling method is employing emoji scores as an additional feature. Considering two aspects, either emoji replacement (F1-score: 77.12%; Time vs. Emoji_less: +0.4%), adding emoji scores (F1-score: 76.66%; Time vs. Emoji_less: -0.48%), or using both of them (F1-score: 77.71%; Time vs. Emoji_less: +0.57%) can be chosen when using LR to construct the sentiment classifier, as they achieved accuracy and F1-score of around 77%, and spent execution time close to just removing all emojis. Although the classifier achieved the best result in accuracy when using the combination of the three methods (F1-score: 77.73%), it took nearly four times (Time vs. Emoji_less: +428.62%) as the time spent by other methods. Therefore, it was not the best choice for practical use when using LR to construct a sentiment classifier.

Figure 20

The Comprehensive Ranking of Different Classifiers Using LR

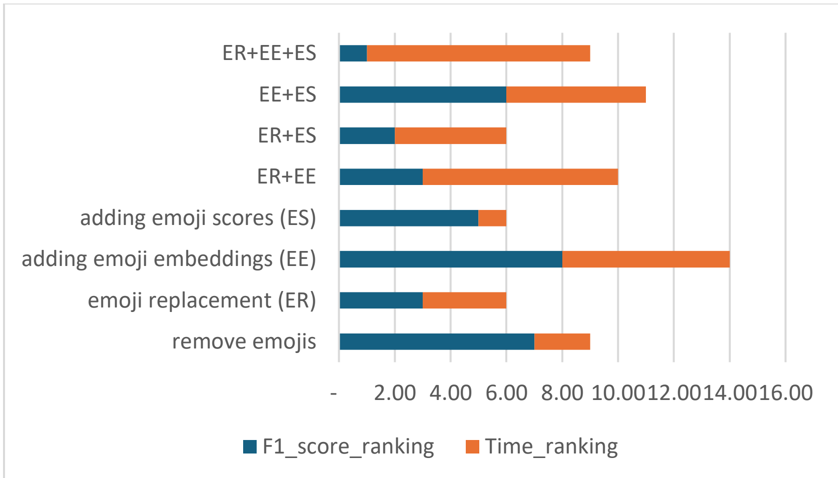
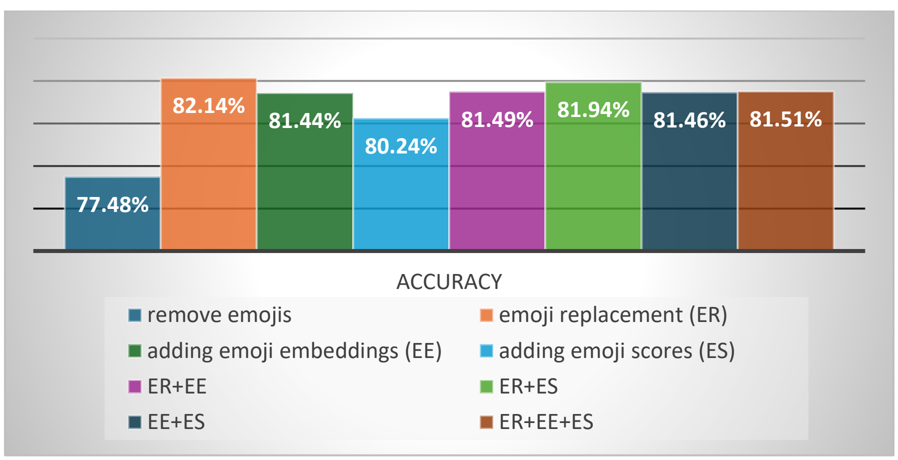
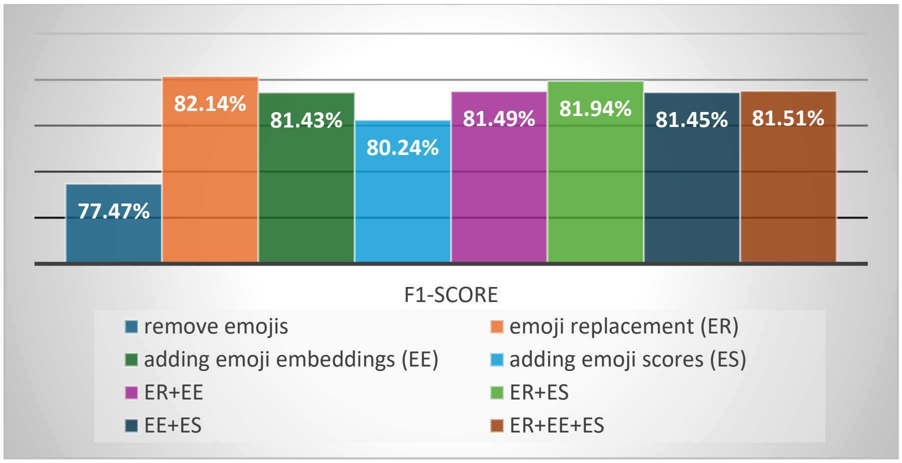


Figure 21

Accuracy (a) and F1-score (b) of Different Classifiers Using BiLSTM-CNN



(a)



(b)

Figure 22

Execution Time of Different Classifiers Using BiLSTM-CNN

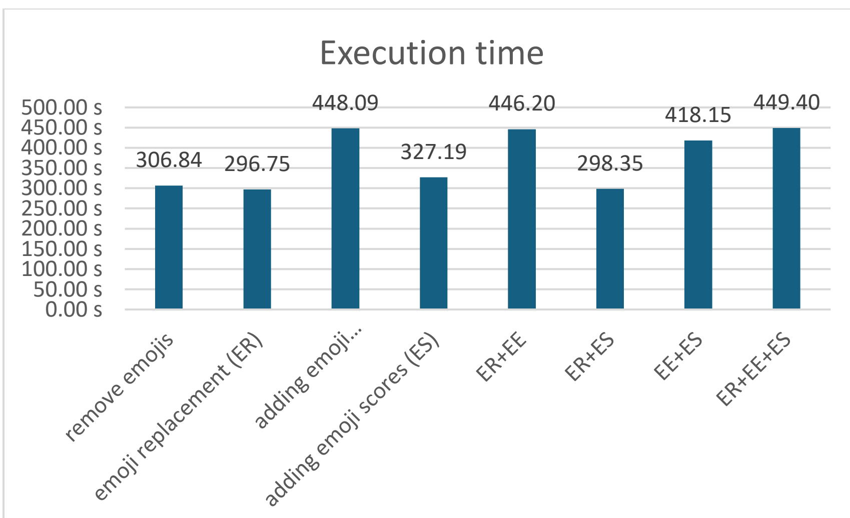


Table 5

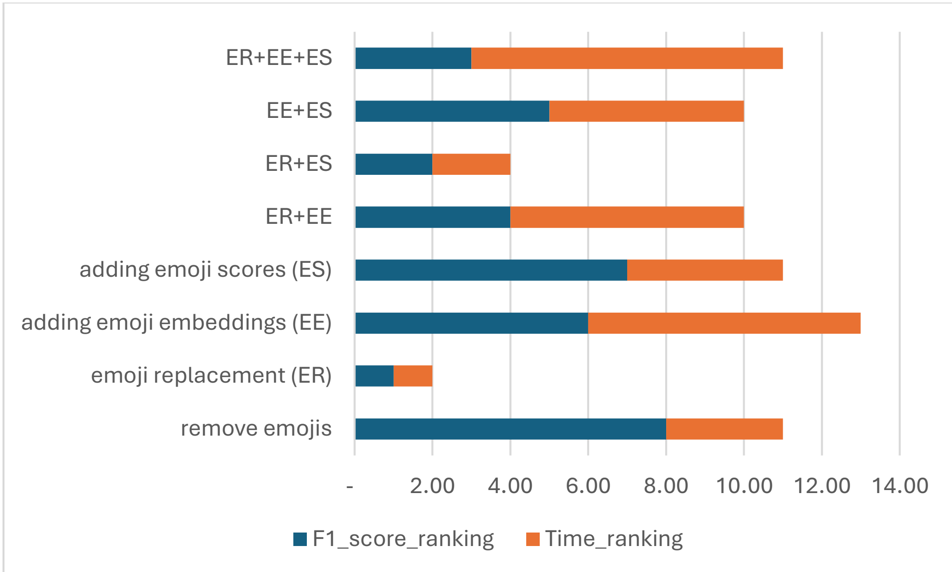
Comparison and Rankings of Different Classifiers Using BiLSTM-CNN

	Variation in accuracy (%)	*Accuracy_ranking*	*Variation in F1_score (%)*	*F1_score_ranking*	*Variation in Time (%)*	*Time_ranking*
remove emojis (EMOJI_LESS)	0.00%	8.00	0.00%	8.00	**0.00%**	**3.00**
emoji replacement (ER)	**6.01%**	**1.00**	**6.03%**	**1.00**	**-3.29%**	**1.00**
adding emoji embeddings (EE)	5.11%	6.00	5.11%	6.00	46.04%	7.00
adding emoji scores (ES)	3.56%	7.00	3.58%	7.00	6.63%	4.00
ER+EE	5.18%	4.00	5.19%	4.00	45.42%	6.00
ER+ES	5.76%	2.00	5.77%	2.00	-2.77%	2.00
EE+ES	5.14%	5.00	5.14%	5.00	36.28%	5.00
ER+EE+ES	5.20%	3.00	5.21%	3.00	46.46%	8.00

When using the BiLSTM-CNN model, even with emoji removed, its ability to recognise sentiment is comparable to any classical machine learning algorithm that takes emoji into account. Any of the three emoji handling approaches helped to increase the performance of classifiers and can contribute to informed decisions. Emoji replacement can make an improvement of 6.01% to accuracy and f-score, adding emoji embeddings can improve them by 5.11%, and adding emoji scores can improve them by 3.56%. From the results of using a combination of emoji processing methods, it appears that while emoji scoring and emoji embedding are effective methods, neither of them provides additional useful information when in a situation where emoji replacement is already in use. Therefore, replacing emojis is the best handling method out of all combinations according to accuracy and F1-score values. In terms of execution time, the best handling method is also the emoji replacement. The BiLSTM-CNN model performs best when using emoji replacement while considering the performance of the classifiers as a whole.

Figure 23

The Comprehensive Ranking of Different Classifiers Using BiLSTM-CNN



In addition to the above findings, it can be seen that SVM, LR and BiLSTM may take less time when processing more features, especially when Emoji Embeddings (EE) are involved. These findings might seem counter-intuitive at first, but they can be explained by the following factors. Firstly, according to the curse of dimensionality (Zimek et al., 2012), adding more features can help the algorithm better distinguish between different classes by adding complementary information to the feature space. This additional information can improve the model's ability to separate classes. Among the algorithms tested, SVM (Figure 13) is particularly sensitive to feature space dimensionality because it aims to find the optimal hyperplane that separates different classes in high-dimensional space. The curse of dimensionality actually works to SVM's advantage to a certain extent. In high-dimensional spaces, data points become more separable, and SVM can leverage this to find a better decision boundary (Ghaddar & Naoum-Sawaya, 2018). This means that adding more features helps create better separability between classes, allowing the SVM to converge faster. Secondly, the reduced computational burden may stem from the synergistic effect of features, which should be verified in future studies. Each feature handling method, ER (Emoji Replacement), EE (Emoji Embedding), and ES (Emoji Scores) provides different information derived from emojis. When combined, the simpler features (ER and ES) help reduce the complexity or computational load required for the more resource-intensive methods like EE. By combining these features (e.g., ER+EE), the computational complexity of relying solely on high-dimensional embeddings (EE) may be reduced. This explains why ER+EE or EE+ES takes less time than EE alone, as the simpler features balance out the resource-intensive embedding process.

4.4.2 The Effectiveness of the Word_Emoji Embedding Matrix

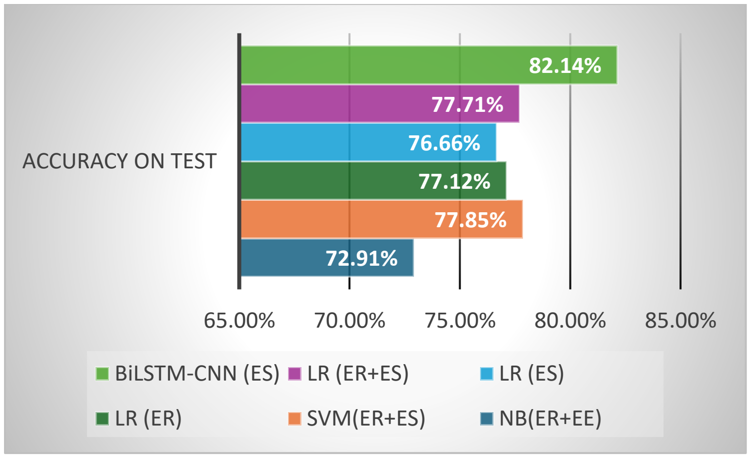
The E-BiLSTM-CNN model proposed in this study creates emoji features in a new method, which converts words and emojis simultaneously based on a new Word_Emoji embedding matrix. With the purpose of testing the effectiveness of the proposed model, this study compared its performance with other classifiers. As shown in Figure 21, Figure 22 and Table 5, this method significantly enhanced the BiLSTM-CNN model's effectiveness (accuracy: 81.44%; F1-score: 81.43%; execution time: 448s) by 5.11% of accuracy/F1-score compared to the model using data samples of plain text (accuracy: 77.48%; F1-score: 77.47%; execution time: 307s) or by 1.50% of accuracy/F1-score compared to the model adding an additional feature of emoji scores (accuracy & F1-score: 80.24%; execution time: 327s). However, in terms of the time taken to train the BiLSTM-CNN model, the classifiers using this method took a longer time than others, which makes it fail to be the best method. The results show that the method "emoji replacement" shows better classification performance than adding emoji embeddings, which agrees with Singh et al. (2019). A possible reason is that there are a large number of emojis (over 2800), some of which do not appear very often. Existing research has, therefore, focused on creating only the most frequently used emoji lexicon to provide emoji scores or pre-trained emoji embeddings, which is incomplete. However, words in their descriptions are much more common, so it is often more beneficial to utilise descriptions for SA on current social networking platforms.

From the perspective of practical use for decision-making, the proposed method is more efficient when identifying the sentiment of new text than those provided by the existing literature (Singh et al., 2019; de Barros et al., 2021). It embeds words and emojis in each tweet at the same time rather than creating word embeddings and emoji embeddings separately and then combining them. Therefore, this technique has the advantage of requiring minimum preprocessing of the text as it does not require removing or separating emojis or computing emoji scores to add features.

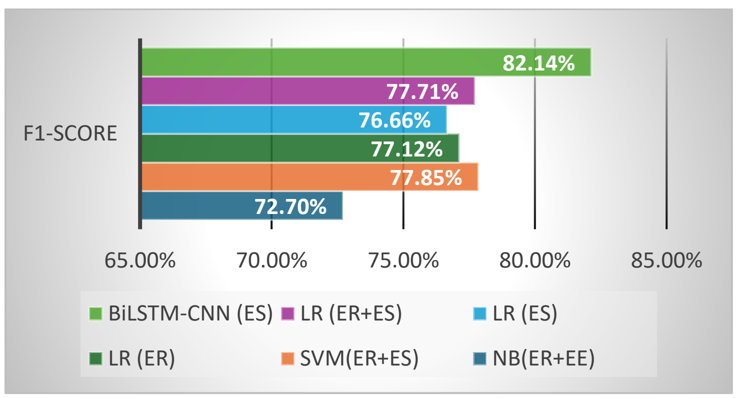
4.4.3 Comprehensive Performance Comparison Among Best Classifiers for Each Algorithm

Figure 24

Accuracy (a) and F1-score (b) of Best Classifiers for Each Algorithm



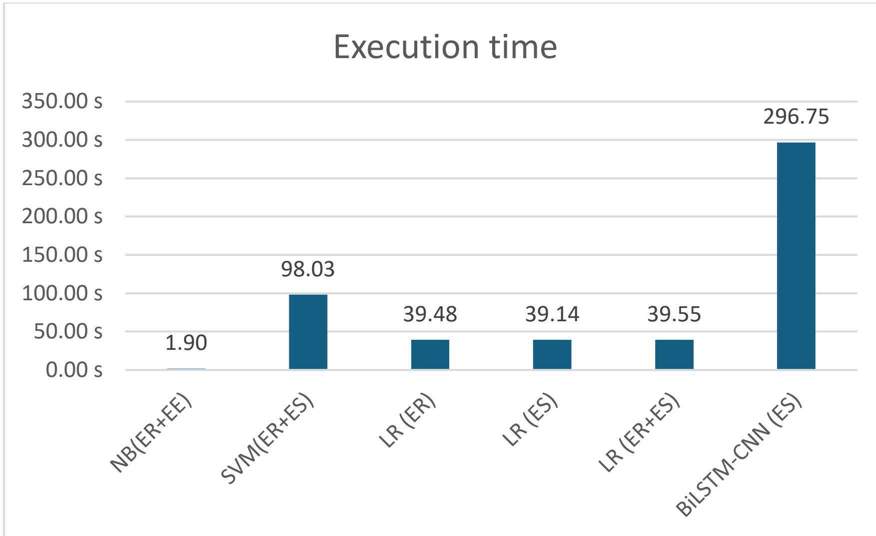
(a)



(b)

Figure 25

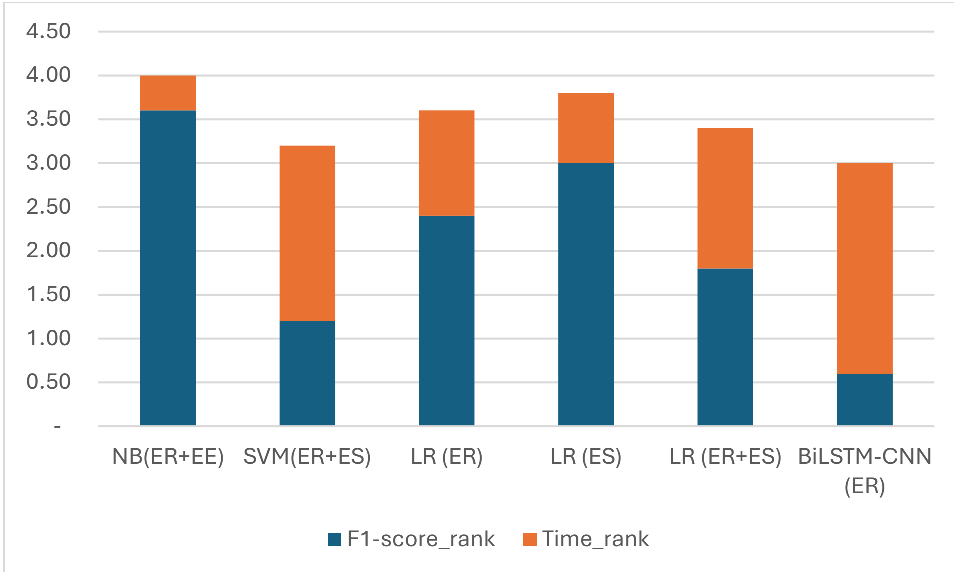
Execution Time of Best Classifiers for Each Algorithm



This study also compared the performance of the best classifiers using each algorithm. Although Naive Bayes was the fastest, it only achieved nearly 72.91% accuracy, which was 5% lower than the other classifiers. The most accurate classifier was BiLSTM-CNN using emoji replacement, achieving 82.14% accuracy and F1-score, but it took a much longer time (15,400 times longer than NB(ER+EE)) due to the nature of deep learning. This study performed a weighted average of their performance based on the F1-score and execution time, and the best classifier was BiLSTM using emoji replacement. Compared to the baseline models, the deep learning model can extract more meaningful information from emoji characteristics due to its powerful feature extraction capacity.

Figure 26

The Comprehensive Ranking of Classifiers for Each Algorithm



4.4.4 Results of Explainable Multi-View SA by LIME

For the purpose of improving the trust of decision makers in the proposed multi-view deep learning SA model, LIME is employed to help understand which features the model picks up on to make predictions. In addition, LIME is a local interpretation tool, which means it is able to explain a specific instance according to the requirements of decision-makers.

Figure 27

Local Explanation for an Online Review by the Multi-view SA model

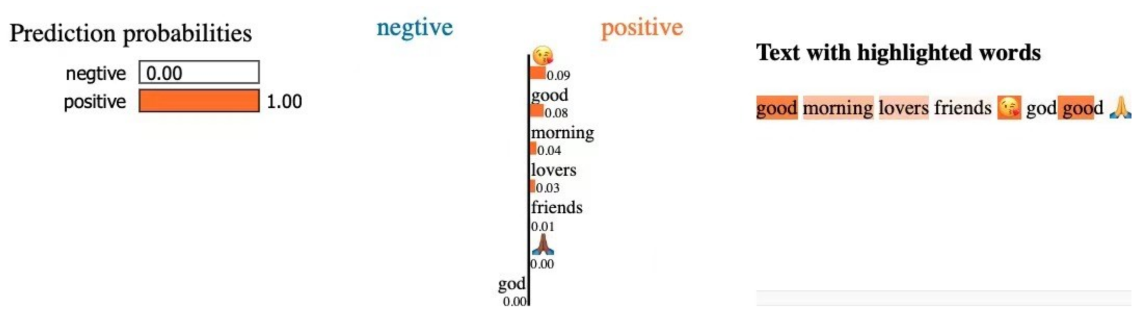


Figure 28 presents the local explanations of the proposed multi-view SA model for a specific online review sample using the LIME technique. The figure shows that the sentiment of this review is predicted as positive by the proposed model with a prediction probability of 100%. To improve the comprehension of the black-box method, LIME is used to visualise the features on which the prediction is based. Two ways have been provided for decision-makers to reference. The first way is by the degree of colour, which is shown on the right side of Figure 29. The deeper the colour, the more significant the feature. The second way is clearer, which is shown in the middle of Figure 30. It uses a bar chart to rank the features in descending order according to their significance value, labelled on the chart. The features located on the right of the line are indicative of positive sentiment, whereas those on the left side represent negative sentiment. According to Figure 31, the three most significant factors determined by the proposed model for the prediction on the given review are the '😘', 'good' and 'morning', which indicate positive sentiment.

4.4.5 Validation Test

To assess the performance of the proposed E-BiLSTM-CNN model, this study conducted a comparison with other studies based on the F1-score and accuracy metrics, as these are the most commonly used and were available in the referenced papers. The following table Table 6 provides a summary of the findings.

Table 6

Performance Comparison of the E-BiLSTM-CNN Model With Other Classifiers and Building Blocks.

Authors	Classifier	F1-score	Accuracy
Lou et al. (2020)	EA-Bi-LSTM	72.18%	87.85%
A. Singh et al. (2019)	EMJ-DESC	70.30%	70.40%
Liu et al. (2021)	CEmo-LSTM (text+E)	-	81.10%
de Barros et al. (2021)	pre-trained BERT model-TweetSentBR	73.95%	75.77%
	pre-trained BERT model-2000-tweets-BR	81.51%	83.16%
This study	E-LSTM (building blocks of the proposed model)	81.33%	81.33%
This study	E-BiLSTM (building blocks of the proposed model)	81.31%	81.31%
This study	E-CNN (building blocks of the proposed model)	80.92%	80.92%

This study	E-BiLSTM-CNN model	81.43%	81.44%

The proposed E-BiLSTM-CNN model demonstrated competitive results in terms of both F1-score and accuracy. Despite the high accuracy of Lou et al.'s (2020) EA-Bi-LSTM model, the proposed model had a significantly higher F1-score, demonstrating a better balance between precision and recall. Moreover, the model outperformed Singh et al.'s (2019) EMJ-DESC model and de Barros et al.'s (2021) pre-trained BERT model (TweetSentBR version) in both respects.

When compared to the best-performing model from de Barros et al. (2021), the pre-trained BERT model-2000-tweets-BR, the F1 scores of the proposed model are almost comparable and only slightly less accurate. However, it is important to note that the proposed model was trained on a dataset with 80,000 tweets, much larger than the 2,000-tweet dataset used in the pre-trained BERT models by de Barros et al. (2021). Despite the lack of F1-score for comparison with Liu et al. (2021), the proposed model's accuracy was found to be similar.

Together with the benefits of the model’s simplified preprocessing pipeline, the use of a realistic emoji proportion dataset, and the application of Explainable AI techniques, these results emphasise the robustness and validity of the proposed E-BiLSTM-CNN model for SA. Moreover, the larger dataset used in this study further contributes to the robustness and generalisability of the results.

According to the various discussions above, the findings of this study first contribute to the theoretical understanding of how emojis and text interact in SA. The proposed E-BiLSTM-CNN model, which incorporates both features in a balanced manner, addresses the limitations of previous models that ignore the sentiment information contained by emoji features or require intensive pre-processing. From an empirical standpoint, the model has demonstrated superior performance when compared to other models. With a competitive F1-score and accuracy, even when trained on a larger, more representative dataset, the E-BiLSTM-CNN model proves to be an effective tool for SA. This success points to a significant advancement in the practical application of SA models in social media contexts. In terms of marginal economic effect, the results of this study could significantly impact sectors that rely heavily on social media data. By applying the more accurate and efficient model proposed in this study, industries and governments can gain more precise insights into consumer sentiment. With the ability owned by the model to handle large datasets and maintain performance, they can analyse larger amounts of data in less time, leading to cost savings. Moreover, by not requiring additional pre-processing steps, resources can be allocated more efficiently, increasing the marginal returns from SA.

In addition, understanding the sentiment of public opinion is crucial in managing market disasters caused by unforeseen circumstances, like unexpected regulations (U-R conflicts) or the COVID-19 pandemic. The E-BiLSTM-CNN model in this study can also assist in such situations. First of all, the proposed model's superior performance in SA can aid in the early detection of shifts in public sentiment. For instance, escalating public discontent due to sudden regulatory changes or public fears during the COVID-19 pandemic can be detected early by analysing social media data. This allows policymakers, businesses, and other stakeholders to respond proactively and avert potential crises. Second, by understanding the prevalent sentiments in real-time, businesses and governments can tailor their communication strategies to better address public concerns, fears, or expectations, to mitigate miscommunications or misunderstandings. Third, the proposed model can provide valuable feedback on the effectiveness of recovery efforts and allow adjustments to be made quickly.

4.5 Summary

4.5.1 Main Findings and Contributions

From a multi-view learning perspective, this study investigates the impact of emojis on identifying sentiments of posts users expressed on social media platforms. This study proposes three emoji handling methods, namely, Emoji Replacement, Adding Emoji Scores, and Creating Emoji Embeddings, and tested how well each sentiment classifier performs when incorporating emoji features processed by these methods individually or in combination. Three classical ML algorithms were employed to construct the baseline classifiers. Moreover, a novel multi-view deep learning model, E-BiLSTM-CNN, was also proposed and compared to the other classifiers. The main finding is that each sentiment classifier improves the performance of the classifiers when dealing with emoji features processed by the three methods, either individually or in combination. These results validate that text and emoji features can be used as different views to provide different sentiment information to the sentiment classification model. The performance of the Word_Emoji embedding matrix, which was implemented in the proposed E-BiLSTM-CNN model, was also evaluated, demonstrating notable effectiveness with a high F1 score of 81.4%.

This research extends the understanding of SA by proposing a multi-view learning approach that regards text and emojis as distinct and valuable sources of sentiment information. A significant contribution is the introduction of explainable SA to this multi-view model. By utilising explainable SA, decision-makers can comprehend how the model develops its decisions, and which features are deemed significant by the model. This enables them to evaluate the prediction themselves, combining their own experience to make the final decision, which can mitigate the influence of misleading decision forecasting on high-stakes businesses.

In addition to the effectiveness of considering text and emojis features in deep learning sentiment classification and providing explainable SA, the current research has made several other contributions. The proposed multi-view SA method is constructed by simulating the real distribution of emojis on the social media platform, which considers the issue of consistency between the dataset used and reality. Moreover, this study considers the efficiency of classifiers to be essential when applied in the real business world. The proposed application framework requires minimal preprocessing of social media posts, which ensures the system's efficiency and allows it to process large volumes of data in a timely and accurate manner. This streamlined approach to preprocessing significantly reduces the risk of errors and inaccuracies, allowing high-stakes businesses to make well-informed decisions based on reliable and accurate SA.

4.5.2 Implications and Stakeholder Benefits

By illuminating the role of emojis in sentiment expression and demonstrating their impact on SA, this study encourages stakeholders to give more attention to non-verbal cues in online communications when crafting policies.

Businesses in sectors such as retail, hospitality, and technology can utilise the study's findings to shape their social media monitoring policies. For instance, recognising the importance of emojis in sentiment expression can help companies in these sectors refine their online customer service. This improved SA capability can, for instance, enable a retail company to more accurately assess the reception of a new product based on online reviews and social media posts, thereby guiding marketing and production decisions. For machine learning practitioners and researchers, the proposed emoji handling methods and the multi-view learning approach can be valuable additions to their toolkits. These novel methodologies can be used or further developed to improve the accuracy and interpretability of SA models in future studies.

The impact of this study extends beyond just business applications. For instance, government agencies could use the proposed SA model to gauge public sentiment towards new policies or public initiatives, such as the cost-of-living crisis in the UK and the government's response to public health events based on social media posts, thereby obtaining valuable feedback for policy adjustments.

By acknowledging the role of emojis in sentiment expression and proposing new ways to incorporate emojis into SA, this study can potentially transform the way SA is performed, leading to a more accurate and comprehensive understanding of online sentiments in various fields.

4.5.3 Limitations and Future Work

The present work has several limitations. While the dataset Sentiment 140 is the most popular dataset used for SA, it was not perfectly categorised as it was labelled by directly using the emoticons in the tweet. Therefore, the accuracy and F1-score may be lower than expected. Since the dataset of tweets containing emojis used in this study is multi-domain, for consistency, Sentiment140 is the best choice among the available datasets. In the future, a primary dataset can be collected. In addition, one potential reason why the method of adding emoji scores does not perform as well as creating emoji embedding methods is that the emoji size (1662 emoji) used to train Emoji2Vec (Eisner et al., 2016) is larger than the emoji size in the emoji sentiment lexicon (751 emoji) provided by Kralj Novak et al. (2015). For future work, this study plans to train emoji embeddings and compute emoji scores based on the same emoji lexicon for a fairer comparison.

Chapter 5 Integrating Network and SA into the Dual-Framework Approach

5.1 Introduction

In Chapter 3 and Chapter 4 of this thesis, a methodological exploration of network analysis and SA was performed. Each of them serves as a key lens through which the intricate interactions in social media discourse can be examined. Network analysis reveals the structure of online communities, including the flow of information, the centrality of influencers, and the clustering of discussions around specific topics. Meanwhile, the proposed innovative multi-view sentiment classifier incorporates emoji features, which help to understand the emotional aspects of social media interactions. The author believes that a good integration of network analysis and SA is able to significantly enhance our comprehension and predictive capacity regarding social media discourse, and the information obtained from this discourse can be valuable for a variety of domains, ranging from social and commercial to political issues. Therefore, this chapter aims to combine these distinct yet complementary analytical approaches into a cohesive dual-framework .

The complexity of social media interactions makes it necessary to combine network analytics and SA into a unified framework. Social media platforms are dynamic ecosystems in which emotions are expressed, shared and shaped through the complicated relationships between users and their networks. Therefore, they serve as more than just informational hubs. According to the literature, most of the existing methods focus on the structural and sentiment aspects of social media data separately, which may result in a disjointed view of how diverse ideas online interact with each other, and how discourse changes and influences the outside world. By combining sentiment and network analysis, the proposed dual-framework closes this gap and provides a more thorough understanding of social media dynamics.

This integration is predicated on the premise that the structure of social networks on platforms like Twitter, Facebook, and Instagram significantly influences the spread and reception of sentiments among users. The complex network of connections means that user-generated content does not exist in a vacuum but is influenced by the structure of its network. For example, sharing negative reviews of vaccinations in a network of vaccine opponents, characterised by being highly connected and interacted, will gain attention more quickly than in groups of vaccine supporters that are less interconnected (Milani et al., 2020). This pattern can be systematically identified by the use of network analysis, which can outline these connections and identify key nodes or influencers who could act as opinion leaders by deciding what information to share. In addition to network analysis, SA can further assess the content shared in these networks by recognising and aggregating the emotional tone of the messages to determine the overall sentiment trend. The proposed SMA framework allows stakeholders to understand not only the presence of positive or negative sentiments, but also their potential scope and impact in the social media network ecosystem.

On the other hand, SA acts as an early warning system when it identifies a growing trend of negative sentiment against a policy, product, or service. The proposed dual-framework takes a deeper look at network structure, rather than just scratching the surface. It consists of identifying the nodes or users at the centre of that sentiment, mapping the channels through which that sentiment is amplified, and understanding the community dynamics that may lead to the spread of the sentiment. This framework aims to identify the 'what' behind sentiment trends, as well as the 'why'. In this way, targeted interventions can be conducted in time by related stakeholders. For example, research indicates that social media has become a major source of false information, particularly during the global pandemic crisis (Alamsyah et al., 2018a). For governments and public health authorities, using the proposed dual-framework is very useful in clarifying rumours in a timely manner to appease the community, develop appropriate strategies and take timely action. Thus, the dual-framework provides a multidimensional analysis that advances traditional SMA by capturing both quantitative and qualitative aspects of online discussions. This approach provides actionable insights for stakeholders while aiding in the understanding of the dynamics of social media. Specifically, policymakers can develop more informed public awareness programmes, enterprises can improve their marketing strategies in a timely manner based on the latest feedback from consumers, and social scientists can discover deep patterns in human digital behaviour. In essence, by bridging the divide between the structural and sentiment layers of social media data, the dual framework enables decisions that are both strategic and responsive, addressing the complex realities of the digital social sphere.

In today’s information age, social media platforms have become a place for the public to freely express their opinions and a tool for governmental or commercial organisations to monitor the public’s reactions and sentiments towards certain issues. For example, in the field of public health, social media platforms often serve as barometers for public sentiment towards health policies and interventions, which can illustrate the practical applications and benefits of the proposed dual-framework . Through the use of this framework, healthcare organisations can identify key influencers and groups that are sceptical about vaccines (Milani et al., 2020), understand the underlying sentiment, and tailor communication strategies to effectively address concerns and misinformation. Similarly, in the business world, companies can use the framework to monitor brand perceptions, track the effectiveness of marketing campaigns (Jain et al., 2021; Kausar et al., 2020), understand the product features that matter most to their customers so as to improve the product design (Wang et al., 2020), and identify potential brand ambassadors or detractors within specific user groups.

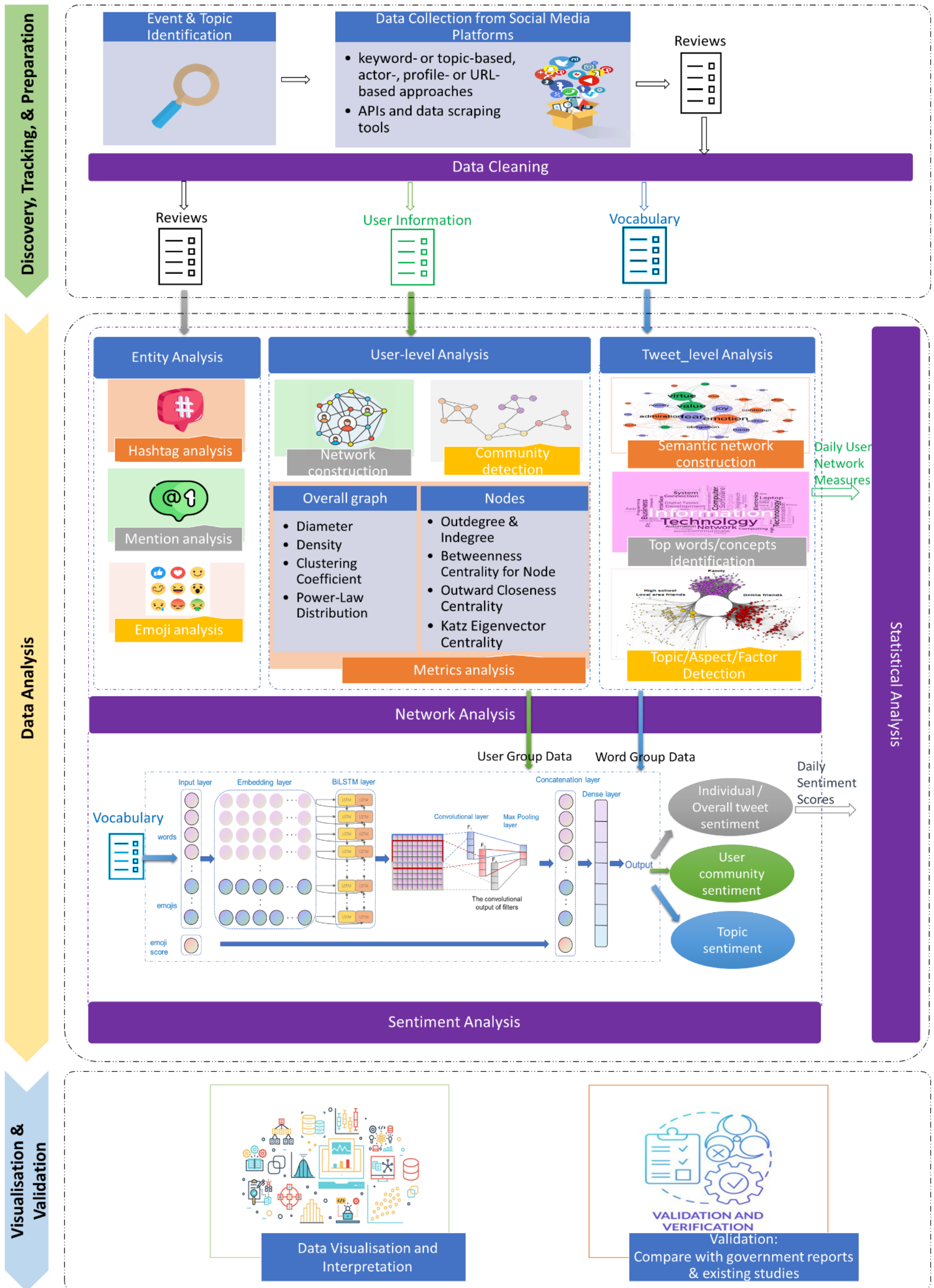
As described in previous chapters, the dual-framework was designed to meet the analytical needs of the different disciplinary areas that acquire data from social media platforms. In this thesis, the effectiveness of the proposed dual-framework will be tested by applying it to two cases from different domains, that is, the social science domain and the commercial domain. Case 1 focuses on social science issues, with the key purposes being the identification of thematic clusters, key influencers, and sentiment trends around social themes. Case 2 focuses specifically on business issues, with an emphasis on detecting consumer sentiment towards specific aspects of the product, brand engagement patterns, and the impact of online customer engagement on business performance. The integration of network analysis and SA allows the dual-framework to provide a multidimensional analysis of social media discourse, thereby enhancing academic research and strategic decision-making. The development and application of this dual-framework are guided by several key principles. First, the framework is designed to be adaptable. It should be able to analyse unstructured data from diverse social media platforms and adapt to constantly advancing social media trends and technologies. Second, it emphasises transparency. The entire process should be clear enough to make it understandable and reproducible for non-expert users. In addition, the results should be interpreted by using visualisation tools to allow non-expert users to extract and interpret complex data insights. Lastly, the framework is constructed with a focus on the ethics of data use, ensuring privacy and data security while taking into account the legal and ethical considerations inherent in social media research.

In the following sections, this thesis will introduce the theoretical foundation of the dual-framework approach, detail how it is applied to social science and business issues through case studies and discuss the methodological innovations that facilitate the integration of network and SA. By integrating network analysis and SA, this dual-framework fills a research gap and embodies a holistic analytical paradigm. It recognises the intricate relationship between the structural and sentimental dimensions of social media, providing insights into the mechanisms driving online discourse and its impact on the real world.

5.2 Integration of Network Analysis and SA

Figure 32

The Dual-framework for SMA



In today's digital age, social media platforms are not only communication tools but also rich sources of data on human behaviour, preferences and interactions. This dual-framework for SMA is based on the understanding that social media is built on relational structures and the sentiments within these structures. This section will explain the theoretical foundations of the proposed dual-framework and highlight the interdisciplinary theories that have guided its development.

Network theory is one major part of the proposed SMA framework. It provides a way of looking at the complex networks of relationships between social media users. The core of this theory is the concept of nodes (individuals or entities) and edges (the relationships between them) (Gongora-Svartzman & Ramirez-Marquez, 2022). By analysing the networks formed by these nodes and edges, patterns of influence, community structures and information flows can be identified (Camacho et al., 2020). The theory suggests that changes in the dynamics within these networks can have a significant impact on the way in which information is disseminated and received, thereby influencing public discourse (Han et al., 2020; Jin et al., 2021). In addition to network theory, SA is the other foundation of the proposed dual-framework , which draws on psychological theory to understand social media as a reflective surface of users' emotional states (Abd et al., 2021; Singla et al., 2022).

This research’s motivation to merge network and SA (Xu et al., 2024) into a unified analytical framework arises from the deeply intertwined relationship that exists between the structural properties of social networks and the sentiment that permeates these digital spaces. This connection shows that understanding social media discussions requires more than exploring the flow of information, ideas, and emotions among social media users separately. The structure of social networks and the sentiments within them influence each other, necessitating a combined analysis for a complete understanding. To be specific, structural properties, such as the density of connections, the presence of highly connected individuals or nodes, and the overall topology of the network significantly influence how sentiments are expressed, shared, and interpreted among users. Similarly, the collective emotional response of a network to external stimuli or internal discussions can reshape network dynamics and then foster the formation of new connections or the strengthening of existing ones based on shared sentiments.

Operationalising the dual-framework approach involves a sophisticated integration of network and SA to extract actionable insights from the massive amount of social media data. This process is designed to map the complex network of user interactions, identify key communities and themes, and measure the public's sentiments toward these focal points. By coordinating these approaches, the dual-framework offers a detailed understanding of social media discourse and its implications for various domains. As shown in Figure 33, the application of the proposed dual-framework is a systematic process that begins with the selection of an event or topic that has captured the public's attention on social media. The popularity of the issue on social media platforms (e.g., volume of discussion, hashtags, and user engagement) determines its relevance and suitability for in-depth study using the proposed framework.

After the selection of the subject for analysis, the next step is the data collection regarding the discourse from available social media platforms. The approaches used to gather data include keyword-based, actor or user-based, profile-based, or URL-based searches. Advanced Application Programming Interfaces (APIs) and data scraping tools can be employed to collect a large amount of social media content, including posts, tweets, comments, and replies related to the chosen issue or subject for analysis.

After data collection, the next step is data pre-processing. It is an essential step that ensures the data’s readiness for analysis. During this phase, the data is carefully cleaned to remove irrelevant content, or any information that does not contribute to understanding the social issue or does not meet the requirement of the network analysis or SA. Although these two analysis components are based on the same raw dataset, their requirements for pre-processing the dataset could be different. For example, network analysis requires information on the username to construct the user networks while SA does not require such information. Therefore, the raw dataset will be pre-processed separately for different analysis components. In addition, steps are taken to anonymise user data to protect privacy and comply with ethical standards for social media research. The dataset is also segmented based on temporal markers, facilitating targeted analysis that can reveal trends over time.

Once the dataset is prepared, the official analysis is performed. Firstly, the framework employs network analysis as a tool to dissect the structure of user interactions on these digital ecosystems, that is social media platforms. By mapping the online user networks, network analysis reveals the pathways through which information flows, and highlights influential nodes, which are individuals or entities that have significant influence over the network due to their central position or high connectivity. It also identifies bridges between different communities, which are key nodes where information travels between different social groups to each other and plays an important role in the dissemination of ideas and emotions. In addition, the network analysis on the text can generate a visual representation of the co-occurrence patterns of words in the social media discourse, helping to recognise the most mentioned concepts, and to identify the aspects of a specific event people are talking about on social media. This step is crucial as it sets the stage for a targeted SA, focusing on the identified communities and their key themes. A detailed introduction to the network analysis part of the proposed SMA framework is presented in Chapter 3.

While network analysis explores the structure of social interactions, SA provides insights into the qualitative dimensions of these interactions. Once user communities and key topics or themes are identified, SA can be performed to understand public opinions or feelings towards them (Yan et al., 2021; Rahman and Islam, 2022). This component of the dual-framework aims to apply sophisticated natural language processing techniques to process large volumes of social media posts to decode the sentimental content embedded in digital discourse. SA classifies and evaluates the emotions expressed, whether they manifest as positive, neutral, or negative emotions, with the aim of constructing a detailed map of the emotional landscapes of social media discourse. As informal languages, such as emojis, are becoming increasingly popular on social media platforms while most existing sentiment methods remove non-alphabetic text, this research proposes and trains an innovative multi-view sentiment classifier that incorporates emoji features. This sentiment classifier considers the sentimental information carried by emojis to decide the sentiment of the posts. By using SA, this research is able to recognise prevalent emotional tones and changes in sentiment and connect these sentimental flows with specific events, topics, or discussions, providing contextual information for the quantitative data revealed by the network analysis. A detailed introduction to the SA part of the proposed SMA framework is presented in Chapter 4.

Once the sentiment scores of individual tweets are obtained, they are aggregated to get the overall sentiment expressed towards each user community or topic. To compare the sentiment expressed by different user communities or across various topics, especially when the number of tweets for each community or topic varies, a weighted sentiment score can be utilised. This score takes into consideration both the sentiment polarity and the number of tweets for each community or topic. By doing so, the weighted sentiment score offers a balanced measure that reflects the intensity of sentiment and the level of engagement, allowing for equitable comparisons across diverse groups and themes. This weighted approach is particularly effective in situations where one community may be more vocal or active than another. It allows researchers and analysts to discern not only the predominant sentiments but also the relative scale of discourse. Therefore, the proposed dual-framework provides a comprehensive toolkit for profiling the complex dynamics of social media platforms. It enables detailed analyses that capture the interactions between network structure and sentiment expression. By using this framework, users can obtain a clear understanding of how digital communities establish and evolve, and how their structure and information flows within it influence both the virtual and physical domains.

Combining network analysis and SA through the dual-framework can guide users to successfully handle the vast data generated by social media platforms, extract network and sentiment features related to their study topics, and finally analyse these features together to provide a holistic view of social media ecosystems. The proposed dual-framework aims to make interdisciplinary innovations in analytical methods. It incorporates advancements in machine learning, natural language processing, and network analysis to enhance the accuracy and depth of social media analysis, thereby informing decision-making in other domains. The practical application of the theoretical foundation provides a blueprint for the application of the proposed dual-framework in a variety of fields, ranging from monitoring public health sentiment and misinformation networks to analysing consumer sentiment and brand networks in the business sector. Acknowledging the rapid evolution of social media context, the dual-framework is designed to be highly adaptable, readily incorporating new analytical techniques that emerge from ongoing network analysis and SA research.

The integration of network and SA within the dual-framework represents an advancement in SMA. By synergising these methodologies, the framework offers a holistic view of the complex dynamics of social media, providing invaluable insights into public sentiment, social networks, and the interplay between them. As social media continues to evolve, this integrated approach will offer a powerful tool for researchers, businesses, and policymakers alike.

5.3 Guidance on Application to Social Science Issues

5.3.1 Introduction

The start of the digital age has made social media a key place for public discussions, allowing more people than ever to share and talk about a wide range of social, political, and cultural topics. In this digital environment, the proposed dual-framework approach becomes an important tool for analysing and understanding the complexity of social science issues as they unfold on platforms such as Twitter. This section provides guidance on how to use the proposed dual-framework to gain insights into the formation of online social networks and their impact on public opinion and social change.

5.3.2 Application Process

The main aim of the proposed framework is to analyse and interpret patterns of social media engagement around socially important topics. Its structure aims to reveal how social networks around these topics are formed and to identify the main topics or factors that drive social media discussions around the issue. Building on this, it also utilises natural language processing techniques to gain insights into the sentiment dimensions of the discourse. At the heart of this framework is the integration of network analysis and SA to reveal common sentiments towards a chosen issue, how those sentiments vary across different aspects of the issue, and how different groups of users express those sentiments.

The first step is to select a social issue. This could be a major public health emergency, such as an outbreak of a new virus, a political change effort, or a large campaign for social justice. The selection is based on how much these issues are discussed online and their impact on society. After that, relevant data is collected from available social media platforms and cleaned for subsequent analysis. Network analysis is first conducted to map the intricate network of social interactions that form around the selected social issue. The purpose of the proposed analytics framework is not limited to understanding how the information spreads through the network, but also what is actually spread. Therefore, network analysis will not only be performed on the user information, but also on the textual information. This involves constructing two types of networks. One is the user network, which is a detailed graph where nodes represent individual users or entities, and the edges signify the interactions between them, such as mentions, retweets, and replies. This structure can highlight influential nodes with significant influence within the network, such as key figures or organisations. Community structures will also be analysed to reveal groups of closely connected users who share common interests or perspectives on the issue. The other type of network is the semantic network. In this network, the nodes represent words of the social media content, and the edges represent the co-occurrence of them. It also delineates community structures, identifying the most significant factors people care about the selected social issue.

While network analysis provides insights into how discussions spread and evolve in the social media ecosystem, the SA component of the analytics framework aims to understand the sentimental dimensions of the discourse. Based on natural language processing techniques, this component adopts the trained emoji-incorporated sentiment classifier to classify the content into various emotional categories to interpret the sentiments expressed by users. Leveraging this innovative approach enhances the accuracy and depth of the SA. By analysing the tone and emotional quality of the discourse, SA uncovers the common sentiments towards the social issue. In addition, based on the community detection results from the previous network analysis component, the sentiments expressed by users will be grouped by the aspects of the social issue people are talking about to understand how the public reacts or feels about each aspect. The sentiments will also be grouped by user groups to explore each group's sentiments and whether there is a certain connection between the types of user accounts and the sentiments.

By combining network and SA components, the dual-framework offers a comprehensive picture of the social issue as manifested in social media discourse. It tracks the evolution of public sentiment over time and across different aspects of the social issue and highlights the role of key influencers and communities in shaping the conversation. This methodology enables a deeper understanding of the complex social phenomena reflected and influenced by social media interactions.

5.3.3 Case Study Example: Cost of Living Crisis in the UK

The effectiveness of the proposed analytics framework for social media discourse in analysing social issues will be tested and demonstrated by a related case study surrounding the cost-of-living crisis in the UK. Some of the main consequences of this crisis are rising prices and stagnating wages. By applying the proposed framework to this issue, a comprehensive analysis of both the structural and sentimental dimensions of the discourse will be performed. The cost-of-living crisis in the UK has become the focus of public attention and discussions on various social media platforms and therefore it is a good subject to evidence the usefulness of the proposed framework.

The network analysis component of the proposed framework will help to map the social interactions related to the cost-of-living crisis. It is expected to identify key roles in shaping the conversation, potentially including economic analysts, political figures, governmental departments, and media accounts, as well as the groups of closely connected users. Additionally, it aims to reveal the formation of distinct communities in online discourse around specific aspects of the crisis. The structure of these networks will provide insights into how information and opinions on the crisis spread through social media networks, and the pathways of influence and the clustering of discussions. Meanwhile, SA is expected to evaluate the public's emotional response to the crisis by analysing thousands of posts. This analysis will reveal sentiments expressed by individuals in response to economic stress. It will also help to observe the shifts in sentiment over time by linking these changes to key events, such as government announcements. This dual analysis not only provides a comprehensive picture of the public's position on the cost-of-living crisis, but also highlights areas where consensus and controversy exist. It highlights the role of social media as a platform for voicing concerns, mobilising support and advocating for policy change.

The proposed dual-framework for SMA aims to offer several benefits for research in the social sciences. Firstly, it gives researchers a strong tool to analyse the dynamics of public discourse on social issues online. By using methods that examine both the connections between social media users and the feelings expressed in their posts, researchers can understand the role of social media in shaping and reflecting public opinion and trends. Secondly, the findings from using this framework can guide policymakers and those who advocate for changes. They can use these insights to craft more effective messages and strategies for engaging with the public on social issues.

The proposed framework in this thesis represents a major advancement in analysing social media conversations about social science topics. By combining network analysis, which looks at how users connect, and SA, which assesses the tone of discussions, it offers a detailed look into online social interactions and public feelings. As social media becomes more influential in shaping societal stories, the insights gained from this framework are extremely valuable. They offer deep perspectives for researchers, policymakers, and society at large, highlighting how online conversations can both mirror and affect current social trends and attitudes.

5.4 Guidance on Application to Business Issues

5.4.1 Introduction

In recent years, companies from all types of industries have been leveraging social media to make smarter strategic choices. Extending from the proposed dual-framework for SMA, the enhanced framework reflects this trend by combining network and SA with statistical techniques to provide actionable business insights. The incorporation of statistical techniques enhances the framework’s ability to evaluate business results by analysing social media trends.

5.4.2 Application Process with Predictive Analytics

The enhanced framework aims to turn social media data into predictive insights that businesses can use. It starts by analysing how people connect and communicate online using network and SA to gain a deeper insight into customer behaviour and how they perceive brands or their products. By incorporating statistical analysis, the framework enhances its ability to evaluate tangible business results based on data from social media metrics. The method examines how different factors, such as sentiment scores, social networking metrics, and other related variables relate to business performance. This improved framework is crafted to help companies have a comparatively comprehensive understanding of the state of social media in which they operate and to forecast possible effects on business performance, such as product sales or the level of customer engagement. An overview of the entire process of the application of the enhanced framework is presented as follows.

The process starts by clearly identifying the business problem or opportunity as the subject of analysis. The business topic may involve evaluating the impact on sales based on how customers feel about a new product launch via social media platforms or how they react to a brand's campaign on social media. During this step, the goals of analysis and the key performance indicators (KPIs) should be determined in order to evaluate business performance.

The second step focuses on data collection and pre-processing. During this phase, a large amount of data related to the specific business issue will be collected from social media platforms. Through the use of APIs and data scraping tools, data is gathered from different platforms, including posts, tweets, comments, and other user-generated content. After that, the collected data goes through a pre-processing stage to make sure they are high-quality and relevant. This stage involves cleaning the data to remove irrelevant information, making user data anonymous to safeguard privacy, and organising the data into segments for a more detailed analysis.

Once the data is ready, the next step involves conducting a network analysis to understand how social interactions are structured around the business issue. This analysis helps pinpoint the key influencers, outlines the community structures, identifies the key factors related to the brands or their products, and reveals how information travels through the network. By getting a clear picture of the social interaction landscape, businesses can identify potential brand supporters or critics and learn more about how news and opinions about their products or services are shared on social media.

In the next step, SA is carried out on the gathered data to measure the emotional tone of the conversation on social media. This step involves classifying the content into different sentiment categories, specifically positive or negative, as outlined in Chapter 4. The emoji-incorporated sentiment classifier is used to get more precise and detailed results. The results from SA provide a detailed picture of how the public feels about a company, helping businesses understand how their customers perceive and emotionally react to their products, services, or brand in general.

The next step is predictive analytics, which involves building a multivariable regression model. This model investigates how social media metrics, which come from the network and SA, relate to business outcomes. The independent variables in this model consist of daily sentiment scores, SNA metrics, and other relevant attributes. The dependent variable is a specific measure of business performance, such as daily sales numbers or customer acquisition rates. This model helps to predict how changes in social media activity could influence these key business metrics. In certain cases, the regression model can be used in a sequential manner, linking independent variables from a particular day with the business results of that same day and the days that follow. This method uncovers both the immediate and the delayed impacts of social media interaction on business results, revealing how long different factors continue to affect outcomes.

Insights gained from the regression analysis are then interpreted to create actionable recommendations. Discovering which social media metrics significantly predict business results allows companies to adjust their marketing approaches, content development, and how they interact with customers to improve their performance.

5.4.3 Case Study Example: Evaluating Box Office Performance

The potential of the enhanced dual-framework to significantly impact business strategies through social media discourse analysis is demonstrated in a focused case study on evaluating box office collections for movie releases. The global movie industry is huge and produces tens of billions of dollars every year, with large variations in budgets and revenue. Characterised by its dynamic market and the crucial role of consumer sentiment in determining a movie's success, the movie industry presents an ideal context for applying the dual-framework . The case study focuses on evaluating the success of movies by analysing the discussions around them before they're released and the conversations that happen after they're out on social media. With the movie industry dealing with changing viewer preferences and the increasing impact of digital platforms on viewership decisions, being able to forecast box office earnings through social media activity is extremely valuable.

In the beginning, the network analysis part of the dual-framework will be applied to create a network of social interactions related to upcoming movie releases. This involves identifying influencers who significantly shape the discussion about a movie, such as movie critics, celebrities, and dedicated fan pages. Additionally, the analysis will reveal the creation of communities within the social network, which may be particular elements of the movie, like its genre, cast, or themes. The network analysis highlights the main pathways of influence and the patterns of conversation that develop, offering a clear view of how the movie is being talked about and by whom.

As with SA in the application to social issues, this step involves analysing a large number of posts to identify whether sentiments are positive or negative. The aim is to understand the public's emotional reactions to promotional materials and early reviews. Building on the results of the clusters identified by the network analysis, followed by SA to monitor how sentiments change over time, especially after promotional events or major announcements, the enhanced framework provides a detailed perspective on the public's anticipation and expectations for the movie. This understanding helps in evaluating the overall mood and interest towards the movie before and after its release.

By combining the findings from network and SA, a multivariable regression model is constructed to link social media indicators with daily box office earnings. This forecasting model takes into account various factors, including the daily sentiment score, daily measures from network analysis that illustrate the pattern and strength of social interactions, and other variables deemed likely to influence box office results. This approach uncovers the extent to which social media trends can predict a movie's box office performance.

The case study aims to confirm that the enhanced framework is effective in evaluating business performance, specifically the success of movies in this case. It is expected to give movie studios and marketers a valuable opportunity to time their promotional activities for maximum impact, helping to ensure that anticipation and interest are at their peak as the movie launches.

Although the case study concentrates on the movie industry, the methods used in the enhanced framework can be applied across many different business areas. This allows companies to predict results based on how people interact with them on social media. This comprehensive method improves how businesses understand customer behaviour online and enables them to make decisions based on data, refining their strategies for better market performance.

5.5 Guidance on the Adaptation for Diverse Applications

The dual-framework approach is built to be flexible and able to grow, aimed at serving the varied requirements of different fields and managing the large amounts of data typical of social media platforms. This section discusses how the framework can be tailored for different uses and expanded to manage the challenges of large social media datasets, ensuring it works well in various situations.

The dual-framework is extremely flexible and can analyse social media discussions in various areas, such as public health, politics, marketing, and consumer behaviour. This flexibility is important for meeting the unique analysis needs of each field. In public health, the dual-framework can be used to track and analyse public sentiment about health programmes, vaccination campaigns, or disease outbreaks. To make it more useful in this area, the framework can include epidemiological data along with social media discussions. This combination enables a deeper analysis of public sentiment in light of current health trends and how effective health communications are. Furthermore, the framework can be set up to analyse data based on location, offering insights into regional differences in health-related opinions and helping to pinpoint where specific communication strategies are needed to tackle particular health issues or counter misinformation. In politics, the dual-framework can be used to study how specific events or policy announcements affect public opinion. Additionally, it can be tailored to map the connections around a politician or policy using ego network analysis, and then assess the related public sentiment. By incorporating data from various political activities, such as debates or legislative changes, the framework can offer a dynamic view of political discussions over time. SA within this framework can also be enhanced to recognise sarcasm and complex political language, increasing the accuracy of these assessments in this intricate area. This improved approach helps political parties and policymakers develop strategies that align with public opinion, leading to more effective governance and communication. In the business realm, for example in brand management, the dual-framework is useful for identifying brand ambassadors and detractors within a network and evaluating consumer sentiment towards a product or service. To deepen the analysis, it can be adapted to include current market trends along with social media metrics. By examining consumer sentiment in relation to market conditions and competitor actions, the framework can provide more detailed insights into brand positioning and consumer preferences. Additionally, incorporating customer demographic data can refine SA, allowing businesses to customise their marketing strategies for specific customer segments. This tailored approach helps companies improve their engagement methods and establish stronger relationships with their target audience.

From the perspective of methods, specific adjustments can also be made to the current analytics techniques of the dual-framework to meet the unique demands of different fields, ensuring that the framework remains responsive and precise in its analytical capabilities. Firstly, analytics can be customised depending on the application. For instance, in public health contexts, SA can be specifically adapted to concentrate on expressions related to fear or misinformation. This adjustment involves refining sentiment classifications and customising language models to accurately interpret communications related to health crises. Such enhancements enable health organisations to better understand and respond to public concerns effectively. To improve the usefulness of the framework, it can also combine social media data with other specific datasets relevant to particular sectors. For instance, in the financial industry, integrating SMA with market performance data can reveal important insights into how public sentiment affects stock prices. By linking SA results with market data, financial institutions can learn more about how public opinion impacts financial markets. This knowledge enables the development of more informed investment strategies and more precise risk assessments. To effectively manage the growing scale and complexity of data in SMA, it is crucial to leverage state-of-the-art technologies. Utilising cloud computing resources and big data processing technologies enables the framework to scale its computational capabilities as required. This scalability is vital for efficiently handling and processing large datasets, which is essential for conducting thorough social media analyses. Furthermore, given the rapid growth of social media platforms and the increasing volume of data, the data analytics methods used should be regularly updated and optimised for large-scale data analysis. This continual refinement ensures the effectiveness of the analyses, facilitating the detection of complex patterns and providing timely insights.

5.6 Summary

Chapter 5 has outlined how network and SA are combined within the dual framework, demonstrating its strength and flexibility for analysing complex social media interactions. This chapter has emphasised the theoretical underpinnings of this integration and explained how the framework is implemented to ensure its effectiveness in various fields.

The dual frameworkleverages the combined strengths of network and SA to thoroughly investigate social media interactions. Network analysis within the framework identifies the structure of online communities, pinpoints key influencers, and clarifies the pathways for information spread. SA complements this by examining the sentimental content of communications, offering insights into public sentiments and perceptions on various topics. This chapter also focuses on the flexibility of the framework through the demonstration of ways that it can be customised for specific uses in the public health arena, politics, and brand management. It discusses how the capabilities of this framework can be enhanced and adapted using advanced technologies such as cloud computing, big data processing, and machine learning. To conclude, the proposed dual frameworkaims to effectively combine network and SA and, in turn, present an in-depth view of online discourse for decision-making by stakeholders using data from social media platforms.

The next chapter will test the effectiveness of the dual frameworkby using it to examine a specific problem, namely the cost-of-living crisis in the UK. This case study will show how the framework helps analyse and understand complex social issues, demonstrating its practical use and ability to offer useful insights. By looking at this real-world example, the next chapter will highlight how well the dual frameworkcan help tackle major societal challenges.

Chapter 6 Application to UK's Cost of Living Crisis Using the Dual-Framework Approach

6.1 Introduction

This chapter applies the proposed dual frameworkto the UK's cost of living crisis to demonstrate its efficacy in extracting meaningful insights from social media discourse. Through this case study, the research illustrates the framework's potential to contribute to a deeper understanding of contemporary societal challenges, thereby affirming the value of integrating SA and network analysis for SMA.

The cost of living in the UK has surged significantly during 2021 and 2022, characterised by soaring prices for essential goods and services, stagnating wages, and increasing energy costs. The annual rate of inflation reached an alarming 11.1% in October 2022, marking a 41-year high. However, it has since eased. High inflation directly impacts the affordability of goods and services for households. Recent data indicates that the annual inflation rate stood at 4.0% in January 2024, remaining unchanged from December. It is important to note that a slowing or falling inflation rate means that prices are rising more slowly than before; it does not mean that price levels are actually falling. According to the UK parliament, food prices rose by 24.8% during the two years from January 2022 to January 2024. It previously took over 13 years, from October 2008 to January 2022, for average food prices to rise by the same amount. UK food and non-alcoholic drink prices were 6.9% higher in January 2024 compared to the previous year, based on the Consumer Price Index (CPI) measure of inflation (Francis-Devine et al., 2024).

The crisis was caused by a number of factors, which may also be linked to each other, and has had a significant impact on the country's economy and society. Among them, one important influence is the Brexit event. The post-Brexit economic adjustment in the UK brings complexities to the trading and labour markets and influences the stability of the supply chain and marketing prices. Global economic challenges have further intensified this crisis. The COVID-19 pandemic disrupted both global and local supply chains, leading to inflation in essential goods and services. Additionally, geopolitical tensions, especially the conflict in Ukraine, have caused global energy prices to rise. This is particularly serious for the UK, which relies heavily on energy imports. Consequently, many people in the UK are experiencing increased financial stress.

This crisis does not only affect the economy but also affects the social fabric of the UK. The ever-increasing cost of living translates to a daily impact on the lives of people, particularly for low-income households. This affects their ability to afford housing, food, and power individually, which has a spillover effect on households, further heightening the problem of disparity or inequality between the poor and the rich. The austerity initiatives implemented over the past decade have undermined public services and social safety nets, leaving many people unsupported and struggling with stagnant wages, precarious employment and high household debt. Some of them are even unable to maintain their health due to stress and anxiety. Further, this crisis is deeply gendered, with women disproportionately bearing the burden of these increases and economic instability. Women form a significant portion of the public sector workforce. They also engage more in unpaid domestic and care work. This dual responsibility of paid and unpaid labour puts tremendous pressure on women, leading to mental and physical health strains as well as financial hardships. These challenges highlight the need for policy interventions that specifically address the unique impacts on women.

The responses of the British Government and the Bank of England to the economic crisis have been under scrutiny. Their strategy, in particular the control of inflation through interest rate hikes and austerity measures, has attracted criticism for its potential to exacerbate economic contraction and inequality. It has been argued that addressing the root causes of inflation or providing support to those most affected is what is most important. A more holistic approach is needed to address both immediate impacts and structural issues. This approach should prioritise social equity, economic stability and the welfare of the most vulnerable to help the UK effectively navigate this unprecedented crisis. The UK's cost of living crisis is not just a temporary economic challenge, it is a generalised problem with wide-ranging implications. With inflation reaching peaks not seen in recent times, the crisis is deepening, profoundly affecting the economic stability and overall well-being of the UK population.

Studying the UK's cost of living crisis is important for several reasons. First, it helps to understand how modern economic problems arise, especially in advanced countries that are closely connected with the global economy. By learning about what caused the crisis, how it affects people, and how well different policies work, the government can improve future economic and social policies. Additionally, looking at how the crisis affects different groups of people is key to creating targeted solutions to help the most vulnerable individuals. Secondly, this crisis as a subject for applying the dual frameworkdeveloped in this thesis is highly relevant. The significant impact of the cost of living crisis on the social fabric of the UK presents a complex landscape of public discourse, sentiment, and interaction that has been widely disseminated across social media platforms. Here, individuals, communities, and organisations express their experiences, concerns, and opinions, making it a rich dataset for analysis to validate the effectiveness of the proposed framework. In the following subsections, the proposed dual frameworkwill be leveraged to dissect the socio-political dimensions of the crisis. It will enable the identification of dominant themes in public discourse, the sentiment surrounding various aspects of the crisis, and the key influencers shaping the conversation. In addition, by integrating quantitative indicators, this framework will facilitate a comprehensive understanding of the cost-of-living crisis, as reflected in social media discourse. The goal is to reveal the subtle social and political factors affecting public opinion and discussions, giving insights into public sentiment and possible social impacts.

To protect the most vulnerable in society against the cost of living crisis, the UK government announced a package of one-off support measures on 26th May 2022. The package contains three payments, namely a £650 Cost of Living Payment to recipients of certain means-tested benefits, a £150 Disability Cost of Living Payment to recipients of certain non-means-tested disability benefits, and a £300 Pensioner Cost of Living Payment to households with at least one person entitled to a Winter Fuel Payment for winter 2022/2023 (Department for Work and Pensions, 2023). This study aims to apply the proposed dual framework to study the cost of living in the UK and people's reactions to the support payment. The following questions are specified:

1. How do key influencers and interaction patterns shape the social media discourse on the Cost of Living Payment?

a) Who are the key influencers in the social media discourse on the Cost of Living Payment, and how do they shape public opinion?

b) How do social media users interact and disseminate information about the Cost of Living Payment?

2. How does public sentiment towards the UK's Cost of Living Cost of Living Payment evolve, and what are the main themes expressed by social media users?

a) How does public sentiment towards the UK's Cost of Living Cost of Living Payment evolve during the policy announcement and payment distribution periods?

b) What are the main themes and concerns expressed by social media users regarding the UK's Cost of Living Cost of Living Payment?

c) What are the key factors contributing to public dissatisfaction with the government's Cost of Living Cost of Living Payment, according to social media discourse?

The use of the dual framework to analyse the UK's Cost of Living Payment serves two main purposes. First, it shows how practical and flexible the dual framework is for studying complex real-world problems. Second, it gives stakeholders, such as policymakers, businesses, and social organisations, valuable insights from social media discussions. These insights can help in designing targeted actions, adjusting policies, and planning strategies to reduce the impact of the crisis and address the concerns of those affected.

6.2 Data and Methods

6.2.1 Data Collection

To comprehensively understand the changes in people's response to the cost of living payments, several distinct periods were identified, namely the announcement period, payment distribution periods, and the periods after each distribution. Although there were three types of support packages announced ('Cost of Living Payment', 'Disability Cost of Living Payment', and 'Pensioner Cost of Living Payment') on the 26th of May 2022, this study will only include the 'Cost of Living Payment' to avoid making the case study over-complicated. As the government split the payment into two payments, five periods have been identified. Specifically, the periods are as follows:

- Announcement period: 2022-05-26 to 2022-07-08
- Payment 1 distribution period: 2022-07-14 to 2022-07-31
- After the payment1 distribution: 2022-08-01 to 2022-08-10
- Payment 2 distribution period: 2022-11-08 to 2022-11-23
- After the payment 2 distribution: 2022-11-24 to 2022-12-03

As this study focuses on the UK case, it was necessary to filter the tweets to find those originating exclusively from the UK. There are two primary ways to achieve this:

- Defining the Place of Origin: The first way is to define the place_country parameter as "GB" while collecting tweets using the API. A disadvantage of this method is that few users actively provide a location when tweeting.
- Matching User Profile Location: Another option is to match the location information within the user’s profile. Since these values are generally not frequently changed by users, this method can be effective. However, a limitation is that the location content is arbitrarily filled in by the user, rather than selected from pre-defined options, so multiple filtering criteria must be defined. To maximise the filtering of users from the UK, this study will first filter the acquired user dataset for locations containing keywords like "UK," "United Kingdom," "GB," "Great Britain," "England,”

“Scotland,” “Wales,” and “Northern Ireland." Subsequently, the tweets from these users will be filtered by author ID.

To determine the best method for collecting the tweets, as a trial, tweets containing the keyword 'cost of living' were collected 10 days before and 10 days after the announcement date of 26th May 2022. This study tried both methods to extract tweets sourced from the UK from all tweets.. The total number of tweets filtered by tweet location amounted to more than 1,800, while those filtered by user profile location exceeded 162,000. Therefore, this study selected the second method to collect the final dataset for this case as a dataset with a larger sample size allows for a more comprehensive and robust analysis. The search terms used to collect tweets for the periods were ‘(cost of living payment) OR (cost of living support package)’. Only tweets from UK users were retained in the final dataset, resulting in a total of 6054 tweets. In addition, in order to avoid duplication of information and bias in specific analyses, such as entity and semantic analyses, a new data set containing only the original tweets was created by removing tweets that referenced others. The amount of data for each period is shown in the table below.

Table 7

Number of Tweets and Original Tweets Across Different Payment Distribution Periods

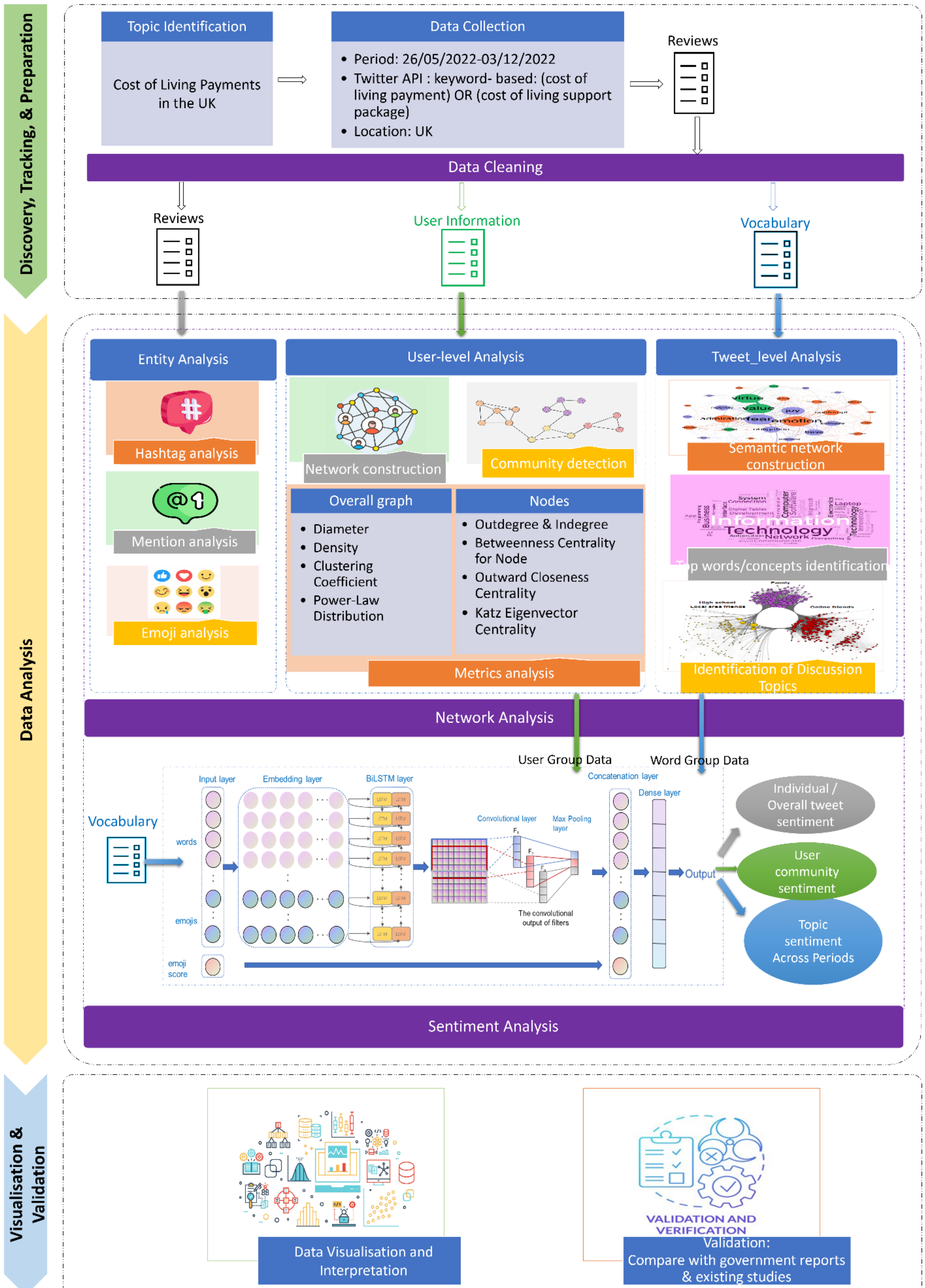
	Announcement period	**1st payment distribution period**	**After the 1st payment distribution**	**2nd payment distribution period**	**After the 2nd payment distribution**
tweets	2333	1286	333	1887	215
original tweets	908	562	130	372	89

6.2.2 Methods

In this chapter, the issue of the Cost of Living Payment in the UK will be used as a case to test the effectiveness of the proposed dual-frameworkfor SMA. The adjusted framework for this issue is shown in Figure 34.

Figure 34

Methodology Framework



In order to address the questions posed by this research that are used to test the effectiveness of the analytics framework, the methodology will adopt entity analysis, network analysis and SA. Initially, an examination of entities will be carried out to establish a fundamental comprehension of the subject of the case. Three entities of tweets, namely hashtags, mentions, and emojis, will be isolated from the content and assessed independently. To be specific, the level of importance of each element is measured by its weighted frequency, which is the sum of retweets associated with each appearance of the element. The most 10 popular entities, as measured by weighted frequency, will be analysed to understand how posts are related to each other and why social media users use these The entity analysis provides an initial overview of the discussion on the topic.

The next step is network analysis, which will be conducted separately for tweets and users. The application at the user level will be performed first, which can provide information for the first research question. First, the user networks for each period are structured, where each user is represented by a node, and a link between two users will be created when they retweet, quote, or reply to one another. The second step is metrics analysis, where metrics measuring the entire network structure and the position of each node will be calculated. The third step is community detection, where the network will be clustered into several groups using clustering algorithms. This step can also indicate the structure of the networks. By analysing the network of connections between users, the most influential users, the communities that emerge within the network, and the types of interactions between users can be identified. When the clusters of closely connected users are identified, the tweets these users posted will be assigned to their corresponding user cluster. After that, the trained sentiment classifier will be implemented to detect each tweet's sentiment, and then the sentiment scores of each individual tweet can be aggregated to ascertain the overall sentiment expressed by each user cluster. To compare the sentiment expressed by different clusters when the number of tweets for each cluster is different, a weighted sentiment score can be used that takes into account both the sentiment polarity and the number of tweets for each cluster. In the next step, the composition of each cluster will be analysed in connection with their sentiment. This analysis aims to find out what types of Twitter accounts the tweets with positive, neutral or negative sentiments come from, respectively, as well as what kinds of information they were expressing.

Then, at the Twitter level, the application of the network analysis can provide information for the second research question. Semantic network analysis will be used to generate a visual representation of the co-occurrence patterns of words in the tweets. In the semantic network, nodes represent word pairs and links represent the co-occurrence of word pairs. Three words are defined as a group of words. In addition, the most mentioned concepts will be identified. After that, the clustering analysis will be conducted to identify the clusters of closely connected words to extract the latent topics. To conduct the clustering analysis, node embedding was selected because node embedding techniques can be applied to various types of networks and are not limited to a specific algorithm or assumption. In addition, it can capture complex relationships and structural properties of the social network. To conduct the final clustering, hierarchical clustering was conducted as its combination with node embedding achieved the highest Jaccard score of 1, meaning that this combination is the most reliable method. The next step is to assign tweets to each community using a rule-based approach. It iterates over each tweet and checks if any keyword from a community is present in the tweet. If a keyword is found, this approach increments the score for the corresponding community. Finally, it assigns the tweet to the community with the highest score. The content analysis is then conducted to summarise and name the community. Once key topics or themes are identified, the sentiment scores of each individual tweet can be aggregated to ascertain the overall sentiment expressed towards each topic. The comprehensive semantic network analysis results for the five periods are presented in the next sub-section.

6.3 Results and Discussion

6.3.1 Entity Analysis

Firstly, the entity analysis was conducted to provide an initial overview of the discussion on the Cost of Living Payment in the UK. The original tweets were analysed in this part to avoid redundancy and improve analysis quality, and the summary of the entities, namely hashtags, entities, and emojis, is presented in the following table.

Table 8

Summary of Tweets, Hashtags, Mentions, and Emojis Analysed During Each Period

	Announcement period	1st payment distribution period	After the 1st payment distribution	2nd payment distribution period	After the 2nd payment distribution
original tweets	908	562	130	372	89
hashtags	129	114	29	194	34
unique hashtags	81	44	18	79	25
mentions	122	62	22	55	13
unique mentions	96	42	19	44	11
emojis	93	67	18	73	14
unique emojis	37	40	10	34	13

The results from the first period, which corresponds to the announcement of the Cost of Living Payment are shown in Table 9:

Table 9

Hashtag Analysis for the Cost of Living Payment Announcement Period

index	word	abs_freq	wtd_freq	rel_value
0	#costoflivingcrisis	7	46	7
1	#legacybenefits	3	41	14
2	#costofliving	18	15	1
3	#energybills	2	11	6
4	#joinaunion	1	7	7
5	#landlords	1	7	7
6	#excludeduk	1	6	6
7	#support	1	6	6
8	#government	1	5	5
9	#theystandwithus	1	5	5

Firstly, according to the hashtag analysis results presented in Table 9, the hashtag *#CostofLivingCrisis* has the highest weighted frequency value and the hashtag *#CostofLiving* has the highest absolute frequency value and the third-highest weighted frequency value. It demonstrates the popularity of the topic *#CostofLivingCrisis* and highlights the public's strong awareness of, and concern for, the economic situation during the announcement period. The hashtag *#legacybenefits* has the second-highest weighted frequency value, which shows that it was highly retweeted, reflecting its importance and the active dissemination of information related to legacy benefits. Moreover, compared to *#CostofLivingCrisis*, *#legacybenefits* has the highest relative value, indicating significant engagement relative to its appearances. It suggests that particular attention has been paid to how Cost of Living Payments will affect beneficiaries of existing benefit schemes during this period. Discussions around *#energybills* (wtd_freq = 11, top 4) may reflect concerns about the adequacy of payments to cover rising utility costs, which is a top concern for many. The emergence of action-oriented hashtags *#joinaunion* (wtd_freq = 7) and references to *#government* (wtd_freq = 5), suggests that people are looking for support and advocacy, as well as scrutiny of government action during this announcement.

Table 10

Mention Analysis for the Cost of Living Payment Announcement Period

index	word	abs_freq	wtd_freq	rel_value
0	@legacybenefits	1	37	37
1	@rishisunak	8	25	3
2	@abiabnormal	3	18	6
3	@probonoecon	1	11	11
4	@jrf_uk	1	11	11
5	@relocationagent	1	10	10
6	@dataloft	1	10	10
7	@edwardjdavey	1	7	7
8	@keir_starmer	1	7	7
9	@the_tuc	1	7	7

Secondly, the results of mention analysis shown in Table 10 reveal the engagement of stakeholders and policymakers during the payment announcement period. The centrality of political figures such as @*rishisunak* in the mentions, indicated by the second-highest weighted frequency value of 25, suggests that the discussion is largely focused on government decisions and their architects. The highest weighted number and relative value of @*legacybenefits* (wtd_freq = 37, rel_value = 37) suggest that the community is likely to be centred around, or reacting to, information disseminated by this account, which may be the main source of information about the impact of the new policy on legacy benefit recipients. Other stakeholders, including opposition figures (@*edwardjdavey*, and @*keir_starmer*), advocacy groups (@*jrf_uk*, and @*the_tuc*), and economic analysts (@*probonoecon*, and @*dataloft*), also appear to have been involved in dissecting the announcement, criticising it, or interpreting its impact.

Table 11

Emoji Analysis for the Cost of Living Payment Announcement Period

index	word	abs_freq	wtd_freq	rel_value	emoji_text
0	👇	7	24	3	backhand index pointing down
1	👏	7	21	3	clapping hands
2	👉	5	17	3	backhand index pointing right
3	🚨	6	12	2	police car light
4	👀	1	10	10	eyes
5	🤔	2	8	4	thinking face
6	⬇️	3	6	2	down arrow
7	😡	8	4	0	pouting face
8	🤷‍♀️	1	3	3	woman shrugging
9	👍	4	3	1	thumbs up

Finally, as shown in Table 11, the results of the emoji analyses reveal people's complex emotional expression of the Cost of Living Payment The pointing fingers (👇, 👉) have the highest frequency value and third-highest frequency value, respectively, suggesting a desire to draw people's attention to more detailed information or actions following the announcement. This could involve directing others to resources or expressing instructions on how to navigate the new policy. The thinking face (🤔, wtd_freq = 8) may indicate the public reflection and concern about the adequacy and specifics of the payment. Meanwhile, the pouting face (😡, wtd_freq = 4) and the shrugging emoji (🤷, wtd_freq = 3) together express a mix of frustration and uncertainty, possibly reflecting dissatisfaction with the announcement or ambiguity about its benefits. Conversely, the applauding (👏, wtd_freq = 21) and thumbs-up (👍, wtd_freq = 3) emojis may indicate recognition of certain aspects of the announcement or solidarity within the community. The emoji 👀 (eyes) has the highest relative value of 10, suggesting a strong emphasis on attention and awareness. This indicates that people may be paying close attention to the details of Cost of Living Payment announcements.

Analysing the hashtags, mentions, and emojis used by people during the announcement about the living wage payment revealed a multifaceted public response. These discussions highlighted how social media reflects public sentiment during major political and economic events.

During the distribution period of the first Cost of Living Payment, the entity analysis reflects a shift in the public discourse as the policy moves from announcement to implementation. The results are shown in the next three tables.

Table 12

Hashtag Analysis for the Distribution Period of the First Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	#universalcredit	7	20	3
1	#costoflivingpayment	23	12	1
2	#costoflivingcrisis	13	9	1
3	#costofliving	18	8	0
4	#unitewin	1	6	6
5	#dwp	7	5	1
6	#mentalhealth	1	3	3
7	#pipayments	2	3	2
8	#pipayment	2	3	2
9	#pensioncredit	3	2	1

Firstly, the hashtags shift from general discussion to more focused questions, with the hashtag *#costoflivingpayment* topping the list, reflecting direct public involvement in the implementation phase. Discussions are likely to focus on the details of payment allocation, eligibility and the adequacy of the amount received. Whilst the *#universalcredit* (wtd_freq = 20) and *#pensioncredit* (wtd_freq = 2) show the breadth of demographic interest, the presence of the hashtag *#dwp* (Department for Work and Pensions) with the weighted frequency of 5 suggests a particular focus on the department's role in administering these payments. The presence of the *#mentalhealth* hashtag (wtd_freq = 3) may indicate an awareness of or concern about the psychological impact of the financial crisis on individuals. In terms of rel_value, the hashtag *#unitewin* has the highest relative value of 6 with only one occurrence. This suggests that the public is interested in collective action and union-related discussions.

Table 13

Mention Analysis for the Distribution Period of the First Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	@dwp	4	44	11
1	@moneybox	1	33	33
2	@paullewismoney	1	33	33
3	@age_uk	5	12	2
4	@mailonline	2	3	2
5	@ageukesussex	1	2	2
6	@borisjohnson	6	2	0
7	@eastbournebc	1	2	2
8	@eastsussexcc	1	2	2
9	@personneltoday	1	1	1

Secondly, the mention analysis reveals key information sources and authority figures in the discourse. *@dwp* (wtd_freq = 44), *@moneybox* (wtd_freq = 33), and *@paullewismoney* (wtd_freq = 33), rank among the top three most mentioned accounts in terms of weighted frequency counts, signalling that the public is seeking information from official sources and trusted financial commentators. The high relative value for these mentions suggests that the public may be reviewing the delivery process or looking for advice on how to get the Cost of Living Payment. The mention of political figures such as *@borisjohnson*, despite a low weighted frequency, shows that his role or opinions were still part of the conversation, although possibly with divided attention.

Table 14

Emoji Analysis for the Distribution Period of the First Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value	emoji_text
0	🚨	4	13	3	police car light
1	🔷	6	6	1	large blue diamond
2	😡	3	5	2	pouting face
3	😅	1	5	5	grinning face with sweat
4	😂	4	2	0	face with tears of joy
5	👉	4	2	0	backhand index pointing right
6	👇🏻	1	1	1	backhand index pointing down: light skin tone
7	😔	3	0	0	pensive face
8	🤔	3	0	0	thinking face
9	😃	1	0	0	grinning face with big eyes

Lastly, the emoji analysis for the first payment distribution period reflects the more diverse emotional responses of the period. The siren emoji (🚨, wtd_freq =13) may represent an alarm or urgent concern, and potentially indicate an immediate reaction to the payment distributions or alerts about related news. The immediate meaning of emojis like the blue diamond (💠, wtd_freq = 6) and the thinking face (🤔, abs_freq = 3, wtd_freq = 0) is less clear, but may symbolise reflection on the value of the payments or considerations about the next steps. Notably, the absence of explicitly positive emojis such as thumbs up and clapping hands from the previous period may indicate a more dispassionate or critical public mood in response to the realities of payment distribution.

The data from this period paint a picture of a public keenly interested in the specifics of the cost of living support they are receiving. The discussions appear to explore the practicalities and complexities of the policy in practice, with varying levels of information-seeking, review, and emotional responses reflecting individual and collective experiences of crisis management.

Next, the entity analysis is also conducted on the Twitter data collected from the period after the distribution of the first Cost of Living Payment The results are shown in the following three tables.

Table 15

Hashtag Analysis for the Period after the Distribution of the First Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	#costofliving	4	13	3
1	#costoflivingpayment	5	6	1
2	#costoflivingcrisis	2	3	2
3	#pensioncredit	2	3	2
4	#costoflivingpayments	1	2	2
5	#universalcredit	1	1	1
6	#torycostofgreedcrisis	1	1	1
7	#benefit	1	1	1
8	#lowincome	1	1	1
9	#helpforhouseholds	2	1	0

Firstly, the hashtag analysis for this period shows that *#costofliving* and *#costoflivingpayments* continue to feature prominently, suggesting that these topics remain at the forefront of public discussion. Whereas the presence of #pensioncredit, *#universalcredit* and *#lowincome* suggests that different groups are discussing the scope and impact of these payments. New hashtags such as *#torycostofgreedcrisis* may represent people's scepticism and criticism of the current UK government's handling of the crisis. In addition, the hashtag #helpforhouseholds may point to discussions about the need for additional or ongoing support for affected households.

Table 16

Mention Analysis for the Period after the Distribution of the First Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	@channel4news	1	24	24
1	@citizensadvice	1	24	24
2	@age_uk	3	9	3
3	@unitemanufactur	1	6	6
4	@jrf_uk	1	5	5
5	@barclaysbizchat	1	1	1
6	@pa	1	1	1
7	@ebrep	1	1	1
8	@simonclarkemp	1	1	1
9	@britishgas	1	0	0

Secondly, the mention analysis shows that *@channel4news* (wtd_freq = rel_value = 24) and *@citizensadvice* (wtd_freq = rel_value = 24) were highly mentioned, with high weighted frequency values and relative values, suggesting that their importance as sources of authoritative information or advice during this period. The continued mention of *@age_uk* (wtd_freq = 9) suggests that older people continue to be a focus group in discussions about the cost of living crisis, likely linked to calls for the government to pay more attention to their struggles in this crisis. The references to organisations such as *@unitemanufactur* and *@britishgas* imply a discussion around the role of industry and the energy sector in the crisis. The range of these references suggests that the public discourse sought different perspectives from the media to support services and industry-related commentary.

Table 17

Emoji Analysis for the Period after the Distribution of the First Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value	emoji_text
0	👇	7	15	2	backhand index pointing down
1	➡️	1	2	2	right arrow
2	👉	2	1	0	backhand index pointing right

3	💰	1	1	1	money bag
4	❗	1	0	0	red exclamation mark
5	🇬🇧	2	0	0	flag: United Kingdom
6	▫️	1	0	0	white small square
7	🙌	1	0	0	raising hands
8	🧐	1	0	0	face with monocle
9	👌	1	0	0	OK hand

Lastly, according to the emoji analysis for this period, emojis such as the backhand index pointing down (👇) and the backhand index pointing right (👉) rank in the top 3, indicating that people's attention continues to be directed to important information or resources that may be useful for people to understand or cope with the consequences of the policy. In addition, although the moneybag (💰) emoji is not used frequently, it may symbolise discussions about financial security or concerns about the adequacy of payments. Other emoji, such as the red exclamation mark (❗) and the British flag (🇬🇧), may signify urgent calls for attention or national anxieties.

In summary, the discussion during this period reflects various conversations. After the first Cost of Living Payment, people are still struggling with the impact of the crisis, and call for continued or enhanced support, with an emphasis on the practical realities faced by various demographic groups. Some are still seeking guidance, while others may be signalling urgency or expressing a critical stance on government measures.

For the period marking the distribution of the second Cost of Living Payment, the data from the hashtags, mentions, and emojis exhibit a specific focus and varied emotional responses, which are as shown in the next three tables.

Table 18

Hashtag Analysis for the Distribution Period of the Second Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	#costofliving	15	21	1
1	#pmqs	6	15	2
2	#costoflivingcrisis	16	7	0

3	#guildford	2	7	4
4	#energybills	3	6	2
5	#costoflivingpayment	24	6	0
6	#blackpool	1	5	5
7	#blackpoolsouth	1	5	5
8	#winterfuel	1	5	5
9	#uknews	3	5	2

Firstly, the hashtag analysis shows that hashtags related to the crisis, such as *#costofliving*, *#costoflivingcrisis*, and *#costoflivingpayment*, rank in the top 5. This indicates that people are focusing on this topic by creating and reusing similar hashtags. The presence of *#pmqs* (Prime Minister's Questions, wtd_freq = 15) suggests the public's concerns about political participation and about government accountability. Notably, tweets during this period featured region-specific hashtags such as *#guildford*, *#blackpool* and *#blackpoolsouth,* pointing to localised discussions. The relative value of these hashtags is higher when compared to hashtags with a higher weighted frequency. This suggests that the discussion of the impact of payments or the crisis itself has received some attention in the context of localisation. Meanwhile, *#winterfuel* reflects seasonal issues related to the cost of living in the colder months.

Table 19

Mention Analysis for the Distribution Period of the Second Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	@rishisunak	3	5	2
1	@govuk	1	3	3
2	@paulmccartney	1	3	3
3	@official_uom	1	3	3
4	@mikemoves12	1	2	2
5	@onemcr	1	2	2
6	@conservatives	2	2	1
7	@jollyestweets	1	2	2
8	@royalfamily	1	2	2
9	@anglianwater	1	1	1

Secondly, the above analyses identified political figures such as *@rishisunak*, suggesting that people are still discussing fiscal policy and its designers. The government's digital service handle *@govuk,* on the other hand, implies that citizens are still engaging or seeking information from official sources. Furthermore, mentions such as *@paulmccartney* may indicate that celebrities are involved in the discussion through publicity or commentary, while references to organisations such as *@conservatives* and *@royalfamily* suggest that there may be a discussion about their role in cost of living issues.

Table 20

Emoji Analysis for the Distribution Period of the Second Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value	emoji_text
0	👑	1	48	48	crown
1	⬇️	10	30	3	down arrow
2	🔴	9	29	3	red circle
3	👇	5	9	2	backhand index pointing down
4	👇🏼	2	6	3	backhand index pointing down: medium-light skin tone
5	👏	5	5	1	clapping hands
6	😊	6	4	1	smiling face with smiling eyes
7	🤔	2	4	2	thinking face
8	🚨	1	4	4	police car light
9	🤣	1	4	4	rolling on the floor laughing

The crown emoji (👑) was used the most frequently (wtd_freq = rel_value = 48) in the discussions among the emojis, which is unusual in this context. It could suggest conversations about national leadership, support, or metaphorical usage in relation to particular announcements or events during this time. The down arrow (🔽 , wtd_freq = 30) and the red circle (🔴 , wtd_freq = 29) may symbolise a recession or the need to stop and pay attention to a certain issue, possibly related to economic or policy implications. Additionally, emojis such as the clapping hands (👏), the smiling face (😊), and the rolling on the floor laughing face (🤣) convey a combination of enthusiasm, approval, and humour. They could also indicate irony at the circumstances or relief at the second payment. The police car light (🚨) retains its presence, likely indicating ongoing urgency or alert to critical issues or updates.

During this period, in addition to the ongoing dialogue on information-seeking and political participation, new topics related to the royal family and regional identity were raised. In addition, emotional responses were more complex than in previous periods. While there were still negative sentiments, such as suspicion and caution, positive sentiments, such as relief and humour also emerged, providing a more complete picture of public sentiment during the second cost of living period.

The results of the entity analysis for the period following the distribution of the second cost of living payment are as follows.

Table 21

Hashtag Analysis for the Period after the Distribution of the Second Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	#givingtuesday	1	7	7
1	#dataforgood	1	4	4
2	#pensioncredit	1	4	4
3	#miltonkeynes	1	1	1
4	#nomorescoffing	1	0	0
5	#skynews	1	0	0
6	#lancashire	1	0	0
7	#chorley	1	0	0
8	#factstolife	1	0	0
9	#payments	4	0	0

Firstly, the entity analysis suggests that people are beginning to focus on topics that may be less pressing, with *#givingtuesday* and *#dataforgood* suggesting that people are beginning to focus on broader social issues or charitable endeavours, which may be suggestive of a community response to current economic challenges. Continued references to *#pensioncredit* reflect the ongoing interest in the specifics of financial support for older people. Localised hashtags such as *#miltonkeynes*, *#lancashire* and *#chorley* suggest regional conversations where communities may be discussing the local impact of Cost of Living Payments or other regional economic issues. The use of more generic hashtags such as *#payments* suggests a wider discussion about financial transactions or support mechanisms, rather than a focus on the crisis as in previous periods.

Table 22

Mention Analysis for the Period after the Distribution of the Second Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value
0	@ucl	1	1	1
1	@gmb	2	0	0
2	@dwpgovuk	1	0	0
3	@bbcbreaking	1	0	0
4	@bbcbreakfast	1	0	0
5	@hmrccustomers	2	0	0
6	@matthancock	1	0	0
7	@peter_aldous	1	0	0
8	@britishgashelp	1	0	0
9	@thesun	1	0	0

Secondly, these mentions suggest a decline in interest in the dialogue. Mentions of media outlets such as *@bbcbreaking* and *@bbcbreakfast* may reflect the spread of news related to payments. Mentions of official bodies and politicians, such as *@dwp* and *@matthancock*, decreased in both frequency and weighted frequency, suggesting that the immediacy of public discourse about government actions or announcements may have declined.

Table 23

Emoji Analysis for the Period after the Distribution of the Second Cost of Living Payment

index	word	abs_freq	wtd_freq	rel_value	emoji_text
0	🧠	1	7	7	brain
1	⤵️	1	7	7	right arrow curving down
2	💥	1	4	4	collision
3	👇	1	3	3	backhand index pointing down
4	🥶	1	0	0	cold face
5	❗	2	0	0	red exclamation mark
6	🎓	1	0	0	graduation cap
7	➡️	1	0	0	right arrow
8	🩺	1	0	0	stethoscope
9	💷	1	0	0	pound banknote

Lastly, emoji analyses at this stage showed a much lower use of emojis, reflecting a less emotional atmosphere. The brain (🧠) and the downward curving right arrow (↩️) may symbolise reflection or the end of a process. The presence of the collision (💥) and backhanded index pointing downwards (👇) emojis may indicate points of conflict or emphasise certain information, but their low frequency suggests that these emojis are less dominant in the dialogue. Cold faces (🥶) may indicate winter-related challenges or may be a metaphor for discomfort. Notably, the absence of strongly positive or negative emojis implies a more neutral or contemplative public mood at this stage.

The period after the second payment distribution appears to mark a transition from acute crisis discussions to a wider array of topics, reflecting a community that is potentially moving from reaction to reflection or adjustment.

6.3.2 User Network Analysis

6.3.2.1 Structure Analysis

Firstly, the network analysis was conducted on the user information to understand their network structure, the information dissemination pattern, and the key influencers regarding the topic of the cost of living crisis in the UK. In this section, the structure of the user networks was evaluated and compared across different periods.

Table 24

Network Information

Network information	Announcement period	Payment1 distribution period	After the payment distribution	Payment2 distribution period	After the payment2 distribution
	2022-05-26 - 2022/07/08	2022-07-14 - 2022-07-31	2022-08-01 - 2022-08-10	2022-11-08 - 2022-11-23	2022-11-24 - 2022-12-03
Total number of nodes	1685	1097	339	1754	231
Total number of edges	1331	713	190	1481	124
Average degree	1.5798	1.2999	1.1209	1.6887	1.0736

Table 24 illustrates the network information for the user network during each identified period. As seen in the table, the size of the network fluctuates across these periods. The largest network occurred during the second payment distribution period, encompassing 1,754 nodes and 1,481 edges. Conversely, the smallest network was observed during the period after the second payment distribution, comprising only 231 nodes and 124 edges.

The announcement period's user network size ranks as the second largest among the five periods, indicative of active participation during that time. As for the payment distribution, the size of the user network in both payment distribution periods is considerably larger than that in the periods following the distributions. Additionally, the average degree of the user network is higher during the payment distribution periods and lower in the subsequent periods. These trends suggest that during the payment distribution period, users were more actively engaged in discussions related to Cost of Living Payments, possibly fuelled by the immediate nature of the payment distribution. In contrast, activity and engagement seem to decrease after the distribution periods, as users may shift their focus or lose interest in the topic, leading to an overall decline in activity and engagement.

Next, the degree distribution is computed to see if it follows a power-law distribution. As shown in Figure 35, the distribution for each period is displayed along a timeline. The distributions appear to follow a power-law pattern, with many nodes having low degree values and a few nodes having high degree values. This pattern is common in many real-world networks, including social networks.

Figure 36

Power-law Degree Distribution

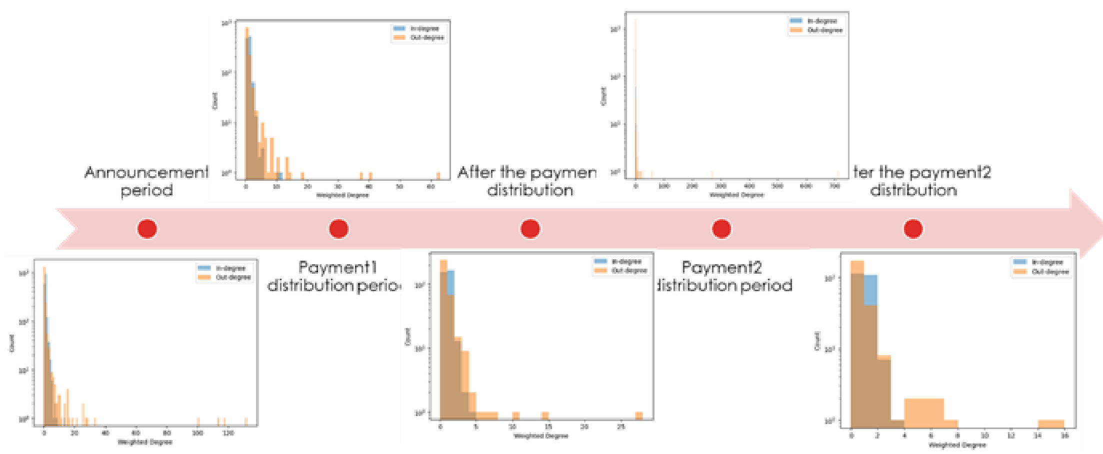


Table 25

Clustering Coefficient of Each Period

	Announcement period		**1st payment distribution period**		**After the 1st payment distribution**	**2nd payment distribution period**	**After the 2nd payment distribution**
	2022-05-26 - 2022/07/08		2022-07-14 - 2022-07-31		2022-08-01 -2022-08--10	2022-11-08 - 2022-11-23	2022-11-24 - 2022-12-03
Clustering coefficient >0	loonylaura	0.0833	HMGMidlands	0.0556			
	andyratcliffe9	0.0833	SNS_CAB	0.0556			
	BlueberriesRok	0.0278	PotteriesGold	0.0167			

	Helen_Barnard	0.0083					
	resfoundation	0.0079					
	MartinSLewis	0.00001					
average clustering coefficient of the network	0.000125		0.000116		0	0	0
Diameter of the network	2		3		2	3	2

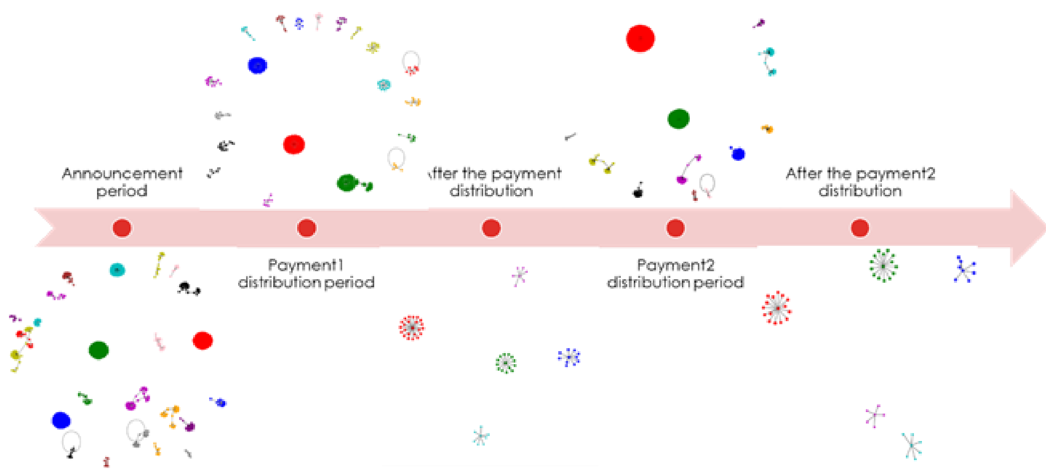
Table 25 illustrates the clustering coefficient of each period. The average clustering coefficient is higher in the announcement period (0.000125) compared to the first payment distribution period (0.000116), indicating that the nodes are more densely connected in the announcement period. In addition, the diameter, which measures the maximum distance between any two nodes in the network, was smaller in the announcement period (diameter of 2) than in the first payment distribution period (diameter of 3), further implying that the former is more closely linked. However, the overall small values of the average clustering coefficients indicate that all the networks are not well connected and are sparsely distributed.

The clustering coefficients of individuals for users are evaluated as well. *Loonylaura* and *andyratcliffe9* are more connected to their neighbours in the announcement period while *HMGMidlands* and *SNS_CAB* are more connected to their neighbours in the first payment distribution period. This variation in individual clustering coefficients suggests that certain users become central communicators or information hubs within the network at specific times. *Loonylaura* and *Andyratcliffe9*, for instance, possibly engage more actively or are sought out more by their peers for information and interaction when announcements are made, while *HMGMidlands* and *SNS_CAB* possibly assume these roles during the distribution of payments.

Figure 37 shows the results of the community detection, which can aid in understanding the organisation and functioning of the network. Firstly, a new network with nodes having a weighted degree more than the average value was extracted from the directed network to enhance clarity. Secondly, the greedy algorithm was applied for community detection. To ensure the significance of the identified communities, a size threshold was established, discarding any community comprising fewer than five nodes. This criterion helps concentrate the analysis on substantial clusters, avoiding a skewed interpretation by overly small and potentially less meaningful groups. The communities are marked using different colours and the top 3 largest communities' nodes are larger than the others.

Figure 37

Community Detection for Each Period



The evolution of the network at different time intervals can be seen in Figure 37. First, people are active only during the payment announcement and distribution periods. During these active periods, the evolution of the community over time appears to have gradually evolved from a more dispersed set of nodes into a smaller but more distinct community configuration. This pattern may suggest a process of maturation of the network or the impact of the disbursement events that led to increased cohesion of certain groups.

6.3.2.2 Key Players Identification

In this section, the key players in the communication and discussion of the Cost of Living Payments were identified based on several metrics. The role of the players was divided into two categories, namely the influential users and the active participants. The main distinction between influential users and active participants lies in their reach and impact within the network. Influential users have the power to shape opinions and drive trends due to their prominent position and wide-reaching connections. Active participants contribute to the daily interactions and discussions within the network but may not have the same broad influence. Both roles are essential in social networks, but they function differently in shaping the network's dynamics and flow of information.

This study evaluated these nodes from five aspects, namely outdegree, indegree, outward closeness centrality, betweenness centrality, and Katz Eigenvector centrality. The degree centrality was measured by outdegree and indegree because this user network is directed, with the outgoing links representing a referenced or mentioned relationship, while the incoming links represent the referencing or mentioning relationship. Outdegree and outward closeness centrality help identify who is playing the key influential roles, while Indegree, Katz Eigenvector centrality and betweenness centrality help determine who is an active participant. Based on these metrics, the key roles for each period were identified. The results are shown in Table 26. For each period, the top 10 user nodes with the highest centrality for each metric are identified. To maintain clarity, this study will only discuss the top 3 key players in subsequent discussions.

Table 26

Key Roles for Each Period

	Announcement period	Payment1 distribution period	After the payment distribution	Payment2 distribution period	After the payment2 distribution
	2022-05-26 - 2022/07/08	2022-07-14 - 2022-07-31	2022-08-01 - 2022-08-10	2022-11-08 - 2022-11-23	2022-11-24 - 2022-12-03
Outdegree	DrFrancesRyan	BorisJohnson	hmtreasury	byewig1921	JackSargeantAM
Indegree	Polytwonk	nuttygothictart	Ben_Everitt	MattCx90	mariagreenie
outward closeness centrality	DrFrancesRyan	BorisJohnson	hmtreasury	byewig1921	JackSargeantAM
Betweenness for NODE	LegacyBenefits	PotteriesGold	foxyjools	BenClaimant	CentralReserva9

Katz Eigenvector Centrality	Polytwonk	nuttygothictar t	Ben_Everit t	MattCx90	mariagreenie

During the announcement period, *DrFrancesRyan*, *JonJonesSnr*, and *MartinSLewis* were identified as the most influential users, with *Polytwonk*, *cleggy261*, and *MusicalLottie* being the key figures in disseminating information. *LegacyBenefits* held the position of an information gatekeeper within this timeframe. In the Payment1 distribution period, the spotlight shifted to *BorisJohnson*, *MrTopple*, and *philofdover* as the most influential users, while *Nuttygothictart*, *birchpolypore*, and *Shukes69* were recognised as the most active in spreading information. *PotteriesGold* took on the role of an information gatekeeper, with *DowningStreet* and *MusicalLottie* continuing to be prominent and active users, respectively.

Following the Payment1 distribution, *hmtreasury*, *SimonClarkeMP*, and *MrHarryCole* emerged as influential figures, with *Ben_Everitt*, *RHJOfficial*, and *LisaLisaw1* leading the charge in information dissemination. For the Payment2 distribution period, *byewig1921*, *Dawn117147265*, and *MartinSLewis* became the most influential users. *MattCx90*, *Independent*, and *sthelenscouncil* were particularly active in disseminating information, with *BenClaimant* serving as an information gatekeeper. During this phase, *MartinSLewis* and *DWPgovuk* reclaimed their central roles, and *Independent* notably took on dual roles as an influential user and information disseminator. *DWPgovuk* was particularly active with each payment distribution period.

In the aftermath of the Payment 2 distribution, *JackSargeantAM*, *josiahmortimer*, and *KatieSchmuecker* were highlighted as the most influential users. The mantle of active information dissemination was taken up by *Mariagreenie*, *HaroldJ70461991*, and *UKCUltd*, while *CentralReserva9* acted as an information gatekeeper, showcasing the dynamic landscape of influence and information management across different periods of payment distribution. Table 26 lists the major players that ranked in the top 1 in different aspects for each period.

6.3.2.3 Public Sentiment Towards the Cost of Living Crisis in the UK

After assigning the tweets to each community detected in the user network and conducting the SA, the results show that during the announcement period, most of the user communities present negative sentiments, and only four communities express positive sentiment. The same results were achieved for both the distribution period of the first and second payment. In the period after the first payment was distributed, eight communities were identified, with three communities expressing neutral sentiment, three communities expressing positive sentiment, and two communities presenting negative sentiments. For the period after the second payment was distributed, nine communities were identified, with five communities expressing positive sentiment, and four communities presenting negative sentiments.

Table 27

Sentiment of User Communities

Period	Positive	Neutral	Negative
Announcement Period	4	4	Majority (25)
First Payment Distribution	4	5	Majority (17)
After First Payment Distribution	3	3	2
Second Payment Distribution	4	4	Majority (25)
After Second Payment Distribution	5	0	4

Neutral communities are mainly made up of official government Twitter accounts and media accounts. They provide and share information with the public. Positive communities are made up of government accounts and a few individual Twitter users. Government accounts often aim to reassure those who have not yet received their payments. Individual accounts may call for participation in petitions or other public actions. There is also some acknowledgement and thanks to the government for these payments. Negative communities are mainly made up of individual accounts. They expressed various forms of dissatisfaction, including with payments, the government, employers and with other individuals.

The results of the clustering coefficient and community detection indicate that the user networks are quite sparse. Consequently, the analysis of the user network was limited to the sentiment within the communities. A more thorough and comprehensive content analysis will be concentrated on the semantic network.

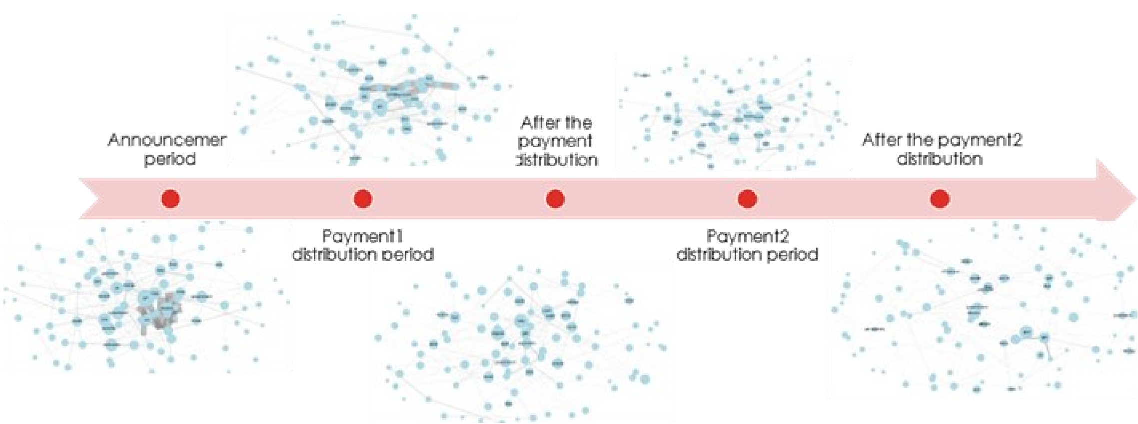
6.3.3 Semantic Network Analysis

6.3.3.1 The Development of Semantic Networks

After the user network analysis, the semantic network analysis was conducted to analyse the text of tweets. When conducting this analysis, the retweets and quotes from the data were removed to avoid the replication of information and bias in the analysis. Search terms were also removed from the final networks because predominant words are highly likely to link all the other words together into a single group, which may distort the results. The co-occurrence of three vocabulary words was selected as the topic and constructed the semantic network. The top 100 words by degree centrality in each corpus were retained for a concise and clear visualisation of the network. The semantic network for each period is shown along the timeline to provide a general visualisation.

Figure 38

The Development of the Semantic Network for Each Period



The top 20 words were computed and organised together first. During these periods, *'get'*, *'people'*, *'help'*, *'payments'*, *'receive'*, and *'crisis'* appeared in every period, and *'government'*, *'one'*, *'credit'*, *'dwp'*, and *'benefit'* appeared four times, which confirms that the semantic networks were effectively constructed, and the topics are around the support payments by the UK government. Even though the search terms were removed from the network, key themes can still be inferred from this network.

In addition, the words *'first'*, *'July'* rank among the top 20 during the announcement period and the first payment distribution period, and the word 'second' ranks at the top during the second payment distribution period. This also confirms the effectiveness of the network as they are consistent with their corresponding period.

After confirming the effectiveness of the network, the analysis of the words shows that, firstly, the words *'but'*, *'paid'*, and *'received'* appeared in the top 20 words from the first payment period. As the payments were distributed automatically, people started to talk about the distribution progress of the payments. Especially in the period after the first payment distribution, the word *'eligible'* ranked first, indicating that many people thought they might receive the payment but did not, leading to heated discussions about eligibility. Another key finding is that there are two specific groups getting the most attention, one is *'students'* and the other is *'pensioners'*. Referencing the policy provided by the government in 2022, students were not included in the supporting target.

6.3.3.2 SA on the Topics Detected

Table 28

SA by Topic Community of Each Period

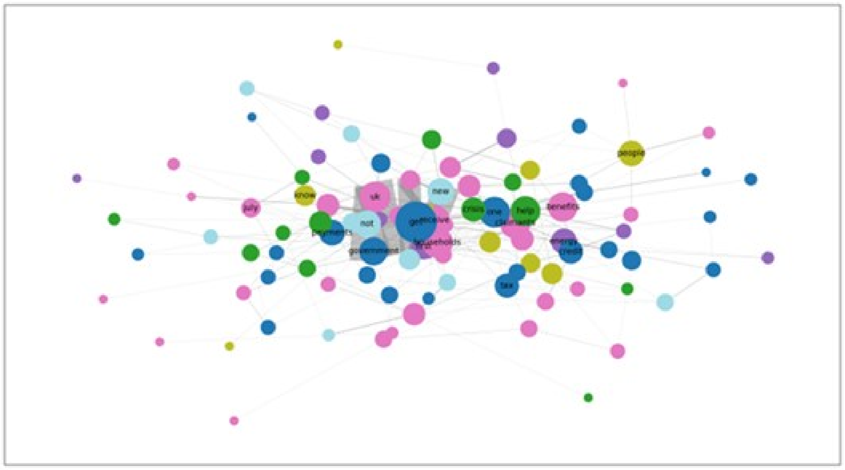
Period	***Community***	***Sentiment Score***	***Sentiment Label***
Announcement Period	**Eligibility**	-0.0444	Neutral
	Main Cost-of-Living Package	-0.1387	Negative
	Energy Bills	-0.0079	Neutral
	Confirmation from DWP	-0.4167	Negative
	Support for Low-Income Households	-0.0638	Neutral
1st Payment Distribution	**DWP Payment**	-0.2712	Negative

	Communication and Execution of the Cost of Living Payment	-0.2407	Negative
After the 1st Payment	**Cost of Living Payment**	-0.0077	Neutral
	Communication and Execution of the Cost of Living Payment	0.1263	Positive
	Employee Support/Benefits	0.1200	Positive
2nd Payment Distribution	**New Government Measures**	0.0000	Neutral
	Impacts and Perceptions of Financial Relief Measures	-0.0164	Neutral
	Receipt of the Second Cost of Living Payment	-0.0297	Neutral
After the 2nd Payment	**Availability of Financial Assistance and Criticism of Support Payment**	-0.1867	Negative
	Winter Fuel Payments and the Pensioner Cost of Living Payment	-0.2000	Negative
	Contact Details	-0.2000	Negative
	Adjustments in Cost of Living Payments	0.1111	Positive

After obtaining an initial understanding of the online discourse on the cost of living in the UK, the combination of node embedding, and hierarchical clustering methods were employed to cluster these words into different communities to identify their topics. The next step is to assign tweets to each community. The content analysis was then conducted to summarise and name the community. Finally, SA was performed to understand the sentiment expressed towards each community. The results are shown in Table 28 and following figures. A detailed distribution of sentiment is presented in Appendix B.1, which shows the proportion of tweets expressing negative, neutral and positive sentiment.

Figure 39

Community Detection Results on Semantic Network for the Announcement Period

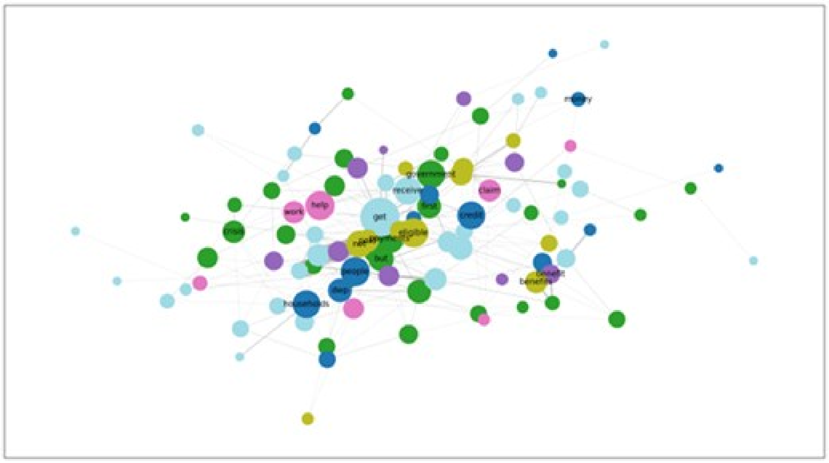


First of all, six communities were identified during the announcement period, represented by six different colours in Figure 30. However, after inspecting the assigned tweets, communities 3 and 6 were combined into one community, resulting in five communities.

The topic of the first community is *Eligibility* for payments and distribution information. The tweets highlight various aspects of the cost of living payments in the UK, including government initiatives, eligibility criteria, specific payment details, and support available to individuals and families. Sentiments towards this subject during the announcement period were predominantly neutral, with a slight negative bias. Most tweets served an informational purpose or prompted others to verify their eligibility. Negative sentiments emerged due to perceived exclusions of certain groups with legacy benefits, claims of unfairness for diligent workers, and critiques of the government's scheme. The topic of the second community is mainly about the *Main Cost of Living Package*, with the prevalent sentiment being negative. The criticism here is more pronounced than in the first topic, with a focus on the exclusion of carers and Personal Independence Payment (PIP) claimants. The topic of the third community is mainly about *Energy Bills*, with the sentiment being neutral overall. While some tweets positively acknowledge the relief efforts for energy costs, others express dissatisfaction with the increasing energy bills and the inadequacy of energy rebates. The topic of the fourth community is *Confirmation from DWP*. During the announcement period, DWP confirmed that five groups would receive a £650 Cost of Living Payment first. There is concern that some might miss out on this payment due to identified loopholes. The topic of the fifth community is *Support for Low-Income Households,* where the sentiment is neutral, with a slight negative bias. Negative sentiments reflect a lack of faith in the government's measures, with concerns about their sufficiency, potential implications, and insensitivity.

Figure 40

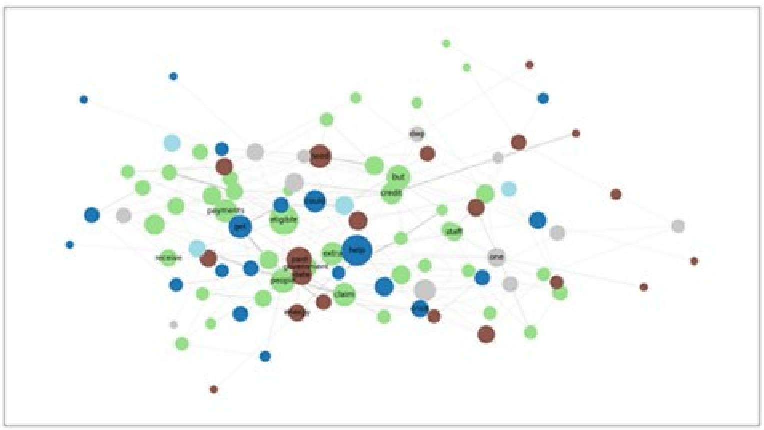
Community Detection Results on Semantic Network for First Payment Distribution Period



Three communities were finally identified during the first payment distribution period. The main topic in the first community that people were discussing was the *DWP Payment*. This topic includes general discussions about eligibility for different benefits, exclusions from certain payments, anticipation of receiving payments, and other overall conversations around DWP payments. The overall sentiment of this topic is considered negative. The tweets with negative sentiments highlighted concerns about eligibility criteria, payment delays, denials, and perceived inequalities in the distribution of support. The main topic of the second community is particularly about the *Communication and Execution of the Cost of Living Payment*. The overall sentiment of this topic is considered negative. Tweets with positive sentiments express gratitude for the receipt of payments. Conversely, the negative sentiments stemmed from criticisms regarding the lack of communication, confusion over qualification criteria, uncertainties about payment timing, and dissatisfaction with the transparency of the process. The main topic of the third community is particularly about the *Receipt of the Cost of Living Payment*, with the overall sentiment being slightly negative. Most of the neutral tweets are from people asking if they are eligible and the date of payment, and different government accounts emphasise that these payments are automatic in nature requiring no personal contact or application. Tweets with positive sentiments generally encouraged pensioners to claim the full Cost of Living Payment, expressed gratitude for having received the funds, or showed support for and acknowledgment of the government's efforts. Negative sentiments arose from individuals who did not receive the payments, including those who were ineligible due to receiving only housing benefits, people on legacy benefits, those who became beneficiaries or applied after the specified cutoff dates, or those who were self-employed.

Figure 41

Community Detection Results on Semantic Network for the Period After the first payment

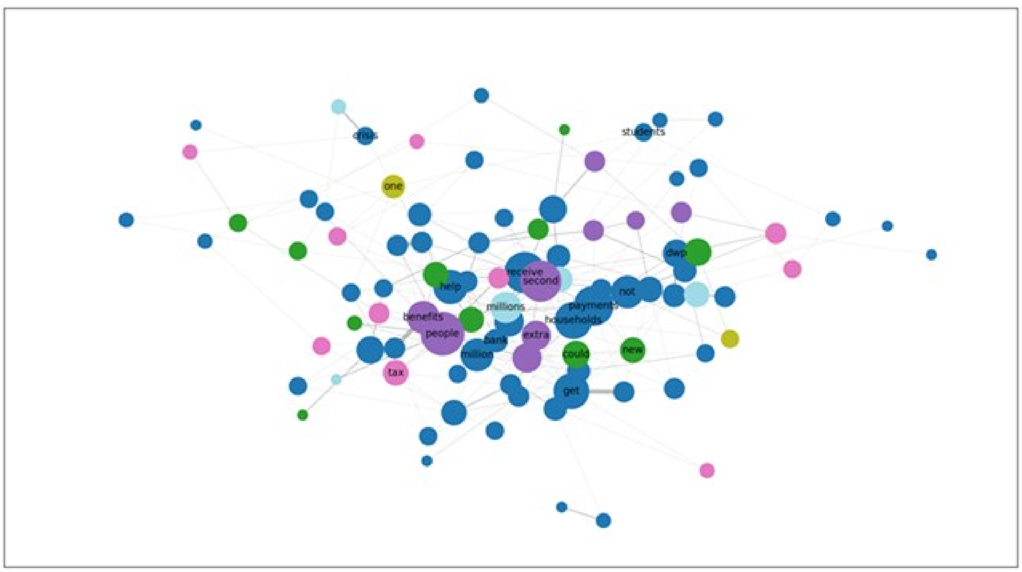


In the period following the first payment distribution, three distinct communities were identified. The main topic discussed in the first community is the *Communication and Execution of the Cost of Living Payment*, with an overall neutral sentiment. However, it was observed that the positive sentiments mostly come from government departments, while negative sentiments came from the public. Positive tweets in this category are generally informative, offering guidance or sharing information about the payment, including how to receive it and eligibility criteria. These tweets differed from neutral sentiment messages by offering reassurance and clarifying the process for claimants. Some tweets also express personal excitement and surprise over receiving a one-time payment to help with rising expenses. In contrast, negative tweets highlighted the difficulties associated with the payment, such as repayment requirements, the rising cost of living, unclaimed benefits, disappointment over not receiving the expected payments, and the inadequacy of the support provided. They criticise the process and express frustration with the management of the payments. There are also warnings about potential scams pretending to offer these payments.

The second topic is mainly about *Employee Support/Benefits* in addition to the support package provided by the government. The overall sentiment is slightly positive. Positive tweets celebrated companies providing financial support to their employees, such as one-off payments, bonuses, or other forms of assistance to help employees cope with the current financial situation, as well as increased payments to staff as a result of union support. Conversely, negative tweets detailed concerns and criticism of the energy crisis and allegations of employers exploiting the situation by providing one-time support packages. The third topic is mainly about *New Government Measures*, maintaining a neutral overall sentiment. The tweets were largely focused on discussing and sharing information about potential new government support initiatives to assist with living costs, characterised by a reporting or informational style devoid of strong sentiment.

Figure 42

Community Detection Results on Semantic Network for the Second Payment Distribution Period

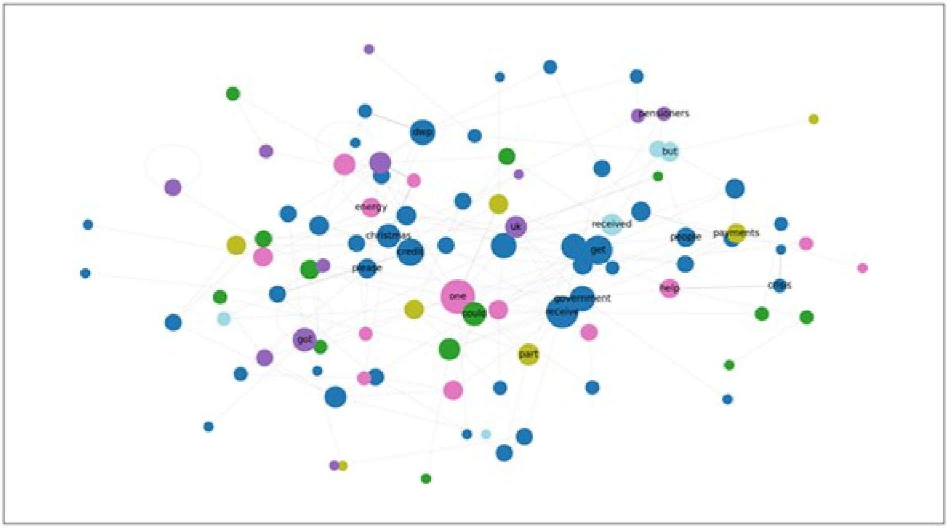


For the second payment distribution period, three communities were finally identified. The main topic discussed in the first community is the *Impacts and Perceptions of Financial Relief Measures*, carrying a generally neutral sentiment with a tendency towards negativity. The neutral tweets in this community predominantly disseminated information, advice, and updates about the Cost of Living Payments, some are sharing how individuals can save money to face the crisis.

The positive tweets are mainly expressions of relief and appreciation over receiving financial assistance. Negative tweets contain criticisms and frustrations concerning the financial support measures and economic struggles. They criticise companies for not providing sufficient support to their employees and vent personal frustrations about their financial struggles or their inability to qualify for certain supports. Some tweets call out people who, in their opinion, are misusing the financial aid or should not qualify for it due to their spending behaviours. The second topic is about *Receipt of the Second Cost of Living Payment*. The overall sentiment of this topic is also considered slightly negative. Tweets mostly delivered factual updates about the second round of financial support, with positive sentiments reflecting the relief and support provided by these payments, especially to those on lower incomes. The negative tweets express dissatisfaction, frustration, or distress related to non-receipt, delays, or the insufficiency of the payments that led to financial distress. The third topic is about *Availability of Financial Assistance and Criticism of Support Payment*, where the dominant sentiment was negative. While neutral tweets provided information about new financial assistance programmes, the positive tweets were few, focusing on the availability of financial assistance and providing tips and resources for saving money. The negative tweets express strong feelings of frustration and dissatisfaction from individuals who feel overlooked or unfairly treated by the aid programmes. There was a sense of injustice among those who believed they were not receiving adequate support despite their tax contributions, while others who were not working seemed to receive aid. Some people suggested that current support measures are not sufficient to deal with the crisis.

Figure 43

Community Detection Results on Semantic Network for the Period After the Second Payment was Distributed



In the period following the distribution of the second payment, analysis of the user communities revealed three main topics of discussion. The first community engaged heavily with the topic of *Winter Fuel Payments and the Pensioner Cost of Living Payment*, where the prevailing sentiment was negative. Most neutral tweets focus on providing information about these two payments. The negative tweets generally express frustration with the lack of clarity regarding the relationship between the Winter Fuel Payments and the Pensioner Cost of Living Payment, concerns about missed payments, the cost of utilities, and criticisms of how the payments are structured. The second topic is mainly about *Contact Details* and was also marked by a negative sentiment. Tweets with neutral sentiments played a role in guiding, particularly students, to update their contact information to claim one-off payments. However, negative sentiment tweets express concern and warning about a scam related to the Cost of Living Payment that intends to steal bank details. The third topic was characterised by a positive sentiment and focused on *Adjustments in Cost of Living Payments*. Neutral tweets are primarily informing about specific adjustments to DWP benefits payments. Positive tweets are about a charity initiative. In this selection of tweets, there are no messages that express a clearly negative sentiment.

6.3.4 Discussion on the Main Findings by Applying the Dual-framework

The application of the designed dual-framework has proven to be able to provide meaningful insights into the UK's cost of living crisis. It was able to identify the factors or aspects of the payments offered by the UK government that people were most concerned about, the most influential players and active participants in the discussion, as well as the corresponding sentiments. In order to further validate the effectiveness of the proposed dual-framework, the results obtained from the framework are compared to the official report from the Work and Pensions Committee (2023), and the existing studies on the cost of living crisis in the UK. In addition to reliability, the official report from the Work and Pensions Committee is especially appropriate for comparison as it uses a different research methodology to achieve similar objectives to the proposed dual-framework. Their report aims to examine the adequacy of the support, the design and delivery of the payment system and the effectiveness of payment delivery. To realise their purposes, they invited organisations and individuals to submit written evidence, and a survey between 3rd and 16th April 2023, along with distributed dialogues with people with a learning disability who were not able to complete the survey to supplement their written evidence (Work and Pensions Committee, 2023). While they use qualitative methods, the proposed dual-framework adopted network analysis and SA as the base modules of the analytics framework. If the results from the dual-framework are corroborated by the findings in the official report, the effectiveness of the framework can be confirmed.

This analysis revealed significant fluctuations in public engagement across different periods, notably during announcements and payment distributions. The largest network activity was observed during the second payment distribution, indicating a peak in public interest and discussion. This finding suggests that such engagement is event-driven; specifically, in this case, the public conversation is significantly influenced by policy milestones. This finding is in line with the agenda-setting theory, and its related studies, particularly within the realm of political communication on social media. Agenda-setting theory suggests that the media does not tell people what to think, but rather what to think about. When media outlets focus on particular events or issues, these topics become the focus of public discussion and debate (James et al., 2019; King et al., 2017). In the context of the cost of living crisis, announcements and distributions are highly newsworthy events that likely received significant media attention, thus setting the agenda for public discourse on social media. According to Lewandowsky et al. (2020), the rise of social media platforms such as Twitter has opened up new avenues for political communication and has had a significant impact on political agenda-setting. This relationship is further supported by studies such as that by King et al. (2017), which show that media coverage influences which issues people discuss on Twitter. The shifting roles of key players and influencers across different phases of the crisis highlighted the dynamic nature of public discourse. As the network analysis shows, the breadth and diversity of participants engaged in these social media discussions resonate with the findings of Jungherr et al. (2019), who argue that the political information cycle on social media involves a wider range of participants and interactions than the traditional news cycle. In this study, the range of users involved in the discussion was broad, ranging from government accounts to individual citizens, thus expanding the dialogue beyond the initial policy announcement. In addition, the role of key influencers in disseminating information and shaping discourse in the analysis coincides with Fazekas et al. (2021), who argue that politicians use Twitter to extend issues from the elite sphere to the public sphere. In this case study, politicians and other prominent users on Twitter acted as key nodes in the network, emphasising their influence in the cost of living crisis. The SA conducted on the user communities identified predominantly negative sentiments during the announcement and first payment distribution, which may indicate public concerns and dissatisfaction. Following the first payment distribution, the discourse shifted to a mix of neutral, positive, and negative sentiments. This shift in sentiment reflects the public's evolving response to the crisis and the government's handling of it.

From the analysis of semantic networks, the reasons underlying these sentiments are identified. First of all, the main factors of public dissatisfaction are the inadequacy of the amount of the payment, the eligibility for the payment, the timing and method of payment distribution, and the vague and evasive way in which the government communicated the information that was of most concern to the public. These main factors are also identified by the official report from the Work and Pensions Committee (2023), which validates the effectiveness of the dual-framework. To be specific, in terms of the factor 'the inadequacy of the amount of the payment', the survey conducted by the Work and Pensions Committee found that while most respondents said that the payments helped, some emphasised that they were still unable to meet their costs fully, especially those who received disability payments, and described as "a drop in the ocean" . As for the factor 'eligibility for the payment', the report clearly lists it as a major aspect under the second section "Access to the cost of living support payments." In this section, the first point is cliff edges. According to the report, it means that when a benefit (in this case, a cost of living allowance) reaches a certain eligibility threshold, the benefit is withheld in full, while those whose benefits are just below that eligibility threshold still receive the full amount . Some people miss out on the cost of living payments due to the receipt of a nil award for Universal Credit during the qualifying period for the cost of living payment, often caused by mismatches between their pay frequency and the Universal Credit assessment period.. Specifically, those who are paid weekly or fortnightly sometimes receive an "extra" pay slip for an assessment period, which artificially inflates their income for that period and potentially reduces their Universal Credit amount to zero. This misalignment meant that they did not meet the eligibility criteria for the payment, even though their annual income would normally qualify. This systemic problem occurs because the Universal

Credit assessment is designed around a monthly cycle and does not take into account changes in the wage scale across employment. The proposed framework also located the same issue in the discourse on the cost of living payments from the Twitter platform. Related users complained that they missed out on this payment due to some loopholes. The cliff-edge nature of the cost of living grant creates a fundamentally unfair income gap, whereby a person can be financially penalised if they earn just above the eligibility threshold, are under sanction, or do not receive an eligible grant during the eligibility period.

In particular, according to the results from the semantic network analysis, concerns were raised about the eligibility criteria for benefits, highlighting the exclusion of groups such as older people not receiving Pension Credit, households not receiving means-tested benefits, households receiving only housing benefit, as well as people on legacy benefits, carers, and students. The former three groups are also identified by the report from the Work and Pensions Committee (2023). As means-tested benefits and Pension Credit are key qualifying factors for receiving Cost of Living Payments, missing out on these benefits means being deprived of supplementary Cost of Living Payments as well (Greater Manchester Poverty Action (GMPA), 2024; Age UK, 2024; Work and Pensions Committee, 2023). In addition, those on low incomes who only receive housing benefits were not eligible for the Cost of Living Payments. This affects a significant number of households, including approximately 100,000 working-age households and 370,000 pensioner households. Housing benefit alone did not qualify them for additional support, despite the likelihood that many recipients would meet the income criteria if they applied for other income-related benefits (Child Poverty Action Group (CPAG), 2024). Aside from the groups discussed above, the dual-framework also identified the other vulnerable groups, including carers and students who are not receiving the payments but also need help and protection against the rising costs. Moreover, due to the automatic nature of the Cost of Living Payment , some people have questions about whether they to qualified for this payment as they would not get any notification of qualification confirmation before they received this payment, if they did qualify. Regarding the timing and method of payment distribution, the report from the Work and Pensions Committee also confirmed this aspect and pointed out that not publishing exact payment windows for each instalment made it more challenging for low-income households to budget (Work and Pensions Committee, 2023, p.24). In addition, according to the results from the dual-framework, some people were not aware of the methods to receive the payments.

The communication method by the UK government on payment support is also a key concern identified by the dual-framework. Twitter users in the UK considered that the way the government delivered the information about the payment was vague, ineffective and invasive, which was also agreed upon by the official report from the Work and Pensions Committee. Although this concern is not listed as a major issue in the report, it pointed out that some people were not even aware of the support, and the information conveyed was too complicated for people with learning disabilities (Work and Pensions Committee, 2023).

In addition to the points discussed above, there is also criticism regarding the expenditure of these payments. Some argue that the payments disincentivise work, favouring those who do not work over hardworking individuals. Others counter by emphasising that most recipients are employed in low-income positions, necessitating such support. A small number of people also argue that government payment is not a long-term solution to the cost of living crisis and that it is not beneficial to the economy. The discussion on social media platforms revealed a deep-seated dissatisfaction with the perceived ineffectiveness and unfairness of the government's approach to the crisis.

By combining the results from several analyses, it can be seen that some people have shifted from a predominantly negative to a predominantly positive or neutral mood, which may be related to the receipt of payments and the alleviation of immediate financial pressures. As the crisis continued, and as its immediate impact on individuals diminished, the discussion of government support expanded to broader social issues such as mental health, charitable actions and local economic discussions, and community responses such as advocating for public actions like petitions.

A side-by-side comparison with the Work and Pensions Committee’s findings provides a comprehensive validation of the proposed dual-framework. The framework successfully identified key concerns among the public regarding the adequacy of the payment amounts, eligibility issues, the timing of payment distribution, and the complexity of government communication. These concerns were also echoed in the Work and Pensions Committee's report, affirming the relevance and accuracy of the framework's outputs, supporting the effectiveness of the analytical approach. Notably, the framework's ability to highlight specific vulnerable groups that were overlooked in direct payments corroborates the Committee's concerns and suggests a high level of precision in the proposed methodology. In addition to the precision, the dual-framework has other strengths compared to the survey the government usually adopts. Firstly, while DWP surveys likely focus on direct questions about the payments and their immediate impact, the proposed dual-framework captures spontaneous discussions on social media. This allows for the exploration of broader and sometimes indirect effects of these payments on people’s lives, such as mental health concerns, the adequacy of the support in the broader context of their finances, and the systemic issues in the payment delivery system. Surveys can be limited by their structure, only gathering responses to predetermined questions. The dual-framework, on the other hand, identifies emerging themes and discussions that may not be directly solicited by survey questions. For example, it can detect growing concerns over issues like the long-term sustainability of such payments or discussions around policy changes that could better address the root causes of financial hardship. Secondly, by analysing social media data, the proposed framework accesses a wider range of voices, including those who might not typically participate in government surveys. This includes younger demographics, more technologically savvy individuals, and those who prefer expressing their views in open platforms rather than structured surveys. Thirdly, the proposed framework utilises network analysis to identify key influencers and the structure of interactions among discussion participants. This approach can reveal how information flows through networks and how influential players impact the spread of opinions and sentiments. Surveys do not typically capture these relational dynamics, which are crucial for understanding the influence patterns and dissemination pathways within social networks. Moreover, while surveys can measure sentiment at discrete intervals, the proposed framework tracks changes in sentiment over time, offering dynamic insights into how public emotions evolve in response to ongoing developments. This is particularly valuable in fast-changing situations like the cost of living crisis, where public sentiment can shift rapidly in response to new information or government actions.

6.4 Summary

This study has successfully developed a comprehensive analytical framework to dissect and understand social media data and applied it to the disclosure surrounding the UK's Cost of Living Payments. By integrating user-level and tweet-level network analysis with SA, the proposed dual-framework provides detailed insights into public perception and interaction patterns on social media platforms.

The findings highlight a dynamic social media landscape where public engagement peaks during significant events such as policy announcements and payment distributions. By analysing key influencers and active participants, the changing roles of different actors are observed in shaping public opinion. The SA conducted across various user communities highlights a predominantly negative public sentiment during announcement and payment distribution periods, shifting to a more mixed sentiment in the aftermath. This reflects the public's complex reactions to government policies and their effectiveness. The semantic network analysis further revealed key public concerns, including the adequacy of government payments, eligibility criteria, and communication clarity. Overall, social media discussions reflect deep dissatisfaction and a perceived lack of fairness in the government's handling of the crisis.

These insights are extremely useful for policymakers, providing immediate feedback on how the public feels and pointing out where policies and communication can be improved. For businesses and social organisations, understanding these dynamics is crucial for aligning strategies with public concerns and sentiments. This framework has the potential for broader application across various domains. There is also potential for enhancing the framework by integrating more advanced machine learning algorithms and exploring deeper semantic analyses. Additionally, long-term studies could help understand how social media discussions change over time in response to ongoing or repeated issues.

This study demonstrates the power of the proposed dual-framework for SMA in comprehending complex and extensive online conversations. It provides a powerful tool for stakeholders to understand socio-economic issues, helping them to make informed decisions and communicate more effectively.

Chapter 7 Movie Performance Evaluation Using the Dual-Framework Approach

7.1 Introduction

In this chapter, the analytical lens is turned to the entertainment industry where dreams come true, and fortunes are made and lost. Specifically, the proposed dual-framework is applied to the field of movie performance evaluation to demonstrate its efficacy in extracting insights from the digital information of social media discourse. The purpose of this case study is to demonstrate the approach's adaptability in revealing the intricate relationship between consumer behaviour or engagement, consumer sentiment, and how they relate to business performance. This will highlight the importance of using both SA and network analysis in business.

The global movie industry is worth billions of dollars. The success or failure of a movie can significantly impact production companies, studios, and other stakeholders. Despite the challenges of the pandemic, the UK is still one of the world's most active markets for cinema and filmmaking. In 2022, box office income in the UK/Ireland region was 1.2 billion dollars, making it the largest market in Europe. By 2026, the UK is expected to be the third-largest market globally, with an estimated revenue of about 4.7 billion dollars (Carollo, 2024). The market is predicted to grow by over 50% between 2021 and 2026. Therefore, understanding what affects movie box office performance is crucial for financial planning and investment in the entertainment industry. Researchers and industry professionals have always been interested in this topic. So far, data about star power (Fan et al., 2021; Liao et al., 2022), genre (Liao et al., 2022; Rubin et al., 2022), and marketing budgets (Rubin et al., 2022) have been the main factors collected and used to predict movie box office in the existing studies. The rise of social media has brought with it an abundance of data that may offer insightful information about audience sentiment, engagement, and influential voices, and their relation to movie performance.

Studying movie box office performance through the lens of social media data is important for several reasons. Firstly, with the rapid development of Web 2.0 technology, user-generated material has emerged as a valuable external resource to help customers make selections about what to buy. Online reviews are crucial when it comes to consumers' movie choices, especially in the movie industry (Fan et al., 2021). According to Caroll (2023), at least 86% of moviegoers read online reviews before selecting a movie to watch. Among them, 21% usually and 12% always do so, which can be considered as a routine before watching a movie. Secondly, social media data offers a unique opportunity to capture real-time audience reactions, conversations, and sentiments towards upcoming and recently released films. These insights can be invaluable for filmmakers, marketers, and distributors in tailoring their strategies to articulate their advertising and distribution efforts, more accurately assessing the performance of their products (Delre & Luffarelli, 2023), and capitalising on positive buzz or addressing potential concerns. Additionally, analysing the interplay between social media discourse and box office performance can shed light on the evolving dynamics of audience engagement, the role of influencers, and the impact of online reviews and recommendations.

The relevance of this topic as a subject for applying the dual-framework approach developed in this thesis is significant. The influence of social media on consumer behaviour and the entertainment industry presents a rich landscape of public discourse, sentiment, and interaction, manifesting across various platforms. Research such as that by Delre & Luffarelli (2023) indicates that the volume of eWOM on social media platforms can substantially influence box office sales, especially during the early stages of a movie's theatrical life cycle. This suggests that the magnitude of early social media buzz is particularly crucial, as early adopters are often more influenced by social appreciation and the desire to be part of a popular trend. They believe that analysing these patterns of eWOM and user-generated content can provide deeper insights into consumer behaviour and the effectiveness of marketing strategies within the entertainment sector. Therefore, through social media platforms, moviegoers, critics, and industry professionals express their opinions, share experiences, and engage in discussions, making it a valuable dataset for analysis through the proposed framework.

The proposed SMA framework, focused on business issues, will be leveraged to dissect the consumer dimensions of movie performance. It will enable the identification of dominant themes in audience discourse, the sentiment surrounding various aspects of films, and the key influencers shaping the conversation. In addition, these qualitative aspects will be quantified into social network measures and sentiment measures in order to evaluate their impacts on the daily revenue of the movie. By making use of these measures, this framework can further evaluate the factors that contribute to a movie's box office success or failure, as reflected in social media discourse.

This chapter aims to apply the proposed dual-frameworkto study the relationship between social media discourse and movie box office performance as well as the methodology's effectiveness in the business domain. The research questions are as follows:

- Who are the key influencers, and what is their impact on shaping audience perceptions and driving engagement with specific movies?

- How can the sentiment and discourse analysis of social media data surrounding upcoming and recently released films help in understanding their impact on audience engagement and box office performance?
- How effective is the proposed dual-framework approach in identifying potential indicators of box office success or failure from the perspective of audience engagement?

This chapter aims to demonstrate the dual-framework approach's usefulness and adaptability in utilising social media data to analyse complex real-world business problems. In this research, the evaluation of box office performance is used as the case study. It also aims to provide valuable information to entertainment industry players, helping them make data-driven decisions. This information can optimise marketing strategies and improve understanding and engagement with their target customers.

7.2 Methods

7.2.1 Data

To realise the purpose of this chapter evaluating the effectiveness of the dual-framework on the movie performance evaluation, a highly rated movie named 'Joker' was selected. It is an ideal choice for this case study due to several reasons. Firstly, its commercial success is noteworthy. Released on 4th October, 2019, it became the first R-rated movie to gross over 1 billion dollars. Secondly, the movie received numerous awards. Joaquin Phoenix won the Best Actor for his portrayal of the 'Joker', and Hildur Guðnadóttir won the Best Original Score at the 92nd Academy Awards. 'Joker' received a total of 121 wins and 247 nominations across various award ceremonies, making it a standout movie of 2019 (IMDB, 2024). Thirdly, although 'Joker' is a comic-book character, it is not a typical comic-book movie as it explores themes of alienation, mental illness, and societal decay. Due to its conflicting nature, it raised large-scale discussion among the public, including social media platforms. Additionally, the movie's marketing strategy effectively utilised social media to attract the public's attention and generate extensive pre-release buzz and post-release discussions. This strong social media engagement provides a valuable resource for analysing how social media interactions affect box office performance. Therefore, the large-scale public discourse and strong emotional responses elicited by the movie ensure a sufficient dataset for this case study, making it an ideal choice.

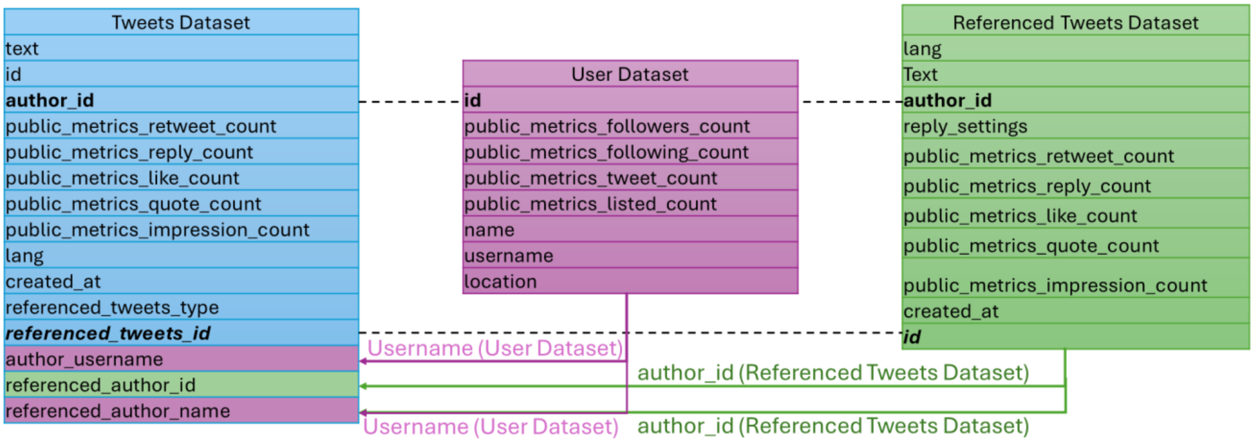
Two main datasets were collected and analysed for this study. The first dataset, referred to as the "Movie Dataset," was collected from BoxOfficeMojo.com, which provides box office information for a range of movies. This dataset includes detailed daily records over a period of nine weeks, including data points such as the date of earnings, day of the week (DOW), box office rank, daily earnings, percentage change compared to the previous day (%± YD), percentage change from the same day the previous week (%± LW), number of theatres, average earnings per theatre (Avg), cumulative earnings to date (To Date), and the day count since release (Day).

The second dataset, known as the "Review Dataset," was collected from Twitter using its API, including tweets from one week prior to the movie's release and continuing through the subsequent nine weeks of its screening period. This dataset is divided into three categories, namely the tweets dataset, referenced tweets dataset, and user dataset.

The tweets dataset includes all tweets that directly refer to the movie and mental health issues. It includes both original posts as well as referenced posts such as replies, quotes, and retweets that sparked dialogue. All of the analysis will be based on this data to measure user engagement and public opinion. The referenced tweets dataset consists of the original tweets of retweets, replies, and quotes, and their features. It is connected to the tweets dataset through its 'id' attribute and the 'referenced_tweets_id' in the tweets dataset. In this way, the author's id of each referenced tweet can be found, defined as the 'referenced_author_id' attribute in the tweets dataset. The referenced tweets dataset also connects to the user dataset by its 'author_id' attribute and the user dataset's 'id' attribute. Together with the newly defined 'referenced_author_id' attribute, the username of each referenced tweet's author can be found, defined as the 'referenced_author_username' attribute in the tweets dataset. The referenced tweets dataset is an important part of the data pre-processing step as it helps to connect users through their activities on the Twitter platform. Finally, the user dataset includes demographic and behavioural data on Twitter accounts that participated in the discussion on the movie topic. This includes metrics such as the number of followers, age of the account, and frequency of tweets, which are valuable for analysing the influence and reach of users who participate in discussions. The tweets dataset and user dataset are connected through the 'author_id' attribute in the tweets dataset and 'id' attribute in the user dataset. In this way, the username of each tweet's author can be found, defined as 'author_username' attribute in the tweets dataset. The connections between datasets are visualised in Figure 44.

Figure 44

Connection Between Datasets



As daily movie box office statistics are accessible only on the Box Office Mojo platform and limited to the domestic market, the review data from Twitter was also confined to its domestic market. Additionally, due to limited computing resources, the data collection period for the two datasets was constrained to the first nine weeks of screen time. In order to learn about the impact of 'Joker' on the mental health issues immediately before its release through the public's reaction, a dataset of specific tweets related to mental health in the week prior to the movie's release was also collected. Therefore, the study began by collecting tweets related to "mental health" or "trauma" from the week prior to the movie "Joker's" release. This initial dataset was substantial, comprising 322,459 entries. Out of these, 1,568 explicitly mentioned the 'Joker' movie, indicating a direct relevance to the movie. The data collection then continued from week 1 to week 9 post-release, specifically targeting tweets that included both the topic of the movie, "mental health", and the movie's name, 'Joker', to ensure the discussions were related to the movie. A total of 48,991 tweets were gathered during this period. Table 29 shows the size of the 'Review Dataset'. To conduct the semantic analysis and SA in the following steps, the tweets will be first pre-processed by several techniques, such as changing case, removing web links and stopwords, normalisation and others.

Table 29

Review Dataset Size

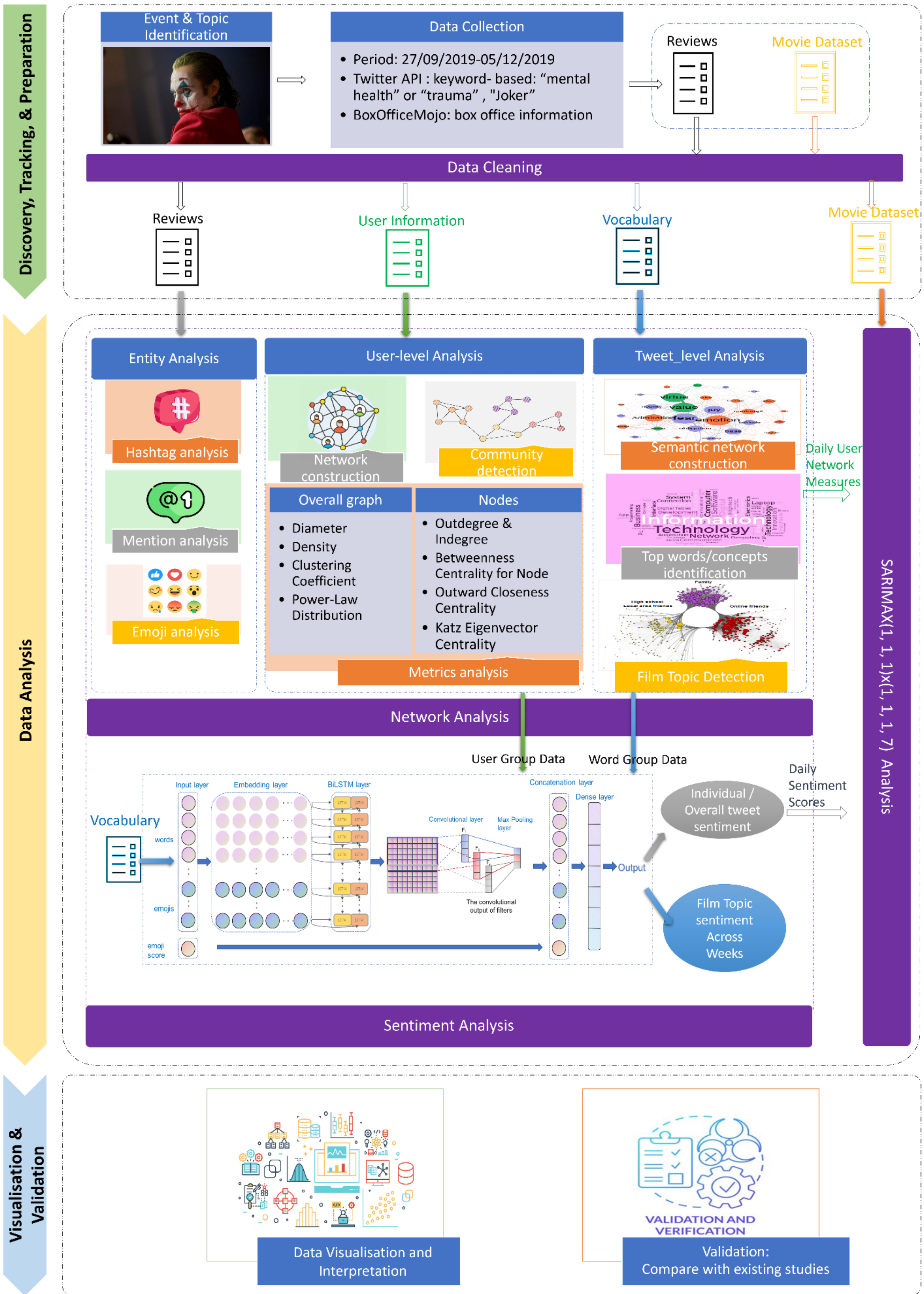
	W0	W1	W2	W3	W4	W5	W6	W7	W8	W9
The number of tweets	1568	33377	8060	3265	1507	705	995	510	378	194

7.2.2 Methods

By referencing the guidance for the application of the dual-frameworkto business issues, the method of applying the network analysis and SA is the same as its application to social issues. As the final purpose of the framework is to explore the relationship between customer engagement online and business performance and enable stakeholders to utilise these insights from social media to inform strategic decisions and improve their understanding of market dynamics, the dual-framework transforms the results from network analysis and SA into quantitative social media metrics and tests their significance to the business performance. In this case study, the business performance refers to the movie box office. Extracted from the complete dual-framework, the methodology framework especially for business applications is shown in Figure 45, which emphasises the data flow between network analysis, SA and relationship evaluation using statistical analysis. Detailed information about network analysis and SA can be found in section 3 and section 4.

Figure 45

Adjusted Dual-framework for Case 2



Discovery, Tracking, & Preparation
Event & Topic Identification
Data Collection
Period: 27/09/2019-05/12/2019
Twitter API : keyword- based: "mental health" or "trauma" , "Joker"
BoxOfficeMojo: box office information
Reviews
Movie Dataset
Data Cleaning
Reviews
User Information
Vocabulary
Movie Dataset
Data Analysis
Entity Analysis
Hashtag analysis
Mention analysis
Emoji analysis
User-level Analysis
Network construction
Community detection
Overall graph
Diameter
Density
Clustering Coefficient
Power-Law Distribution
Nodes
Outdegree & Indegree
Betweenness Centrality for Node
Outward Closeness Centrality
Katz Eigenvector Centrality
Metrics analysis
Tweet_level Analysis
Semantic network construction
Top words/concepts identification
Film Topic Detection
Daily User Network Measures
Network Analysis
User Group Data
Word Group Data
Vocabulary
Input layer
Embedding layer
BiLSTM layer
Convolutional layer
Max Pooling layer
The convolutional output of filters
Concatenation layer
Dense layer
Output
words
emojis
emoji score
Individual / Overall tweet sentiment
Film Topic sentiment Across Weeks
Daily Sentiment Scores
Sentiment Analysis
SARIMAX(1, 1, 1)x(1, 1, 1, 7) Analysis
Visualisation & Validation
Data Visualisation and Interpretation
VALIDATION AND VERIFICATION
Validation: Compare with existing studies

The major aims of this dual-framework in this case are to explore the social media buzz surrounding the ‘Joker’ movie, and to evaluate their impact on its box office performance. To realise these two aims, two primary datasets will be collected and analysed, namely a ‘Review Dataset’, and a ‘Movie Dataset’. After data collection and pre-processing, the following steps will be conducted.

The first step is to perform a network analysis. The entity analysis will be first performed to extract entities, namely hashtags, mentions and emojis, from the text and analysed separately. Their weighted frequency will be calculated by taking into account their absolute frequency and the weights associated with the entity's occurrence, which is the number of retweets a tweet received. The most popular entities will be analysed to understand how the posts are related to each other, and why social media users use these entities. After that, the user networks will be constructed, where each user represents a node, and a link is created between two users when they retweet, quote, or reply to one another. Weights will be assigned to the edges to reflect the influence of users. The next step is metrics analysis, which will be conducted on two levels, overall graph level and individual level. On the overall graph level, the metrics such as the network size, power-law distribution, clustering coefficient, density, and diameter will be computed to measure the entire network structure. On the individual level, metrics such as outdegree, indegree, outward closeness centrality, betweenness centralities for node and edge, and Katz Eigenvector centrality will be computed to measure the position of each node. The next step is community detection to identify groups of closely connected users by using clustering algorithms. Based on the metrics analysis and community detection results, it is possible to gain a sense of the main pathways of information dissemination and the patterns of dialogue and engagement that develop, giving a clear picture of how the movie is being talked about and who the talkers are. After the performance of the user network analysis, the semantic network analysis will be conducted. The first step is to extract word pairs (that are subjects and objects) from sentences to construct semantic network. The top 100 words, as ranked by degree centrality in each corpus, will be retained in order to better represent the whole data set. In the semantic network, the nodes represent words and links represent the co-occurrence of word pairs. Then, the influential words and themes can be identified based on the visualisation of networks and the degree centrality measure. After that, clustering analysis will be used to extract latent topics from the co-occurrence patterns using node embedding and hierarchical clustering techniques. The semantic analysis can help identify what specific aspects of the ‘Joker’ movie drove them to share their opinions on Twitter.

The next major step is to perform SA to classify the sentiment of each tweet. For this task, a pre-trained sentiment classifier will be employed. With the sentiment of each tweet, the sentiment of each group in the networks can be understood. In addition, this analysis facilitates the analysis of how each group perceives the latent topics related to the movie ‘Joker’.

For the purpose of evaluating the relationship between social media buzz and the box office performance of ‘Joker’, the last step is to transform the results from the network analysis and SA into quantitative social media metrics. To be specific, in terms of the network analysis, aside from the social network metrics used to evaluate the structure of the overall network, the metrics used to evaluate the individual nodes will be averaged to provide an overall level of moviegoer engagement on Twitter. As for the SA, the daily sentiment score will be obtained by averaging the sentiment of all tweets per day. According to Delre & Luffarelli (2023), the volume of eWOM on social media platforms can substantially influence box office sales. With at least 86% of moviegoers routinely reading online reviews before selecting a movie to watch, this thesis hypothesizes that moviegoers’ online social engagement impacts a film’s box office performance with a time lag. Therefore, the specific hypotheses are developed:

- H1: Moviegoers’ interaction around the movie from the previous day, indicated by average degree centrality, average closeness, average betweenness, average edge betweenness, average eigenvector, and average Katz centrality, has a significant positive impact on the movie’s daily box office.
- H2: Moviegoers’ perception of the movie from the previous day has a significant positive impact on the movie’s daily box office.

For the purpose of testing these two hypotheses, time series analysis will be conducted to evaluate the moviegoers’ online social engagement with the movie’s box office performance. The lag effect will be tested by regressing the social media metrics at time t-1 with the daily box office at time t. Therefore, the user network analysis and SA will be conducted on each day to obtain the daily social media metrics for 64 days of the screen time, including one day before the movie’s release.

After quantifying the social media metrics, the time series analysis will be conducted to evaluate their relationship with the box office performance. The dependent variable is *‘daily’* box office, and independent variables are *‘theatres’, ‘total_nodes’, ‘total_edges’, ‘average_degree_centrality’, ‘average_closeness’, ‘average_betweenness’, ‘average_edge_betweenness’, ‘average_eigenvector’, ‘average_katz’, ‘clustering_coefficient’, ‘density’*, and *‘sentiment’*.

The analysis begins with preprocessing the dataset, which contains daily revenue and various social media metrics. Missing values are handled by forward filling to keep the information consistent. After that, this study performs Exploratory Data Analysis (EDA) to understand the patterns and characteristics of the data. By calculating summary statistics, it first provides a basic understanding of the data, including the mean and the range of numbers. Correlation analysis is performed and visualised through a correlation matrix to explore the relationships between different variables. For the time series analysis, the 'daily' box office data is plotted to visualise the trend over time. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are also created to understand how the data points are related over time. These charts help in choosing the right time lags for the model. Next, this study performs a seasonal decomposition of the time series by dividing the data into trend, seasonal, and residual components. This step helps to reveal patterns in the data, such as repeated seasonal effects. This study tests the stationarity of the 'daily' time series using the Augmented Dickey-Fuller (ADF) test. This test is important because many time series models (e.g., ARIMA) require the data to be stationary, as indicated by the ADF statistic, p-value, and critical values. The Seasonal AutoRegressive Integrated Moving Average (SARIMA model is finally used because it can handle both seasonal and non-seasonal data. The study uses 'daily' revenue as the dependent variable and social media metrics as independent variables. The SARIMA model parameters (p, d, q) and seasonal parameters (P, D, Q, s) are determined from the ACF and PACF plots. Following the selection of the appropriate model and its parameters, this study fits the model to the data. It summarises the results, including the coefficients of the model terms and overall fit statistics. The study then checks the model adequacy with residual diagnostics. It produces residual plots and examines the ACF and PACF of the residuals to ensure there are no remaining autocorrelations.

7.3 Results and Discussion

7.3.1 Initial Analysis

Through the analysis of the number of tweets collected from the week before the release of ‘Joker’ and the subsequent weeks, it is clear there is a notable trend in the discussion volumes that provides an initial overview of the movie's impact and the public's engagement over time.

According to Table 29, in the week leading up to the movie's release, there were 1,568 tweets that directly mentioned ‘Joker’ alongside mental health. This number is relatively modest compared to the explosion of tweets immediately following the release. The lower volume of tweets during this pre-release week suggests that while there was some anticipation and discussion regarding the themes of the movie, the conversations hadn't yet reached a wider audience. This period likely represents the initial reactions from viewers who had seen trailers, previews, or participated in early screenings, focusing on the movie's intense themes of mental health and societal neglect. In the first week of the movie's release, the number of tweets increased dramatically to 33,377, indicating a surge of interest and discussion about the movie among general audiences. This spike reflects that the movie's themes are resonating with a wider demographic. Following the initial surge, the number of tweets dropped significantly in the following weeks, but the second week's tweets were still impressive compared to the weeks that followed with 8,060 tweets, indicating continued robust discussions. By week 3, the volume drops to 3,265, and this downward trend continues into later weeks, settling at lower levels towards the end of the observed period. This gradual decline is typical of cinematic releases where the initial buzz wears off over time, but sustained discussions in the first few weeks post-release highlight the movie's impact and the depth of audience engagement with its themes (Delre & Luffarelli, 2023; Rubin et al., 2022). The data clearly shows that 'Joker' had a significant impact on public discourse about mental health, particularly immediately following its release. Over time, as the immediate reactions were shared, the volume of discussion decreased, but the early intensity of the conversations likely contributed to a lasting impression that continued to influence views and discussions well beyond the cinema.

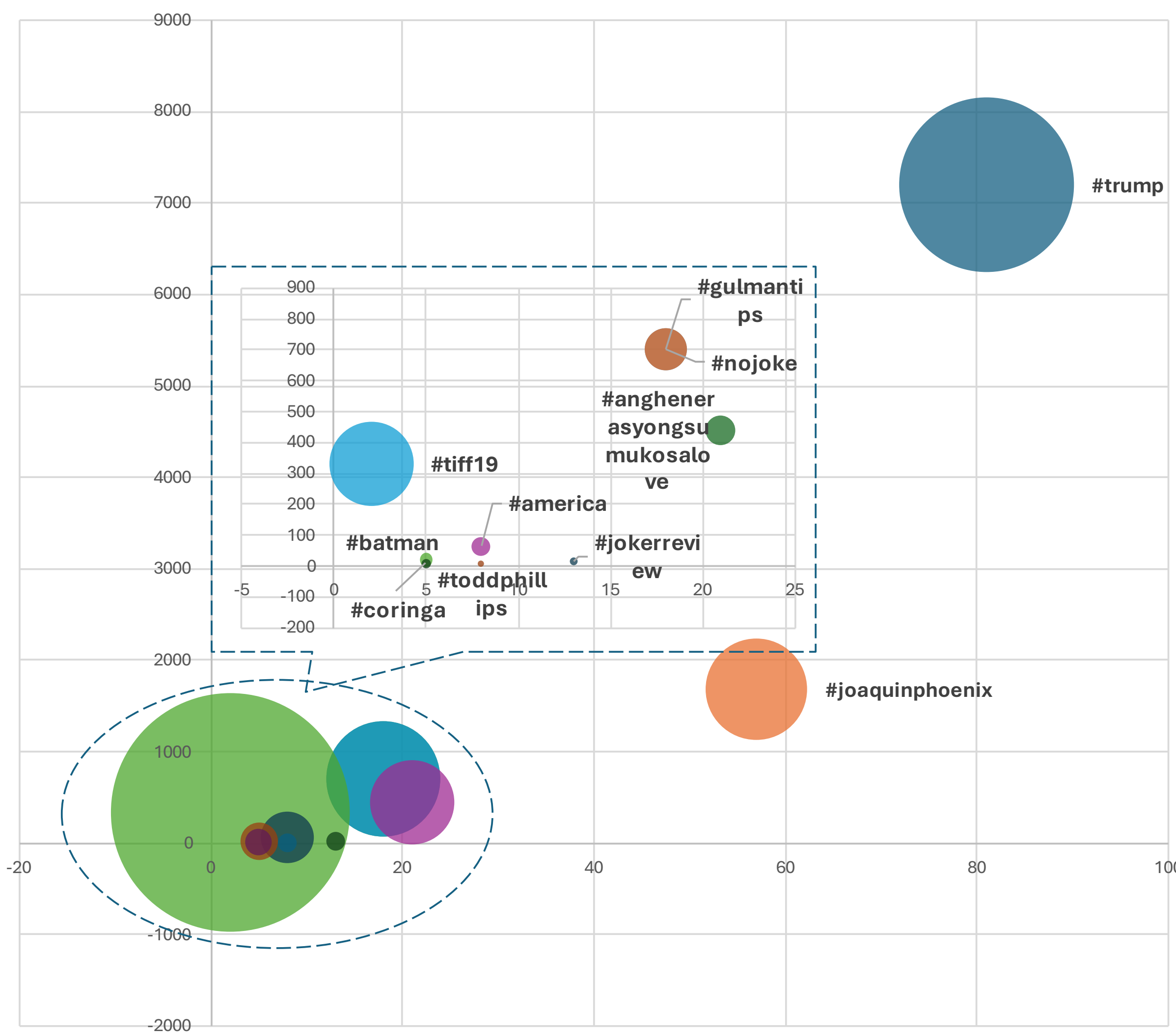
7.3.1.1 Entity Analysis of the First Week Pre-Release of 'Joker'

The entity analysis was conducted on a weekly basis. The results for the week prior to the release of the movie are shown below. The X-axis represents the absolute frequency of the entities, which is the number of times an entity appears in the dataset. Bubbles further along the X-axis have a higher absolute frequency, showing how frequently the entity was used. The Y-axis denotes the weighted frequency of the entities, representing the sum of retweets associated with each appearance of the entity. Bubbles positioned higher on the Y-axis have a greater weighted frequency, indicating a more significant presence within the dataset. The size of the bubbles corresponds to the relative value, which represents the average weight per occurrence of the entity. Larger bubbles indicate that each time the entity appears, it tends to generate a large amount of engagement or influence. The most important bubble can be determined by considering these factors together: high Y-axis placement, large bubble size, and significant X-axis positioning.

This bubble will represent the entity with the greatest influence, popularity, and usage within the dataset.

Figure 46

Hashtag Analysis of the First Week Pre-Release of 'Joker'

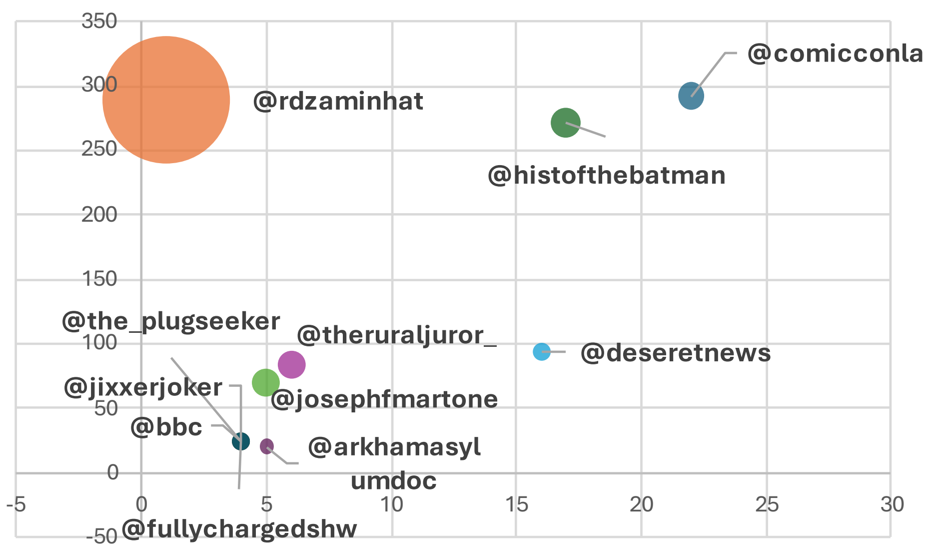


Firstly, in terms of hashtag analysis, shown in Figure 46, the discussion around 'Joker' prominently featured the hashtag *#trump*, indicating that the movie was frequently contextualised within political discourse, perhaps reflecting its thematic resonance with current socio-political issues.

The hashtag *#joaquinphoenix* highlighted the community's focus on the actor's performance, signalling strong interest and appreciation for his role. Additionally, hashtags like *#gulmantips* and *#nojoke* were also widely used, likely pointing to specific promotional content or thematic elements of the movie that resonated with the audience. The hashtag #tiff19, associated with the Toronto International Film Festival, ranked fifth. It highlights the movie's influence in the official movie world and shows that its critical reception may be part of the social media conversation.

Figure 47

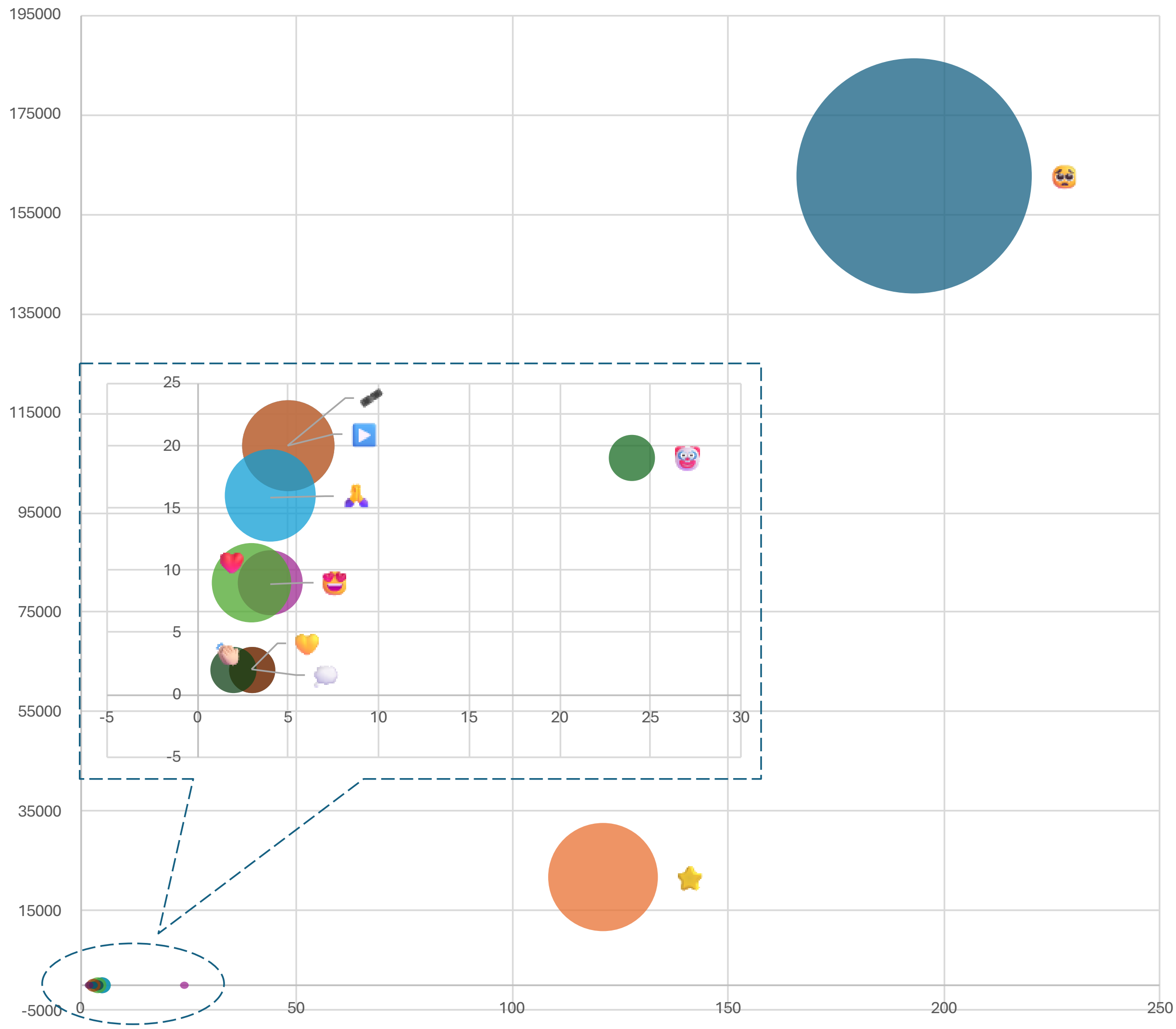
Mention Analysis of the First Week Pre-Release of 'Joker'



Secondly, from the respective of mention analysis shown in Figure 47, engagements with *@comicconla* indicated that 'Joker' was a topic of interest at fan-centric events like Comic Con, highlighting effective promotional strategies and fanbase interactions. The account *@rdzaminhat*, despite only a single tweet, garnered considerable attention, illustrating how powerful individual tweets can be in shaping the discussion. Interactions with niche-focused accounts such as *@histofthebatman* and broader media outlets like *@deseretnews* demonstrated the movie's wide appeal, engaging both dedicated fans of the Batman lore and a general news-following audience. This variety in mentions points to diverse ways of engaging audiences, from specialised fan groups to wider public forums.

Figure 48

Emoji Analysis of the First Week Pre-Release of 'Joker'



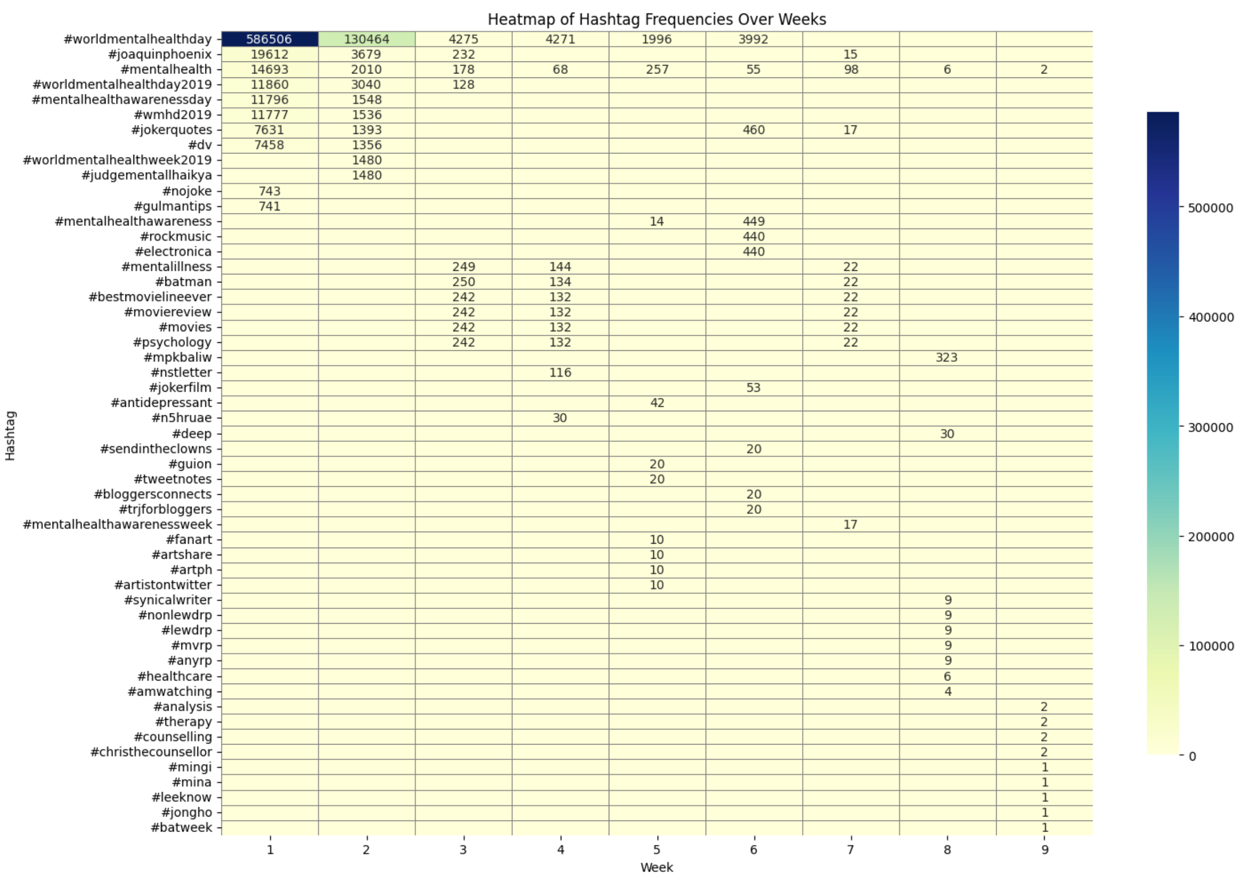
Thirdly, the analysis of emojis revealed that the frequent use of the '🥺' emoji was prominent, indicating that the movie caused a strong emotional reaction. This might be linked to its themes of isolation or being socially ignored. The star emoji ⭐ was frequently used to convey high expectations or approval, reflecting positive anticipation and likely contributing to the pre-release buzz. In contrast, the clown face emoji 🤡, directly representative of the 'Joker' character, was less frequently used, indicating its role was more symbolic but less central in the broader discussion prior to the release. The rest of the top-ranked emojis also indicate that audiences were looking forward to the movie. Overall, the entity analysis from tweets about 'Joker' shows a complex mix of social media interactions involving political, emotional, and promotional aspects. This blend of emotional reactions and thematic conversations highlights the strong impact 'Joker' has on various levels of social media discussion.

7.3.1.2 Entity Analysis of Weekly Trends Over Nine Weeks Post-Release of 'Joker'

Next, the entity analysis was conducted on each week of the nine weeks after the release date. The results were compared to identify if there were any changes or patterns in the discussion over the period. The hashtag analysis results are first presented below in Figure 49. The complete entity analysis results are shown in Appendix C.

Figure 49

Heatmap of Hashtag Weighted Frequencies Over the Weeks

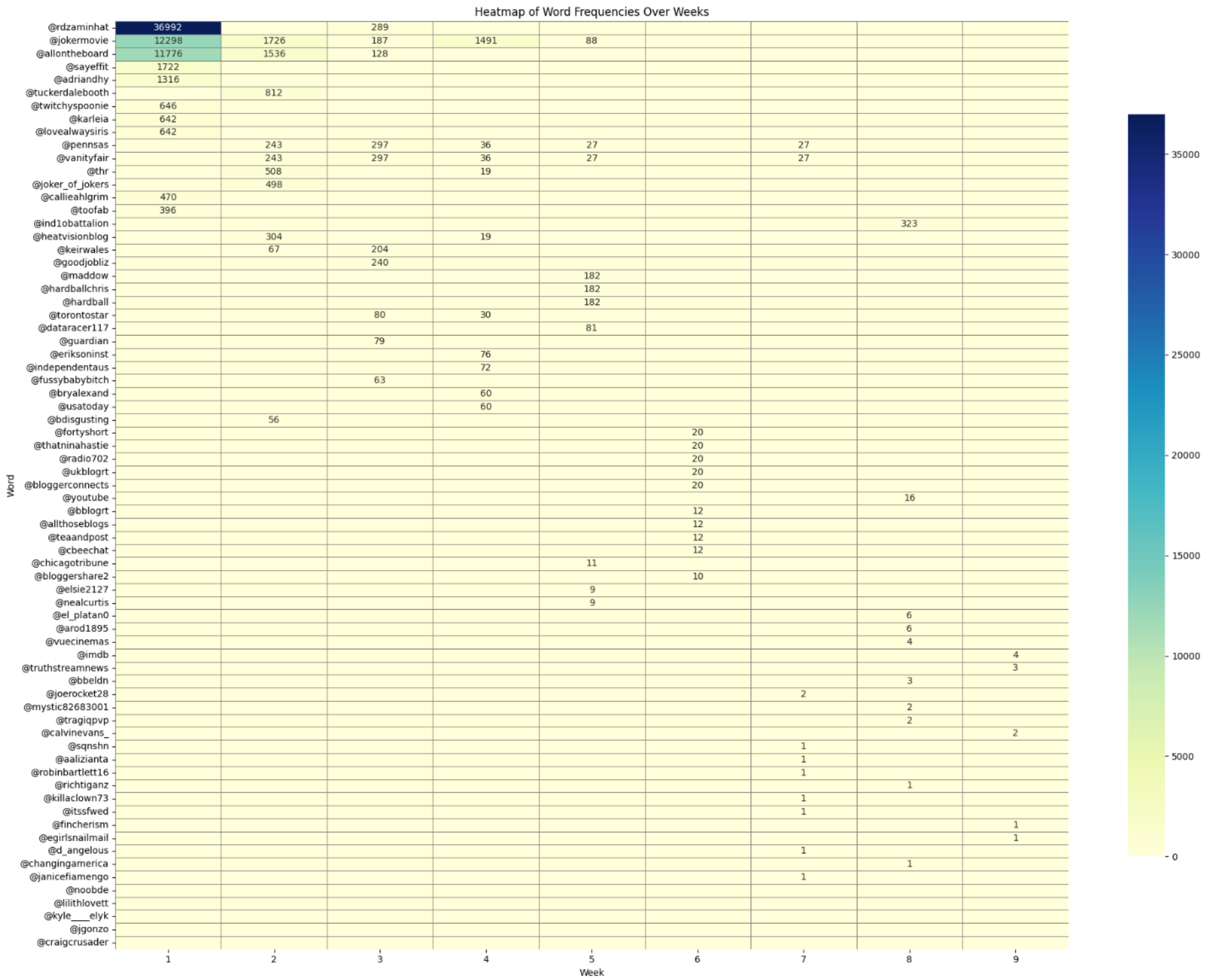


During the initial two weeks following the release of 'Joker', there is a pronounced emphasis on mental health-related hashtags. *#worldmentalhealthday* and its variants

(*#worldmentalhealthday2019*, *#mentalhealthawarenessday*) consistently appear with high weighted frequencies, suggesting robust engagement on these topics coinciding with the movie's thematic concerns about societal neglect and mental health issues. The presence of *#joaquinphoenix* remains strong, indicating ongoing discussions about his performance. In week 3 and week 4, a continued emphasis on mental health-related discussions was observed, with new topics such as *#mentalillness* and *#psychology*. The ongoing discussion on *#joaquinphoenix and the* presence of *#batman* indicates that discussions around the movie 'Joker' and its characters remain active. Additionally, new hashtags such as #movies and #moviereview reflect ongoing interest in the movie's reception and critiques. The new hashtag *#bestmovielineever* suggests that the movie was receiving positive feedback. By weeks 5 to 6, while the focus on mental health continues with *#mentalhealth* still appearing prominently, there's a noticeable diversification in the subjects of discussion. Hashtags like *#electronica* and *#rockmusic* emerge, possibly reflecting the influence of the movie's soundtrack on its audience or thematic promotional events. The consistency of *#jokerquotes* suggests a continued engagement with the movie's dialogue and key moments. In the final three weeks, there is a notable decline in the frequency and weighted impact of hashtags. While mental health remains a topic of discussion, the introduction of less related hashtags such as *#mpkbaliw* and a shift towards general content like *#movies* and *#moviereview* indicates a broadening of the context in which the movie is discussed. The emergence of specific content-related hashtags like *#therapy* and *#counselling* in week 9 points to a more focused discussion possibly on the therapeutic aspects of the movie's narrative or its impact on viewers. The hashtag trends show that initial concerns focused on mental health, which coincided with the movie's release and may have been amplified by the fact that it coincided with World Mental Health Day. The sustained discussion around Joaquin Phoenix's portrayal indicates a strong connection made by the audience with his character's depth and complexity. As the weeks progress, while the intensity of discussions wanes, the breadth of the topic expands to encompass aspects of the movie beyond its immediate narrative.

Figure 50

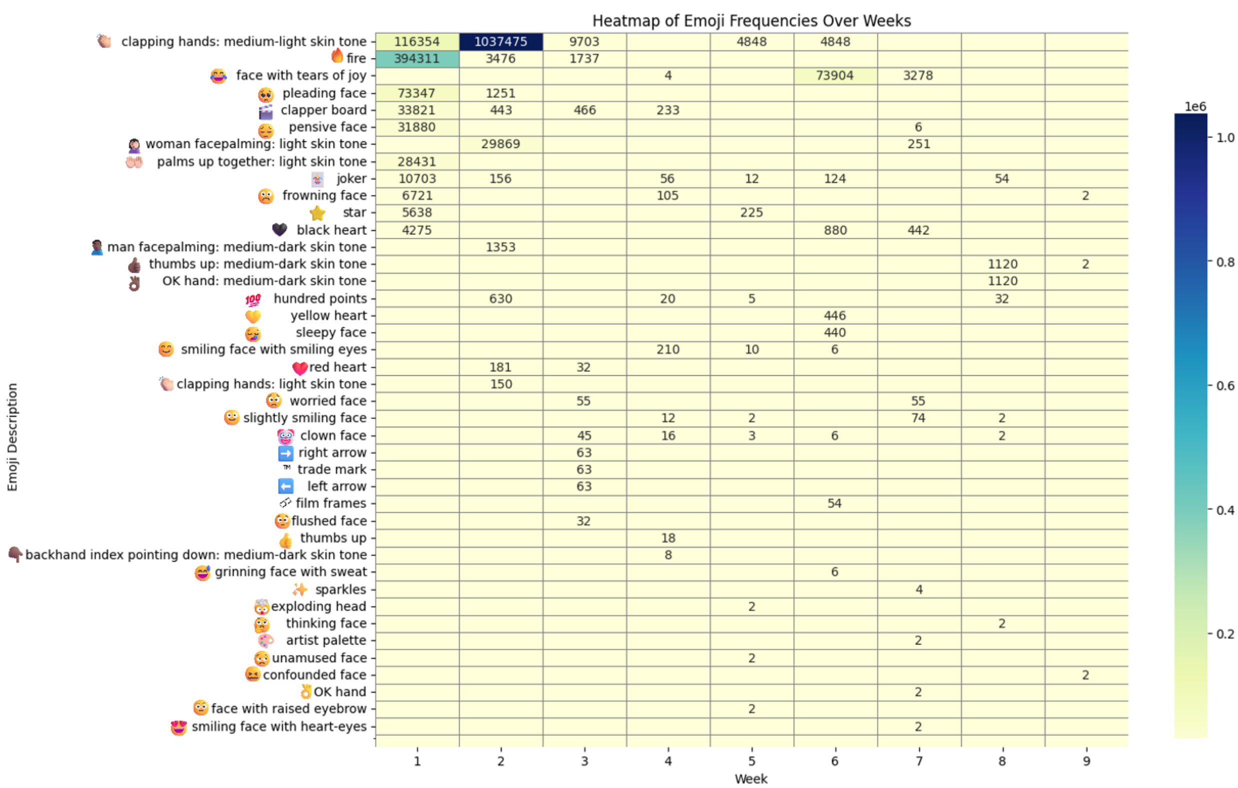
Heatmap of Mention Frequencies Over the Weeks



Secondly, the mention analysis was also conducted to identify the trends over the nine weeks after the movie’s release (Figure 51). The first three weeks show a concentration on highly influential accounts like *@rdzaminhat* and *@jokermovie*, reflecting robust engagement with content directly related to ‘Joker’ or influential personalities discussing the movie. Accounts like *@allontheboard* and *@sayeffit* also achieved high frequency, suggesting their thematic or promotional involvement which resonated with the audience. In week 3, mentions of traditional media outlets like *@torontostar* and *@guardian* began to appear, suggesting a shift towards broader media coverage and away from initial influencers. In week 4, the mentions of *@jokermovie* stabilised at 1,491, while new influencers and media accounts such as *@eriksoninst*, *@usatoday,* and *@independentaus* emerged. The presence of thematic accounts like *@heatvisionblog*, which focuses on entertainment technology, suggests discussions were branching into specific aspects of the movie's production or thematic elements. In the last three weeks, there is a noticeable decline in the frequency and impact of mentions, with a shift towards less directly related accounts. By week 9, mentions like @*imdb* and @*truthstreamnews* suggest a tapering of direct engagement, moving towards more generic or retrospective discussions about the movie. Over the course of the nine weeks, the trend moved from intensive, focused discussions of influential accounts and those directly related to the 'Joker', towards a broader, more dispersed discussion involving a variety of media outlets and thematic accounts.

Figure 52

Heatmap of Emoji Frequencies Over Weeks



Lastly, according to the emoji analysis (Figure 52), the first week shows a very high engagement with emojis, signalling strong emotional reactions to the movie's release. The 🔥 (fire) emoji leads, suggesting intense excitement or acclaim, while 🥺 (pleading face) indicates a significant emotional impact, likely resonating with the movie's darker themes. The frequent use of 🎬 (movie camera) and 😔 (pensive face) emojis highlights the thematic and emotional discussions surrounding the movie. Engagement remains high into the second week, with 👏🏻 (clapping hands with light skin tone) surging to the forefront, reflecting widespread applause or approval. The continued presence of 🥺 (pleading face) and a new entry, 🤦🏻‍♀️ (woman facepalming with light skin tone), might indicate mixed reactions or emotional complexity in audience responses. By the third week, emoji use declines but remains focused on specific sentiments. 👏🏻 (clapping hands with light skin tone) remains high, maintaining a theme of approval or celebration. The introduction of emojis like 😟 (worried face) and 🤡 (clown face), the latter possibly directly referencing the 'Joker', indicates ongoing thematic discussions. During weeks 4 to 6, the use of emojis further decreases. The 🎬 (movie camera) emoji remains somewhat consistent, suggesting ongoing discussions about the movie's content. Interestingly, 😂 (face with tears of joy) spikes in week 6, possibly indicating a shift towards more light-hearted or humorous reflections on the movie. The final three weeks see a substantial decline in emoji usage. Notable emojis include 😂 (face with tears of joy) and 🖤 (black heart), with the latter possibly denoting a deep affection for the movie that persists. The introduction of more niche emojis such as 🎨 (artist palette) and 🌻 (sunflower) in week 8 might reflect specific thematic discussions or community engagements that are less directly related to the movie.

7.3.2 User Network Analysis Results

7.3.2.1 Structure Analysis

A. Overall Structure

In this section, this study firstly examined the evolution of the user networks centred on discussions related to the 'Joker' movie over a span of nine weeks. The analysis focused on several key network properties: the total number of nodes and edges, average degree, clustering coefficient, network diameter, and the degree distribution's adherence to a power law. The results are shown in Table 30 and Figure 53.

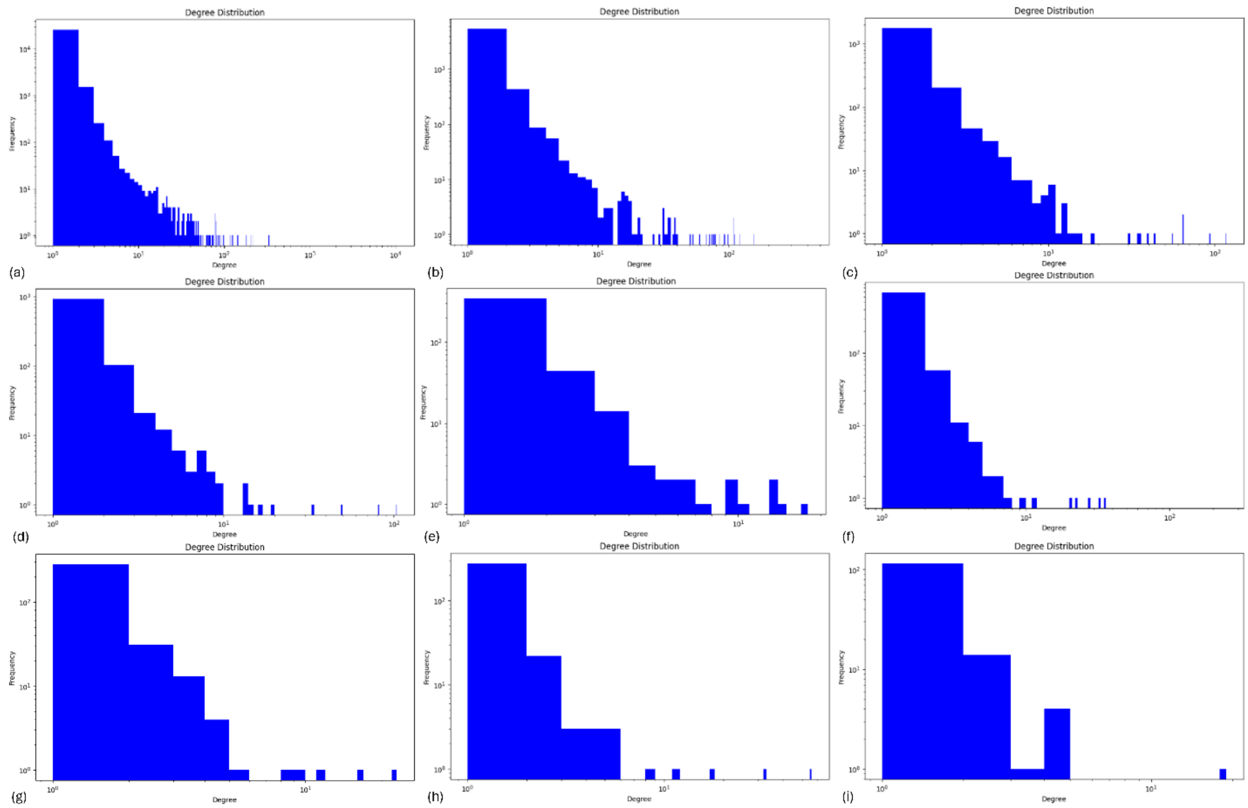
Table 30

Network Information

Network information	**Week 1**	**Week 2**	**Week 3**	**Week 4**	**Week 5**	**Week 6**	**Week 7**	**Week 8**	**Week 9**
Total number of nodes	31995	8093	3337	1561	713	1003	559	412	226
Total number of edges	27609	5467	1700	857	300	645	234	239	90
Average degree	1.72583	1.35104	1.01888	1.09801	0.84151	1.28614	0.83721	1.16019	0.79646
average clustering coefficient	0.00003	0.00038	0.00018	0.00032	0.00000	0.00000	0.00000	0.00000	0.00000
Diameter	1	2	1	2	1	1	1	0	1
Estimated alpha for power law fit	0.8494	1.0555	1.3689	1.2921	1.9696	1.0424	1.8544	1.1979	1.4991

Figure 53

Power-law Degree Distribution



Firstly, the results in

Table 30 show a significant drop in the number of both nodes and edges, from 31,995 and 27,609 in week 1 to 226 and 90 in week 9, respectively. This trend highlights a burst of activity around the release of the movie, followed by a rapid decline in user engagement. This pattern is indicative of event-driven spikes in social media networks, where initial excitement and discussion settle down after the peak of interest wanes. The decrease in the average degree over time with some fluctuations suggests that not only is the number of users decreasing, but also the overall degree of interconnectivity between these users is decreasing. The highest average degree of connectivity (1.72583) was observed in week 1, dropping to 0.79646 in week 9. The decrease in the average number of connections per user suggests that as the size of the network decreases, the remaining users tend to make fewer connections, possibly retreating into more closed conversations due to a decrease in general interest.

Secondly, the clustering coefficients are very low values across all weeks, approaching zero in the later weeks. This suggests that the network has a very sparse local clustering. This implies that users do not tend to form tightly knit clusters, and interactions are more spread out rather than concentrated among neighbouring nodes. In addition, the diameters vary slightly, with most being very low (1 or 2) and week 8 having a diameter of zero, which may be due to a disconnected or extremely sparse network. In such large networks, the low diameters indicate that the longest path between any two nodes is short despite the size of the network, which is typical of networks with extensive coverage but shallow interactions.

Lastly, according to the estimated α for power-law fit in

Table 30, the alpha values range from about 0.85 to nearly 2.0, indicating varying degrees of inequality in node connectivity. Lower values suggest a few nodes with very high connectivity compared to others, while higher values indicate a more uniform distribution of connections. The α values for most weeks are close to 1, suggesting that the structure of the corresponding user networks was heavily influenced by their hubs, which likely included key influencers or active individuals who significantly shaped the discourse. In contrast, weeks with higher alpha values (e.g., Week 5 with alpha = 1.9696) suggest a more evenly distributed connectivity, where influence was more democratically spread across a larger subset of users. However, overall, the power-law distribution in this period supports the notion of scale-free properties, which is common in social networks where few users or hubs dominate the interactions. The same pattern can also be seen in Figure 53. Most nodes have low degrees, and the frequency of node occurrences decreases rapidly as the degree increases, which closely follows a power-law distribution.

The evolution of these network properties over the course of several weeks highlights the transition from a highly active, event-driven online discussion to a more passive, sparsely connected one following the release of the movie. This trend may reflect the natural life cycle of interest in movie-related content on the web, whereby initial bursts of activity driven by anticipation and immediate reaction give way over time to less frequent, more reflective discussions.

B. Community Detection

The analysis of Twitter networks and community structures over nine weeks post the release of 'Joker' reveals a typical temporal dynamic evolution of event-driven public discourse (Figure 54). First, many isolated nodes are observed from each week's user network. While these individual Twitter users tweeted about the 'Joker' movie, they did not directly participate in the broader discussion network, nor were they retweeted by others. This may indicate that the users' various personal views or opinions were not relevant to the broader and more interactive community conversation. The presence of isolated tweets may also infer that not all tweets sparked further discussion or interaction. This may reflect a pattern where tweets either do not reach an audience ready to engage or are self-contained and do not require or trigger further interaction. Secondly, in terms of the evolution of the user networks, the initial three weeks show densely connected networks with one or several large central clusters. This high density likely indicates a strong, unified response to the movie's release, with discussions heavily centred around key themes such as its portrayal of mental health. As discussions mature, the networks start showing signs of fragmentation in week 4 to 6. This could be indicative of the audience branching out into more specific or diverse topics concerning the movie, possibly discussing various interpretations. The appearance of smaller, more numerous clusters suggests that new voices or less dominant themes are gaining traction. By the end of these weeks, the network becomes sparser and more decentralised. This pattern usually signals that the initial wave of interest has died down and the remaining discussion may be sustained by smaller, more focused groups.

Community detection (Figure 56) further illuminates this progression, showing a transition from a unified community to multiple dispersed groups by the study's end. In the first week, a high level of interaction among various communities, which were presented in different colours, focused on different aspects of 'Joker' and its depiction of mental health was identified. This suggests robust engagement across multiple demographics or interest groups. In week 2, the network remains relatively dense but begins to show signs of segmenting into smaller clusters. This may indicate the emergence of specialised discussions or divergent opinions as more viewers have seen the movie and began sharing their perspectives. As the weeks progress, further fragmentation is visible, with several smaller communities and more isolated nodes. This could reflect a declining interest in the topic as time passes, or the culmination of discussions as most salient points have been thoroughly explored.

These patterns further illustrate the typical lifecycle of social media discussions following a high-impact event like a major movie release. Early discussions are likely driven by immediate reactions and widespread interest, which gradually diversify into more specialised topics or diminish as public interest shifts to new subjects.

Figure 55

User Network Evolution Over Nine Weeks

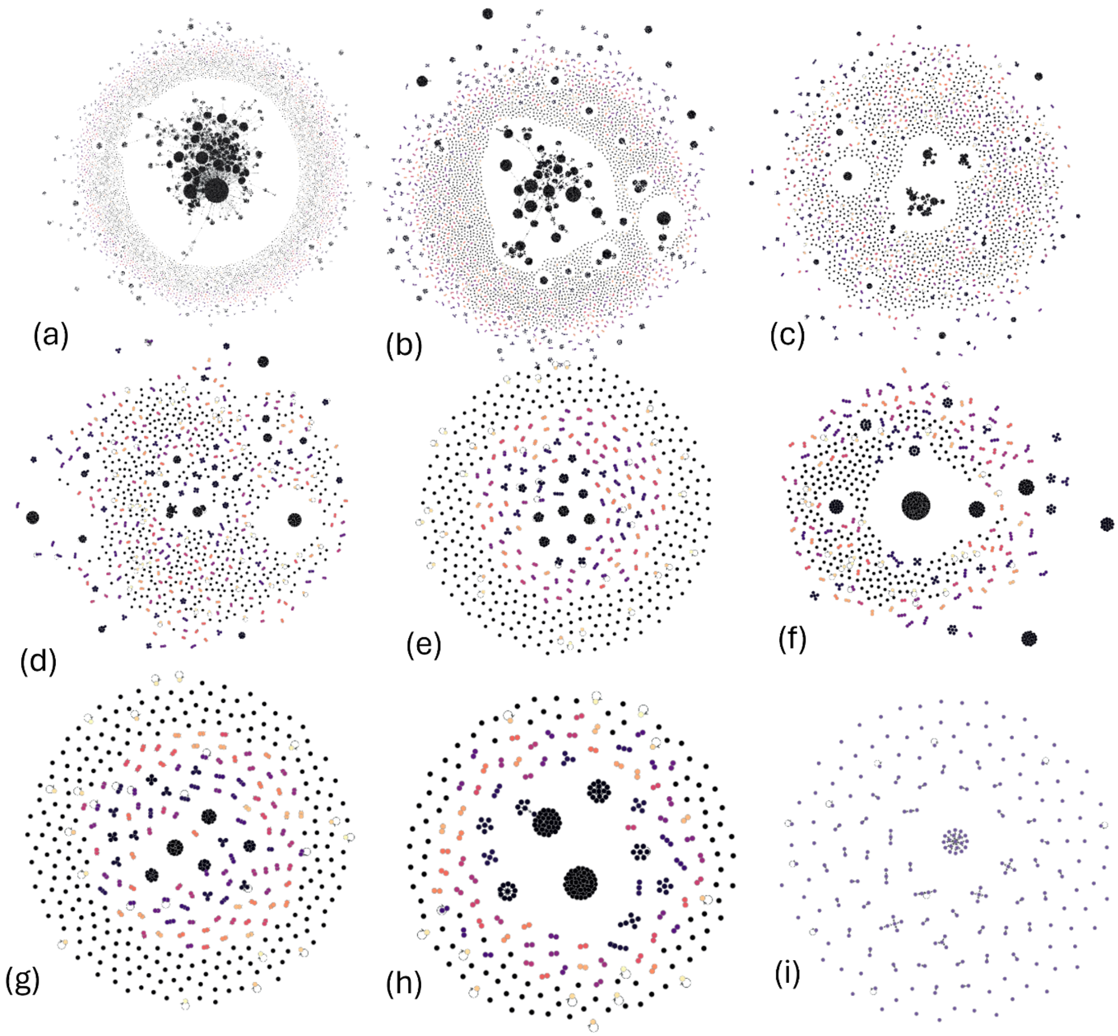
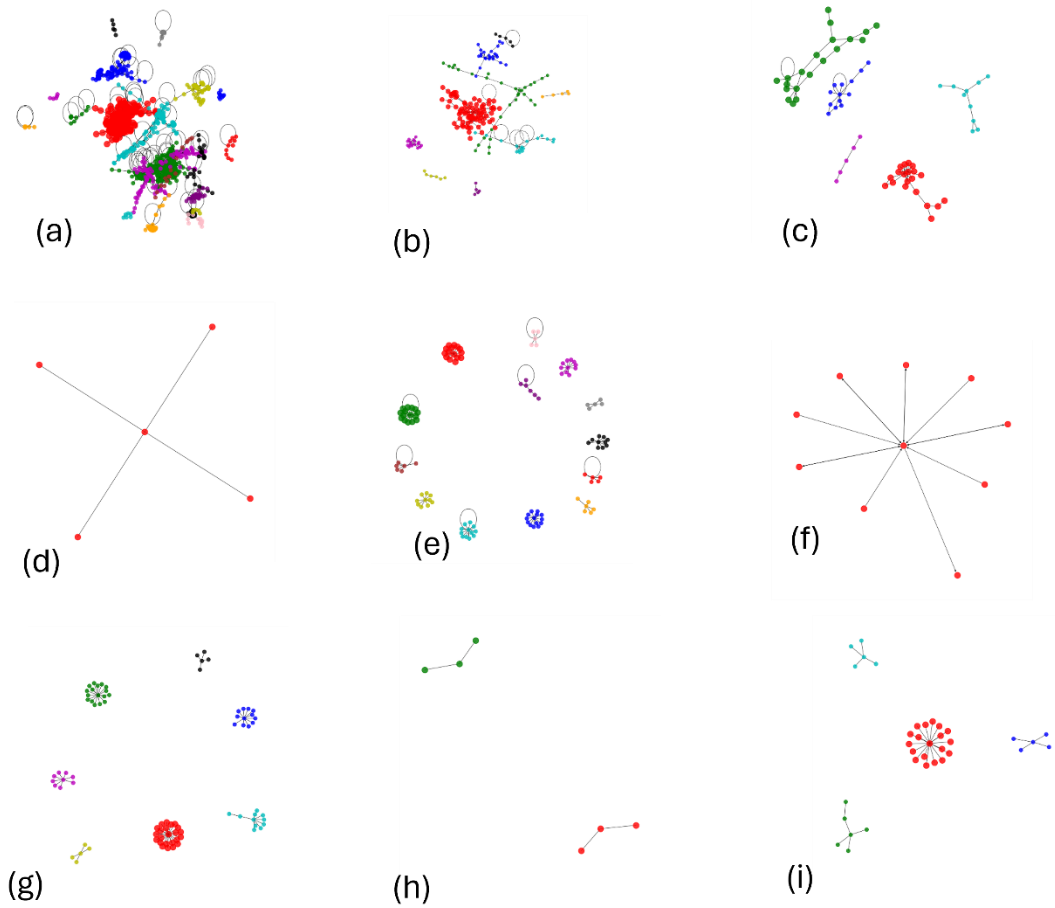


Figure 56

Community Detection Results for Each Week from Week 1 (a) to Week 9 (i)


(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)
(i)

7.3.2.2 Key Players Identification

Table 31

Key Players for Each Week

Centrality Metrics	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9
Weighted Out-Degree	__3tharii	andreacompton	guardian	levelupdub	HotPaperComics	AaronBastani	TheLivingHeru	judeblay	aaminahiss s
Weighted Outward Closeness	__3tharii	andreacompton	guardian	levelupdub	HotPaperComics	AaronBastani	TheLivingHeru	judeblay	aaminahiss s
Weighted In-Degree	phantomx1313	phantomx1313	Keirwales	mat_aurelio	UnwantedLife_Me	UnwantedLife_Me	SeanEubanks001, StateOfReds13, UnwantedLife_Me	Hello_Tailor, bbepodagency, sisinife, Astral52, Btdocs	rudyglove27
Weighted Katz Centrality	phantomx1313	phantomx1313	Keirwales	mat_aurelio	UnwantedLife_Me	UnwantedLife_Me	SeanEubanks001, StateOfReds13, UnwantedLife_Me	Hello_Tailor	rudyglove27
Betweenness Centrality	__3tharii	Keirwales	Keirwales	mazatx	UnwantedLife_Me	UnwantedLife_Me	DrSolonyus	bbepodagency, ctab82485789	Nick_Hausman

Throughout the nine weeks following the release of 'Joker', certain Twitter users stood out as key influencers, information disseminators or connectors in generating discussions about the movie. Using weighted out-degree and weighted outward closeness centrality measures, the network analysis revealed key influencers for each week (Table 31). In the first two weeks, *_3tharii* and *andreacompton* were identified as the most influential moviegoers. Their tweets highlighted a quote from the movie about mental illness, “The worst part of having a mental illness is people expect you to behave as if you don't.” Their tweet not only sparked a heated conversation, but also created an emotional connection with the audience, demonstrating their ability to tap into the movie's core message. By the third week, *guardian* became a key influencer, posting a tweet about the dangerously misleading portrayal of mental illness in the ‘Joker’. This user’s tweet presented a critical viewpoint that introduced a more analytical and controversial angle to the discussion, sparking further debate and discussion. In the fourth week, *levelupdub* defended the movie's portrayal of mental illness and trauma, arguing that critics may need a deeper understanding of these issues. The most influential figures identified in the fifth week and seventh week were *HotPaperComics* and *theLivingHeru*, respectively, according to the user network analysis. Both of them offered a personal interpretation of the causes of mental health, with *HotPaperComics'* viewpoints on societal expectations and *LivingHeru's* focus on childhood trauma. Their central position in the user networks may be because their opinions resonated with other moviegoers and then deepened their associations and reflections on the subject of mental health.

In week 6, *AaronBastani* attracted a great deal of attention for his humorous critique of the movie's social structure through the mockery of the movie's content. As the weeks progressed, week eight’s *judeblay* began to steer the conversation by criticising *Vue's* decision to continue screening the movie despite people's concerns and accusing it of being insensitive to the movie's impact on mental health discussions and wider social issues. Finally, in week 9, *aaminahisss* was the most influential user with the same movie quote as the one most quoted in weeks 1 and 2, suggesting that this quote remained an important part of the conversation around the movie as the heat of the other topics faded.

This development highlights the key role played by different influencers in the narrative around the ‘Joker’ movie. They were effective in engaging different movie audiences in discussions about the movie during its release.

In addition to key influencers, the user network analysis adopted weighted in-degree and weighted Katz centrality to identify key information disseminators who, by referencing tweets from other users, became the focus for receiving and disseminating important content about the ‘Joker’. In the initial two weeks, *phantomx1313* showed strong inward activity in both metrics, highlighting a consistent role in actively reaching out. This suggests that *phantomx1313* was a central disseminator of information, initiating numerous interactions that could quickly reach many parts of the network. *Keirwales* and *mat_aurelio* emerged as influential in weeks 3 and 4, respectively, indicating that they made significant contributions to disseminating information or exerting influence during this period. *UnwantedLife_Me* played a central role in spreading information about the ‘Joker’ from week 5 to 7. Its consistent influence suggests a stable central position in the network communication structure. In weeks 7 and 8, the active nodes diversified significantly. During week 7, several new influencers appeared and in addition to *UnwantedLife_Me*, *SeanEubanks001* and *StateOfReds13* became the main disseminators of information in the users' network. After that, the task of active information dissemination was taken up by *Hello_Tailor*, *bbepodagency*, and others in week 8, followed by *rudyglove27* in week 9.

Lastly, the user network analysis adopted the betweenness centrality metric to identify crucial connectors or bridges within the network. These nodes are instrumental in facilitating the flow of information across the network discussing 'Joker', indicating their strategic importance in maintaining connectivity and flow within the network structure.

In the first week, *_3tharii* was considered a key bridge, and he was also considered the most influential user of the first week. These two critical roles confirmed that he resonated with different audience groups by quoting lines from the ‘Joker’ movie. *Keirwales* took on this bridging role in the second and third weeks, and this continuity demonstrates their strong position in the network. Moreover, he or she became the most critical messenger in week 3, which indicates his or her shift to a primary channel for the efficient flow of information. By the fourth week, *mazatx* emerged as the central bridge, suggesting a shift in the network’s dynamics. In weeks 5 and 6, the roles of gatekeeper and information disseminator were both overtaken by *UnwantedLife*_M. Their recurring role indicates that they were central in not just receiving and disseminating information but also in connecting conversations that might otherwise have remained isolated within the network. The seventh week saw *DrSolonyus* stepping in as a significant bridge. In the eighth week, the network’s bridging function was shared among *bbepodagency* and *ctab82485789*, highlighting a week of particularly diverse and possibly fragmented discussions that required multiple nodes to connect various threads effectively. The analysis wrapped up in the ninth week with *Nick_Hausman* serving as the key bridge.

7.3.3 Semantic Network Analysis Results

7.3.3.1 The Development of Semantic Networks

In the semantic network analysis, the retweets and quotes from the data were removed to avoid the replication of information and biases in the analysis. Search terms of the movie's name 'Joker' and its main topic 'mental health' were also removed from the original tweets datasets because predominant words are highly likely to link all the other words together into a single group, which may distort the results. In addition, the semantic network analysis was conducted based on the occurrence of bigrams, which are pairs of words in a tweet. As a pilot study, the trigrams and bigrams were both adopted to test their ability to extract the major concepts from the discourse on the movie 'Joker'. The results were compared and showed that while bigram analysis identified several clear and relevant concepts such as '*mental illness*', '*worst part*', '*joaquin*, *phoenix*', etc., the concepts identified by trigram analysis kept showing the same sub-concepts. For example, from the bigram analysis and trigram analysis of week 1, presented in Table 32, among the top 20 trigrams, the phrase "*mental health*" appeared ten times while it only appeared once in the results of the bigram analysis. Therefore, the use of bigrams is more effective in identifying the most mentioned or discussed concepts related to the movie 'Joker'.

Table 32

Bigram Analysis and Trigram Analysis of Week 1

Week 1	**gram2**	**count**	Week 1	**gram3**	**count**
1	(mental, illness)	3934	**1**	(mental, illness, people)	1380
2	(illness, people)	1381	**2**	(illness, people, expect)	1338
3	(people, expect)	1343	**3**	(part, mental, illness)	1333
4	(part, mental)	1333	**4**	(worst, part, mental)	1319
5	(worst, part)	1323	**5**	(people, expect, behave)	1294
6	(expect, behave)	1301	**6**	(people, mental, illness)	109
7	(joaquin, phoenix)	445	**7**	(jokermovie, worst, part)	84

8	(arthur, fleck)	165	**8**	(behave, arthur, fleck)	84
9	(comic, book)	119	**9**	(expect, behave, arthur)	83
10	(people, mental)	116	**10**	(expect, behave, jokermovie)	77
11	(mentally, ill)	109	**11**	(mental, illness, not)	74
12	(last, night)	105	**12**	(portrayal, mental, illness)	68
13	(new, movie)	88	**13**	(mental, illness, society)	66
14	(behave, arthur)	86	**14**	(thing, mental, illness)	65
15	(jokermovie, worst)	84	**15**	(movie, mental, illness)	61
16	(go, see)	82	**16**	(mental, illness, but)	59
17	(behave, jokermovie)	77	**17**	(expect, behave, dont)	57
18	(illness, not)	75	**18**	(expect, behave, worldmentalhealthday)	47
19	(movie, but)	71	**19**	(mental, illness, violence)	45
20	(portrayal, mental)	68	**20**	(worst, thing, mental)	45

In the first week, the discussion was dominated by direct references to the movie and its lead actor, '*Joaquin Phoenix'*, along with the thematic discussion of 'mental illness'. Bigrams like "*go, see*" and "*movie, but*" in the initial two weeks and later weeks again point to the fact that moviegoers had different views on the movie, including recommendations and conditional critiques. Since the third week, a diversification of discussion topics can be observed, indicating that moviegoers started to reflect on the movie from different aspects after watching it. There is a noticeable emergence of bigrams like "*depiction, mental*" and "*dangerously, misinformed*" in the third week, suggesting a shift towards critiquing the movie's messages and its informational content concerning mental health. In the fourth week, the emergence of bigrams including "*white, men*", "*need, female*", "*female, reboot*" and "*reboot, woman*" indicate that moviegoers were perhaps at that point comparing the movie ‘Joker’ with other movies. In week 5, the new bigrams such as “*comment, thread*” and “*blog, post*” emphasise the emergence of more detailed reviews and critiques being shared via blogs, reflecting a move towards more formalised discussions and critiques. Specifically, "*accurate, portrayal*" indicates a shift towards evaluating the accuracy of how mental health issues are depicted in the movie, suggesting viewers are critically assessing the representation. In week 6, the discussion still focused on review points indicated by bigrams such as "*reviewed, point*" and “*point, view*". Notably, the appearance and sustained mention of terms related to critiques ("*view, criticisms*," "*justified, unfair*") suggest a potential discussion on the movie’s societal impact and the fairness of its portrayals. In week 7, the new bigrams such as “*finally, watched*” reflects more viewers were commenting on the movie after watching it, leading to potentially more informed and personal reactions. In addition, specific appreciations were expressed through the new bigrams like "*thought, provoking*" and " *big, screen*" in week 7. In week 8, the bigrams *“tattooed, forehead”* and "*illness, tattooed*" could point to discussions on specific scenes or characters where mental illness is visually represented, adding another layer to the critique of the movie’s portrayal. The bigram "*blue, story*" in week 8, and "*dark, disturbing*" and "*watching, stop*" in week 9 highlight a view that finds the movie’s themes or scenes to be sad, unsettling and intense. Throughout the nine weeks, "*mental illness*" and its related bigrams, as well as the movie line *(“illness, people”, “people, expect”, “part, mental”, “worst, part”, “expect, behave”*) consistently appear in the discussions, highlighting the central role this theme played in public discourse around the movie. The discussion evolved from an initial focus on character “*arthur, fleck*” and actor "*Joaquin, Phoenix*" to deeper debates about the movie’s societal messages and its portrayal of fairness ("*justified, unfair*"). This indicates a shift in public engagement, from reactive to reflective, as viewers had more time to digest and discuss the movie’s content. In addition, while the volume of discussion decreases over time, the sustained presence of specific themes in later weeks highlights that the movie continued to deeply engage viewers, prompting ongoing debates about its more controversial aspects.

The results from the bigram analysis were also confirmed by the top words with the highest degree centrality in the corresponding semantic networks (Figure 58). The terms "*movie*," "*mental*," and "*illness*" form the backbone of the discussion throughout the nine weeks, emphasising the central theme of mental health in public discourse related to the movie. The consistent mention of "*phoenix*" across the weeks highlights the strong impact of Joaquin Phoenix’s portrayal of the lead character, which remained a focal point of discussions. The evolution from immediate terms like "*see*" and "*think*" to more reflective terms such as "*issues*," "*watching*," and "*comment*" in later weeks suggests a transition from initial reactions to more thoughtful and sustained engagements.

This ongoing conversation reflects the movie's profound impact on perceptions of mental health and the complexities of its depiction in popular media.

Figure 57

Heatmap of Bigrams Over the Weeks

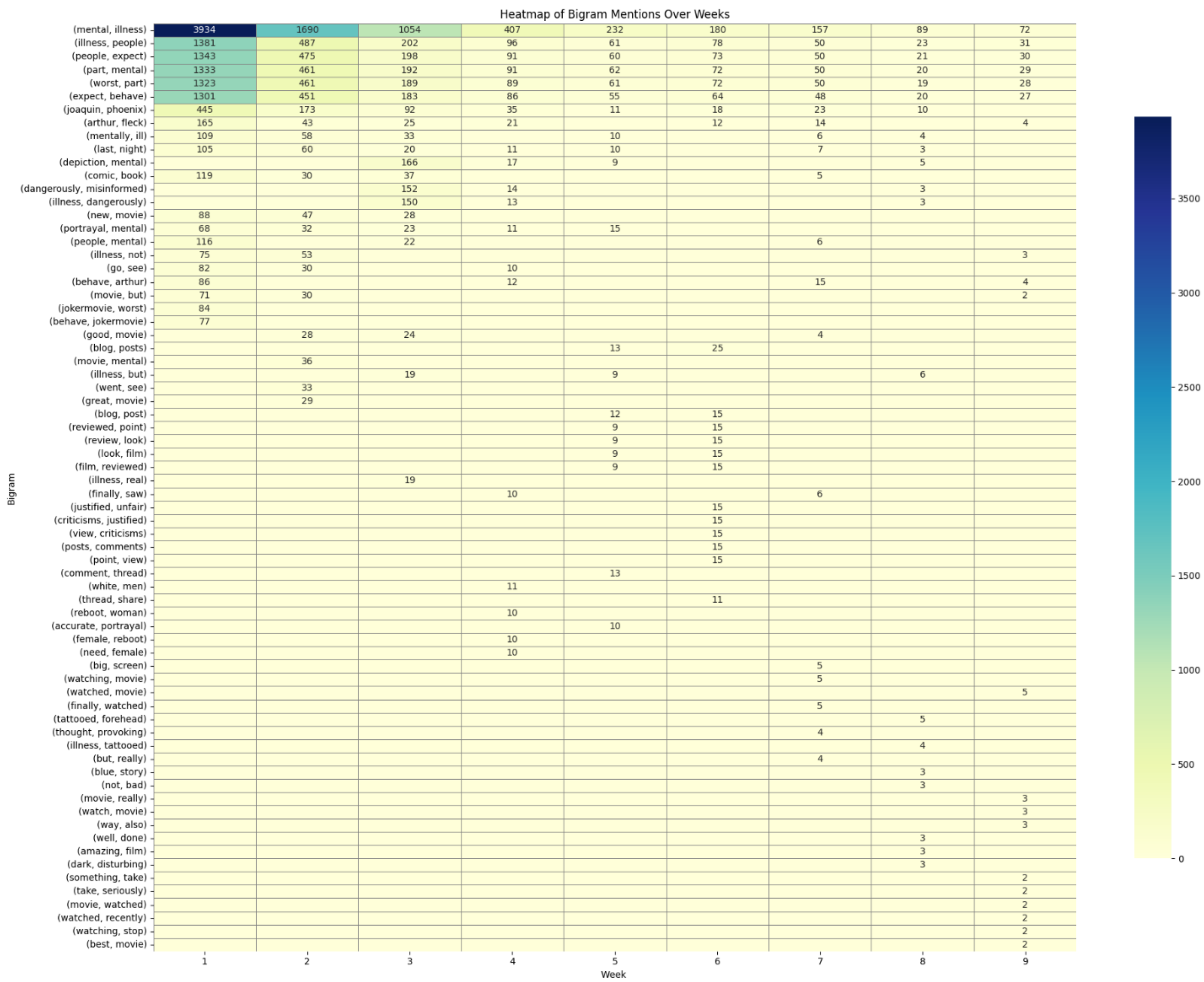


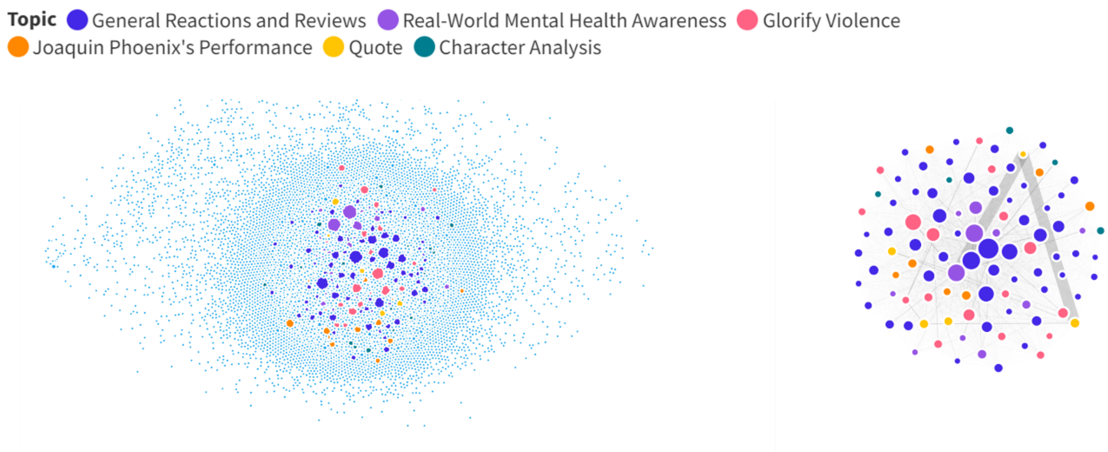
Figure 58

Top Words with the Highest Degree Centralities Over the Weeks

7.3.3.2 SA on the Topics Detected

Figure 59

Semantic Network of All Bigrams (left), and Community Detection Results of Top 100 Words (Right)



SA of tweets related to 'Joker' over the nine weeks following its release reveals the complexity and evolution of the audience response. By examining sentiment trends over these weeks, the study can identify specific patterns and changes and gain an understanding of how moviegoers' emotions about various aspects of the movie have evolved over time. The semantic network of all bigrams for the first week is shown on the left side of Figure 59. Due to the large size of the network and limited computing power, the top 100 words with the highest degree of centrality were extracted for community analysis, and the result is shown on the right side of Figure 59. The visualisation of the semantic network and its community detection results for other weeks are shown in Appendix D. After community analysis and SA, the sentiments of topic communities are summarised for each week, which is shown in Table 33. A detailed distribution of sentiment is presented in Appendix D, which shows the proportion of tweets expressing negative, neutral and positive sentiment.

Table 33

SA by Community of Each Week

Week	*Topic*	*Average Sentiment*	*Average Sentiment Label*
W1	Character Analysis	1.5156	Positive
	General Reactions and Reviews	1.4826	Neutral
	Glorify Violence	0.4542	Negative
	Joaquin Phoenix's Performance	1.8720	Positive
	Quote	1.0994	Neutral
	Mental Health Issues and Its Portrayal in the movie	1.6509	Positive
W2	Character Analysis	1.3297	Neutral
	General Reactions and Reviews	1.4286	Neutral
	Joaquin Phoenix's Performance	1.9052	Positive
	Mental Health Issues and Its Portrayal in the movie	1.4593	Neutral
	Quote	1.1883	Neutral
	Viewing Experience	1.6444	Positive
W3	Character Analysis	1.2090	Neutral
	Joaquin Phoenix's Performance	1.6581	Positive
	Mental Health Issues and Its Portrayal in the movie	1.1824	Neutral
	Misrepresentation of Mental Health	0.0247	Negative
	General Reactions and Reviews	1.4756	Neutral
	Quote	1.2000	Neutral
	Viewing Experience	1.6321	Positive
W4	Character Analysis	1.3542	Neutral
	General Reactions and Reviews	1.5039	Positive
	Joaquin Phoenix's Performance	1.7091	Positive
	Mental Health Issues and Its Portrayal in the movie	1.2454	Neutral

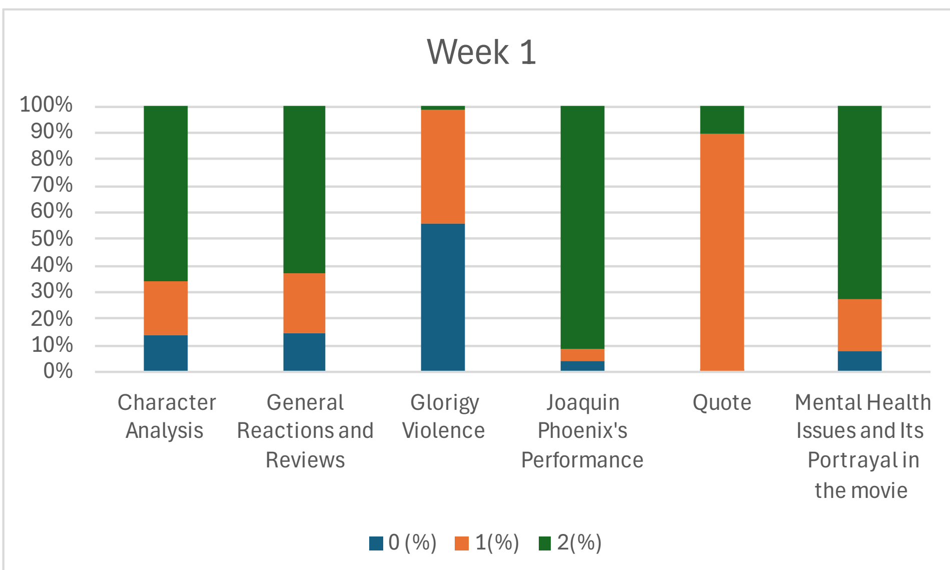
	Misrepresentation of Mental Health	0.3871	Negative
	Quote	1.1889	Neutral
W5	Character Analysis	1.4017	Neutral
	General Reactions and Reviews	1.0789	Neutral
	Joaquin Phoenix's Performance	1.9167	Positive
	Mental Health Issues and Its Portrayal in the movie	1.1467	Neutral
	Quote	1.1311	Neutral
	Blogging and Social Media Engagement	1.0714	Neutral
W6	Blogging and Social Media Engagement	1.0222	Neutral
	General Reactions and Reviews	1.4262	Neutral
	Joaquin Phoenix's Performance	1.8235	Positive
	Mental Health Issues and Its Portrayal in the movie	1.2877	Neutral
	Quote	1.1111	Neutral
W7	Character Analysis	1.3684	Neutral
	General Reactions and Reviews	1.2414	Neutral
	Joaquin Phoenix's Performance	1.7742	Positive
	Mental Health Issues and Its Portrayal in the movie	1.3423	Neutral
	Quote	1.0400	Neutral
	Viewing Experience	1.5263	Positive
W8	General Reactions and Reviews	1.2241	Neutral
	Joaquin Phoenix's Performance	1.5484	Positive
	Mental Health Issues and Its Portrayal in the movie	0.8846	Neutral
	Quote	1.0476	Neutral
W9	Character Analysis	1.1333	Neutral
	General Reactions and Reviews	0.9355	Neutral
	Joaquin Phoenix's Performance	1.5870	Positive
	Quote	1.0323	Neutral

A. Week-by-Week SA

Positivity dominated the first week. The moviegoers' comments on topics of *Character Analysis, Joaquin Phoenix's Performance* and *Real-World Mental Health Awareness* were all positive. Many viewers praised Arthur Fleck's complex character and Joaquin Phoenix's brilliant performance. Many appreciated the movie's realistic portrayal of mental health issues and found Arthur's descent into madness both tragic and fascinating. However, even in the early stages, there were some concerns about the movie's depiction of violence and its potential to glorify negative behaviour (*Glorify Violence*). Initial positive reviews suggest that the movie was a great success in its initial stages, with high levels of audience engagement.

Figure 60

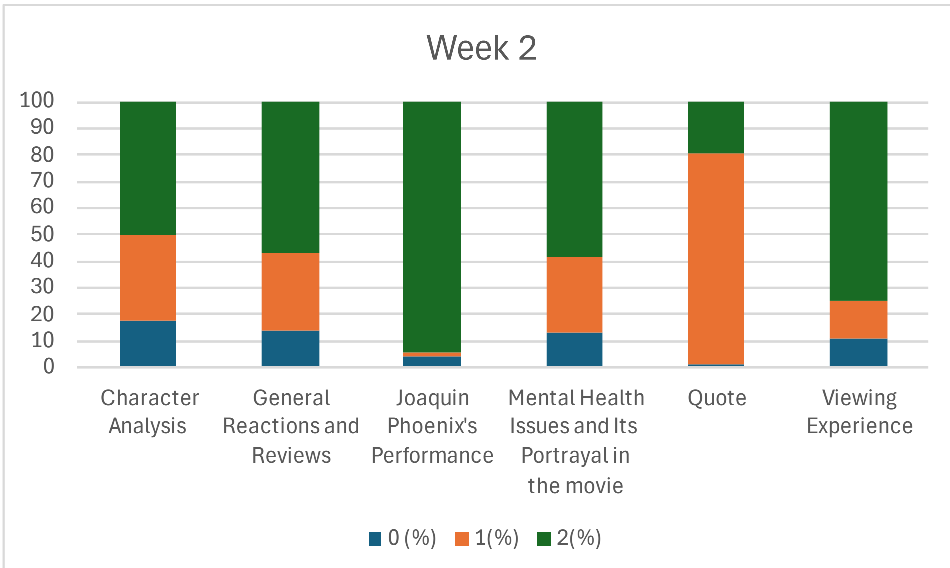
Sentiment Distribution Across Topics for Week 1



In week 2, audience reviews remained largely positive but began to show signs of diversification. While *Joaquin Phoenix's Performance* continued to be praised, more viewers started to show different insights into the movie's pacing and thematic content. This week marked the beginning of a trend where neutral and critical voices became more prominent. Viewers began to question the movie's handling of sensitive topics, and concerns about the portrayal of mental health became frequent. This suggests that as the movie's audience grew broader, evaluations of the movie became more complex and critical.

Figure 61

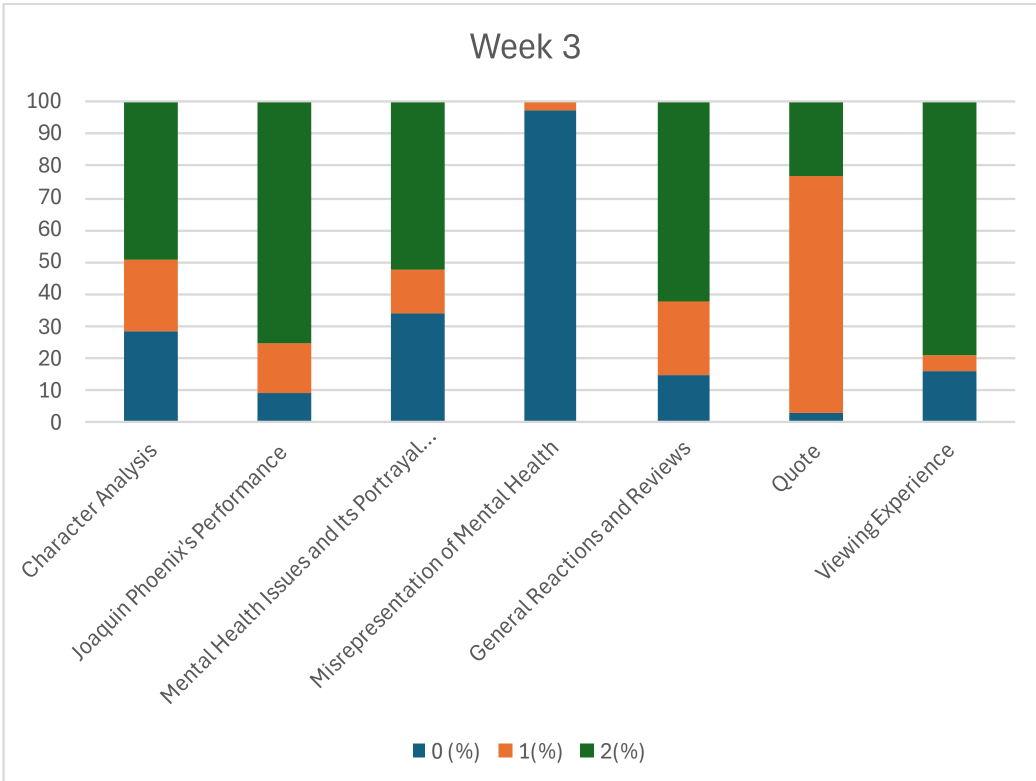
Sentiment Distribution Across Topics for Week 2



By the third week, the mood of the audience had changed significantly. While Phoenix's portrayal of the 'Joker' continued to receive favourable reviews, the depiction of mental health issues led to growing awareness and concern about the movie's social impact. The topic of *Misrepresentation of Mental Health* was identified by the community detection and divided from the topic of *Mental Health Awareness and Its Portrayal in the Movie*. They criticised the movie's narrative for oversimplifying mental health issues and likely reinforcing harmful stereotypes. This week marked a turning point, with moviegoers posting more comments about the potential negative impact of the movie, reflecting a deepening of audience engagement and critical analysis.

Figure 62

Sentiment Distribution Across Topics for Week 3



Week 4 continued this trend of growing criticism, particularly regarding the *Misrepresentation of Mental Health.* The overall sentiment became more polarised, with strong opinions both for and against the movie. Positive sentiments still acknowledged the movie's artistic achievements and Phoenix's performance, but the volume of neutral and negative feedback increased. Viewers increasingly expressed discomfort with the movie's dark themes and its potential to mislead or stigmatise mental health issues. This polarisation suggested that while the movie was still generating significant discussion, it was also provoking strong, divided reactions.

Figure 63

Sentiment Distribution Across Topics for Week 4

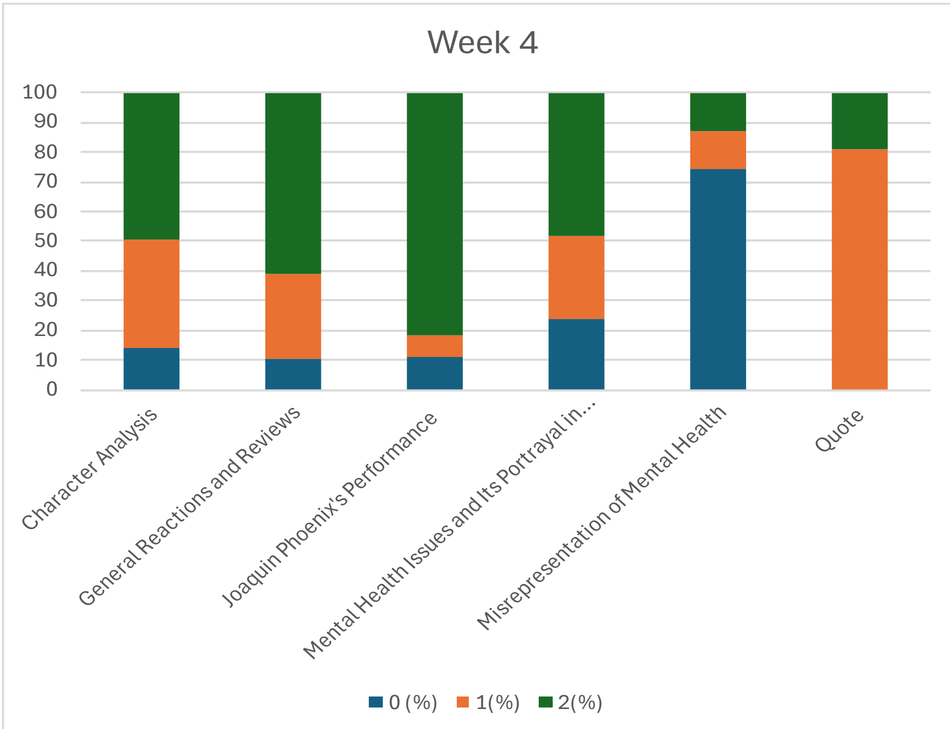
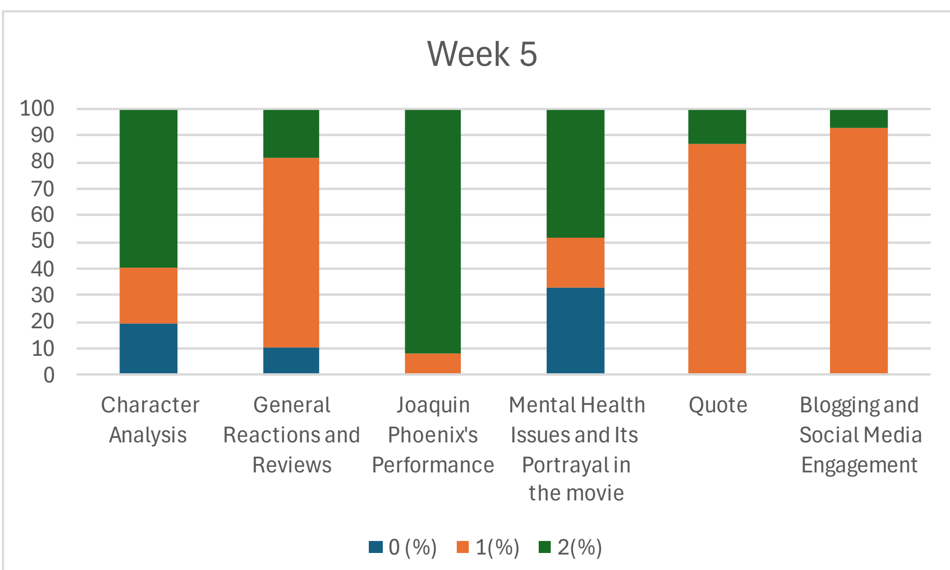


Figure 64

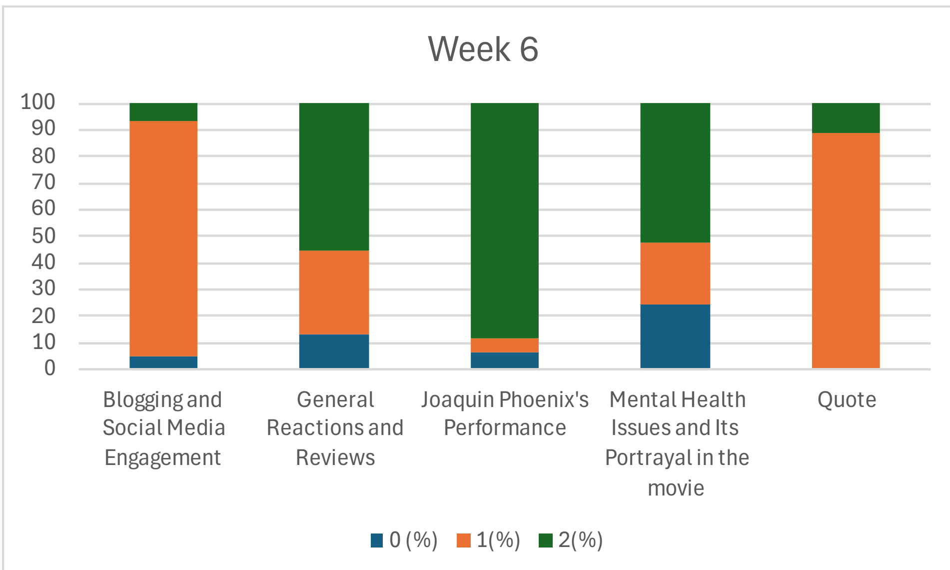
Sentiment Distribution Across Topics for Week 5



In the fifth week, the emotional distribution reflected a more balanced and critical perspective. Whilst the artistic merit of the movie and Phoenix's performance continued to be praised, the portrayal of mental health issues continued to be a controversial topic, with a significant amount of negative feedback about the movie's potential to misrepresent mental health conditions and its overall disturbing tone. The increase in neutral sentiment suggests that moviegoers were still having a balanced discussion as they weighed up the movie's strengths and controversial elements. This period marked a shift towards more reflective and nuanced audience engagement.

Figure 65

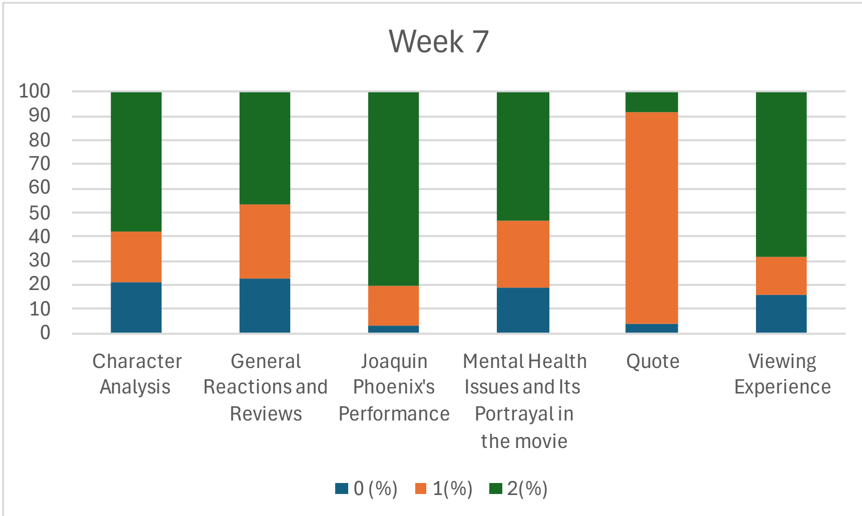
Sentiment Distribution Across Topics for Week 6



In week 6, overall positive sentiment continued to decline, with neutral sentiment dominating the discussion. Social media and blogs played an important role in maintaining the movie's visibility, with discussions tending to emphasise the movie's impact. However, the portrayal of mental health issues , continued to be the focus of criticism. Many felt that the movie was misrepresenting mental health issues by linking them to violence, making the situation more difficult for real-life people with mental health problems.

Figure 66

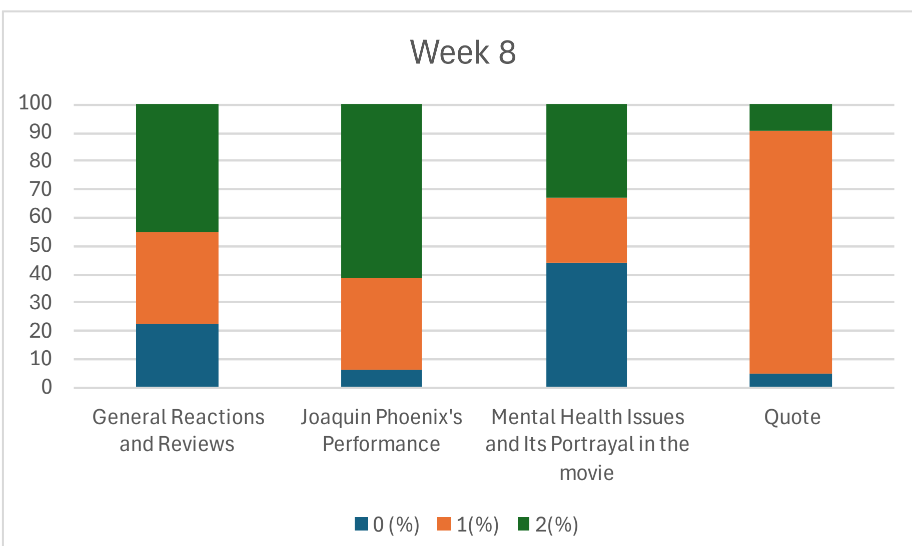
Sentiment Distribution Across Topics for Week 7



By week 7, sentiment trends indicated a further stabilisation of opinions. Positive reactions to Phoenix's performance remained, but overall sentiment is predominantly neutral. Viewers continue to express concern about the movie's portrayal of mental health issues. Criticism focused on potential negative stereotypes and the tense, disturbing nature of the movie. The distribution of sentiment reflects a mature and critical approach to audience engagement, recognising both the artistic merit of the movie and its controversial subject matter.

Figure 67

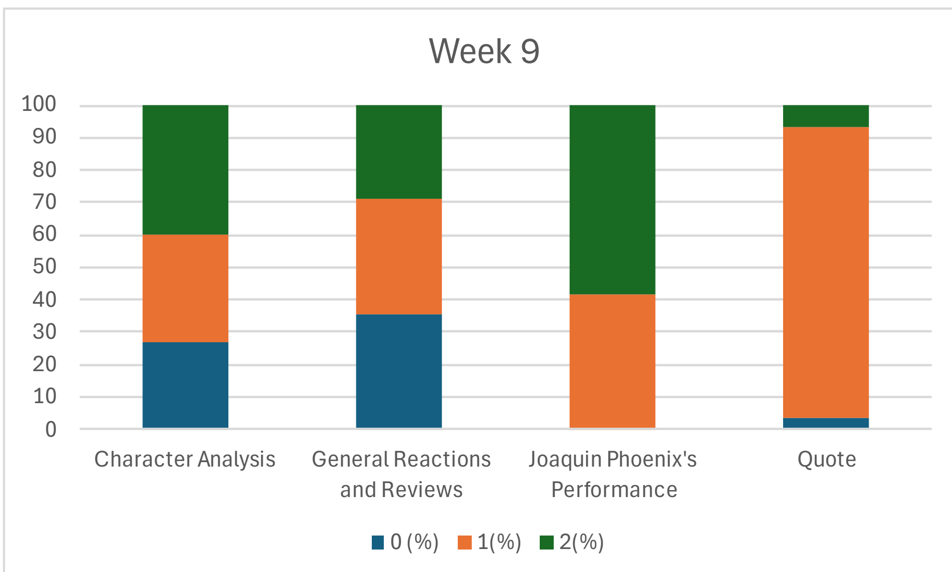
Sentiment Distribution Across Topics for Week 8



In week 8, sentiment analyses showed a steady increase in neutral and negative sentiment. Positive reactions weakened, while growing concerns about the movie's impact on societal perceptions of mental health. The portrayal of mental health issues remained a significant point of contention, with viewers divided over its effects and potential harm. This period marked a continuation of the critical and reflective discussions that had emerged in previous weeks.

Figure 68

Sentiment Distribution Across Topics for Week 9



By week 9, sentiment had largely stabilised to a neutral stance. Positive comments on Phoenix's performance were consistently positive, but the overall assessment had become more balanced and nuanced. Concerns about the movie's portrayal of mental health issues were prominent, which suggests a lasting impact on viewers' perceptions. The discussion has matured into a comprehensive review that reflects the complexity of the movie's themes and its social impact.

B. Comparative Analysis of Sentiment Trends Based on Topics

The first topic is *Character Analysis*. In the first few weeks, analyses of the character focused on the complexity and depth of Arthur Fleck's transformation into the ‘Joker’. Positive emotions dominated, with moviegoers appreciating the movie's nuanced portrayal of Arthur's mental health struggles and social neglect. Twitter often praised the movie for portraying Arthur as a relatable and tragic figure. Over time, perceptions changed considerably. While the depth of Arthur's character continued to be recognised, the negativity began to become more prominent. An increasing number of more viewers expressed dissatisfaction with the sympathetic portrayal of a character caught up in violence. By week 3, viewers began to criticise the moral issues involved in portraying such a troubled character in a relatable manner. The audience's concern that Arthur Fleck's violent behaviour might generate idolatry or sympathy became stronger. In later weeks, the audience's mood stabilised and their view of the character of Arthur Fleck became more balanced. Positive sentiments persisted but were tempered by constant criticism. Audience participation evolved into deeper reflection on the moral and ethical implications of the movie. By week 9, the character analysis demonstrated a mature dialogue in which the audience weighed the movie's artistic intent against its potential social impact.

The second topic is *General Reactions and Mixed Reviews*. Within weeks of its release, the movie ‘Joker’ received strong reactions and buzz from moviegoers who used the word ‘masterpiece’ to describe it. Many different aspects of the movie, including the storytelling, the acting, the powerful social message, and the technical aspects of the cinematography and soundtrack were well received by its viewers. However, starting around the second week, opinions became more balanced. While many still appreciated the movie's artistic qualities, some felt that the pacing was slow and that the movie did not quite meet their expectations. By week 5, this category had become more diverse and critical. Discussions began to focus on the movie's controversial themes and their impact on society. In addition to issues such as excessive hype, negative sentiments highlighted the movie's dark tone, which some found difficult to accept. The graphic content was also a point of contention, with some viewers feeling it was excessive and not handled responsibly. This trend continued with mature and mixed reactions in Week 7, ranging from praise for the movie's artistic achievements to critical comments on its content.

The third main topic is *Joaquin Phoenix’s Performance*. Throughout the filming period, Joaquin Phoenix's performance was consistently praised. From the very beginning, his portrayal of the ‘Joker’ was universally praised for its depth, intensity and emotional range. While positive reviews remained high, neutral and negative reviews increased slightly over time. Some viewers found Phoenix's performance too disturbing or difficult to accept. At the end of the nine weeks, Phoenix's performance was still praised by most. This shows that Phoenix's performance was seen as the best element of the movie, even though other aspects of the movie received more criticism.

The fourth topic is *Mental Health Awareness and Its Portrayal in the Movie*. In the first few weeks after its release, the movie was largely praised for raising awareness of mental health issues. Positive reviews highlighted that the movie realistically portrayed Arthur's struggles and the social neglect he faced. Moviegoers appreciated the movie's role in sparking important conversations about mental health. However, criticisms increased as time went on. By week 3, viewers began to worry that the movie might misrepresent mental health issues. Negative sentiment criticised the movie for oversimplifying complex situations and perpetuating harmful stereotypes. By week 5, there were additional concerns about the movie glorifying negative behaviour as a response to mental health struggles, which was seen as irresponsible and potentially harmful. These concerns continued to grow, with viewers expressing unease about the movie's portrayal of mental illness and its potential impact on public perception. By week 9, the dialogue had evolved into a debate about the responsibility of filmmakers in portraying sensitive topics, highlighting the need for accurate and empathetic representation.

The fifth main topic is *Misrepresentation of Mental Health*. From the outset, the misrepresentation of mental health was a major point of contention. The criticism was most intense in the third and fourth weeks of the movie's release, which was identified by the community detection analysis as a separate hot topic of discussion. In the other weeks, it was presented as a part of Mental Health Awareness and Its Portrayal in the Movie topic. Viewers' primary concern was that the movie's association of mental illness with violence was irresponsible and had the potential to perpetuate the harmful stereotypes of people with mental illness in real life.

The sixth most discussed topic is *Quotes*. Over the nine weeks, quotes from the movie were widely shared and appreciated, especially the quote “The worst part of having a mental illness is people expect you to behave as if you don't.” Positive and neutral sentiments prevailed as viewers reflected on memorable and impactful dialogue. However, moviegoers also debated the appropriateness and impact of some quotes, reflecting a deeper engagement with the movie's themes. The discussion around quotes remained predominantly neutral, suggesting a steady but reflective engagement.

The next major topic is *Viewing Experience*. The viewing experience was recognised as a more prominent topic in weeks 2, 3 and 7, with the underlying audience sentiment towards the viewing experience being positive. Viewers praised the movie as immersive and engaging, with many calling it an unforgettable experience. However, negative comments about the viewing experience began to increase as time progressed. The criticism centred on the movie's disturbing content and the emotional toll it took on viewers. Some found the graphic content and dark themes of the movie unacceptable and detracted from their overall enjoyment of the movie.

The last topic is *Blogging and Social Media Engagement*. This topic was identified in weeks 5 and 6, with an overall neutral but slightly negative sentiment of 1.07 and 1.02, respectively. This category includes tweets about the movie's presence and discussion on social media platforms and blogs. Positive tweets highlighted the high level of engagement the movie generated on social media and noted that the movie was popular and sparked conversations. Negative tweets criticised the nature of online reactions to the movie, particularly those that downplayed serious themes or sought attention through controversial content.

7.3.4 The Impact of Social Media Buzz on Movie Performance

7.3.4.1 Data Exploratory Analysis

For the purpose of evaluating the relationship between the social media buzz surrounding the movie 'Joker' and its performance, a SARIMA analysis was performed. The user network analysis was conducted on the tweets of each day to obtain the daily social network metrics. The daily sentiment score was also generated by averaging the sentiment of all tweets per day. This thesis defines the daily metrics from the network analysis and SA as social media metrics. The results of the SARIMA analysis are presented as follows.

Table 34

Descriptive Statistics

	count	*mean*	*min*	*max*	*std*
daily	64	5175600	131115	39350693	7708859
theatres	63	3103	1146	4374	1196
total_nodes	64	799	22	12051	1846
total_edges	64	589	8	10988	1626
average_degree_centrality	64	0.0083	0.0002	0.0346	0.0081
average_closeness	64	0.0038	0.0001	0.0152	0.0036
average_betweenness	64	0.0000	0.0000	0.0001	0.0000
average_edge_betweenness	64	0.0002	0.0000	0.0019	0.0004

average_eigenvector	64	0.0114	0.0000	0.0703	0.0151
average_katz	64	0.0847	0.0091	0.2132	0.0516
clustering_coefficient	64	0.0001	0.0000	0.0027	0.0005
density	64	0.0042	0.0001	0.0173	0.0040
sentiment	64	1.2793	0.8235	1.6349	0.1907

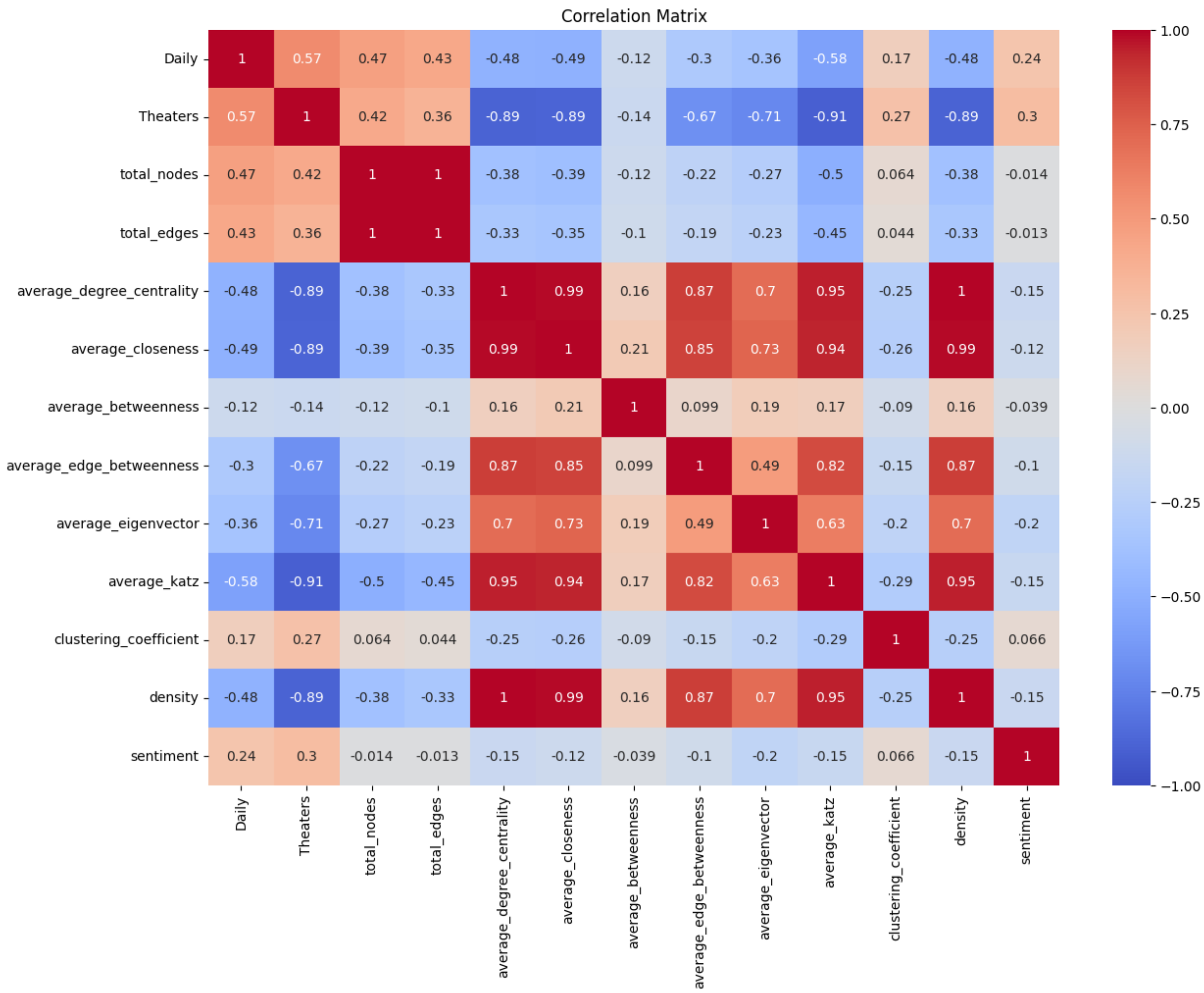
First, according to the descriptive statistics in

Table 34, the dataset comprises 64 observations. There is a considerable variation in daily box office revenues with a mean of $5175600.1250 and a standard deviation of $7708858.97, suggesting significant disparities in movie earnings. Regarding the *Theatres* variable, there are 63 observations with an average count of 3,103.49 theatres. The number of theatres ranges from a minimum of 1,146 to a maximum of 4,374 and a standard deviation of 1,195.60. The social networks analysed show a wide range of sizes, with an average of 798.59 nodes and 588.81 edges, and standard deviations of 1,845.90 and 1,625.56, respectively. This suggests that the degree of network connectivity varies from one observation to another. Network metrics further reveal a low degree of connectivity and centrality, with average degree centrality at 0.0083 and closeness centrality at 0.0038, both exhibiting minimal standard deviations (0.0081 and 0.0036, respectively), which points to sparse connectivity within the networks. Similarly, low betweenness centrality (mean = 0.000002) and edge betweenness (mean = 0.000199) indicate the absence of dominant bridging nodes or edges that control information flow. The eigenvector centrality averages 0.0114, with a standard deviation of 0.0151, indicating a lack of concentrated influence across the networks. The Katz centrality has an average value of 0.085, implying moderate node influence within the networks. The clustering coefficient and network density, with means of 0.000144 and 0.0042, respectively, further corroborate the overall sparsity and lack of tightly knit clusters within these networks. Collectively, these statistics illustrate a landscape of loosely connected and structurally diverse networks surrounding the movie ‘Joker’. Finally, the *Sentiment* variable has an average value of 1.279252 with a standard deviation of 0.190665, ranging from 0.823529 to 1.634906. The variation in sentiment might reflect differing opinions or reactions to the movie 'Joker' within the social networks.

A correlation analysis was also performed to assess the correlation between the social media metrics and daily box office, and the results are shown in Figure 69.

Figure 69

Correlation Matrix of Variables

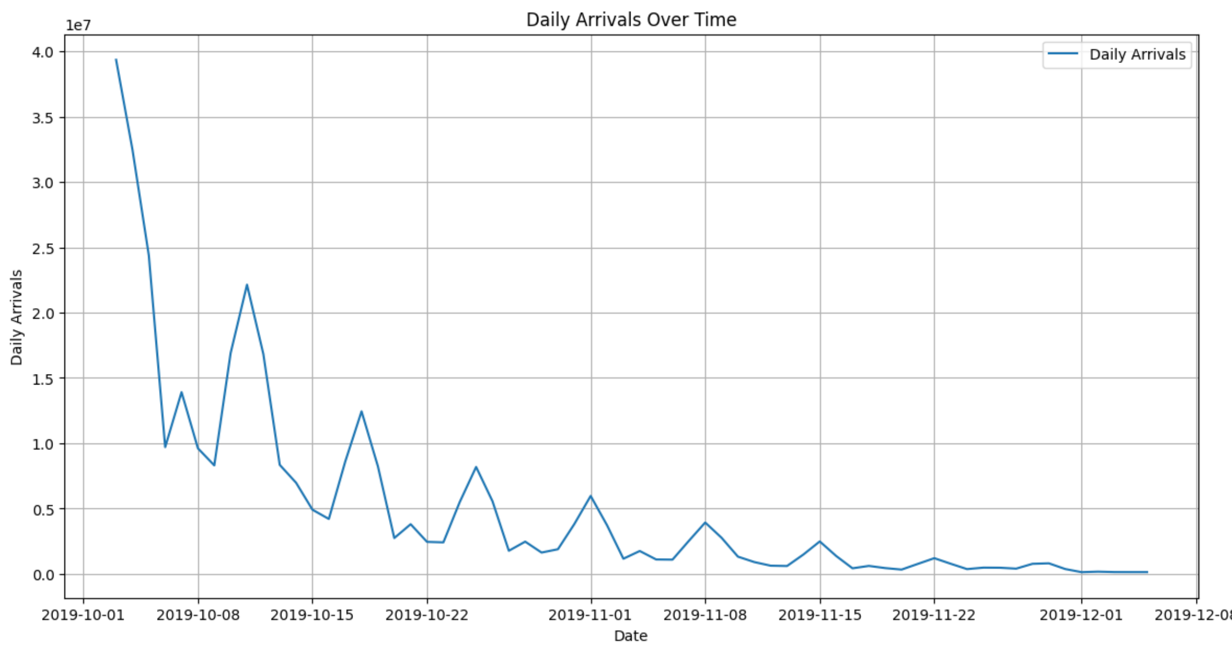


The correlation between *daily* and other variables shows a mix of positive and negative relationships. Notably, there is a moderate positive correlation between *daily* and *theatres* (0.57), indicating that an increase in the number of theatres is associated with higher daily box office. Similarly, *Daily* shows moderate positive correlations with *total nodes* (0.47) and *total edges* (0.43), suggesting that larger and more connected social networks are linked to higher daily box office. The correlation between *daily* and *sentiment* is comparatively weak but also positive, which indicates that the greater the tendency for people to go and see the movie after reading the online review, the more likely it is that the next day's movie box office will increase. In the meantime, some social network metrics show negative correlations with daily box office. *Average degree centrality* (-0.48) and *average closeness* (-0.49) both exhibit moderate negative correlations, indicating that higher centrality and closeness within the network are associated with lower daily box office. Additionally, the average Katz centrality (-0.58) shows a strong negative correlation with *daily*, further supporting the notion that centrality metrics might inversely relate to the number of daily box office.

7.3.4.2 Stationarity Testing of Daily Box Office Revenues

Figure 70

Time Series Plot of Daily Box Office Revenues



As shown in Figure 70, the time series plot of daily box office revenues shows a significant decline over time. Initially there is a sharp peak, indicating a high level of daily revenue at the beginning of the observation period. This is followed by a rapid decline in box office revenues, with subsequent fluctuations becoming less pronounced over time. The overall trend shows a decline in daily revenues, suggesting that the initially high revenues quickly diminish. This also indicates that the data is likely non-stationary and require differencing to make the series stationary. Therefore, the parameter of the non-seasonal differencing is defined as 1. The Autocorrelation Function (ACF) and PACF plots are presented in Figure 71 to illustrate the temporal dependencies within the time series. The ACF plot shows significant positive autocorrelation at the initial lag, which gradually decreases over subsequent lags. This pattern indicates that the daily revenues are correlated with their past values, but the strength of this correlation diminishes over time. The observation suggests that the moving average order (q) might be 1 or 2. The PACF plot also exhibits significant spikes at the initial lags, suggesting the presence of autoregressive components in the time series. The result indicates that the autoregressive order (p) might be 1 or 2. Therefore, the non-seasonal parameters are (p,d,q)=(1,1,1) or (2,1,2).

Figure 72

ACF and PACF Plots

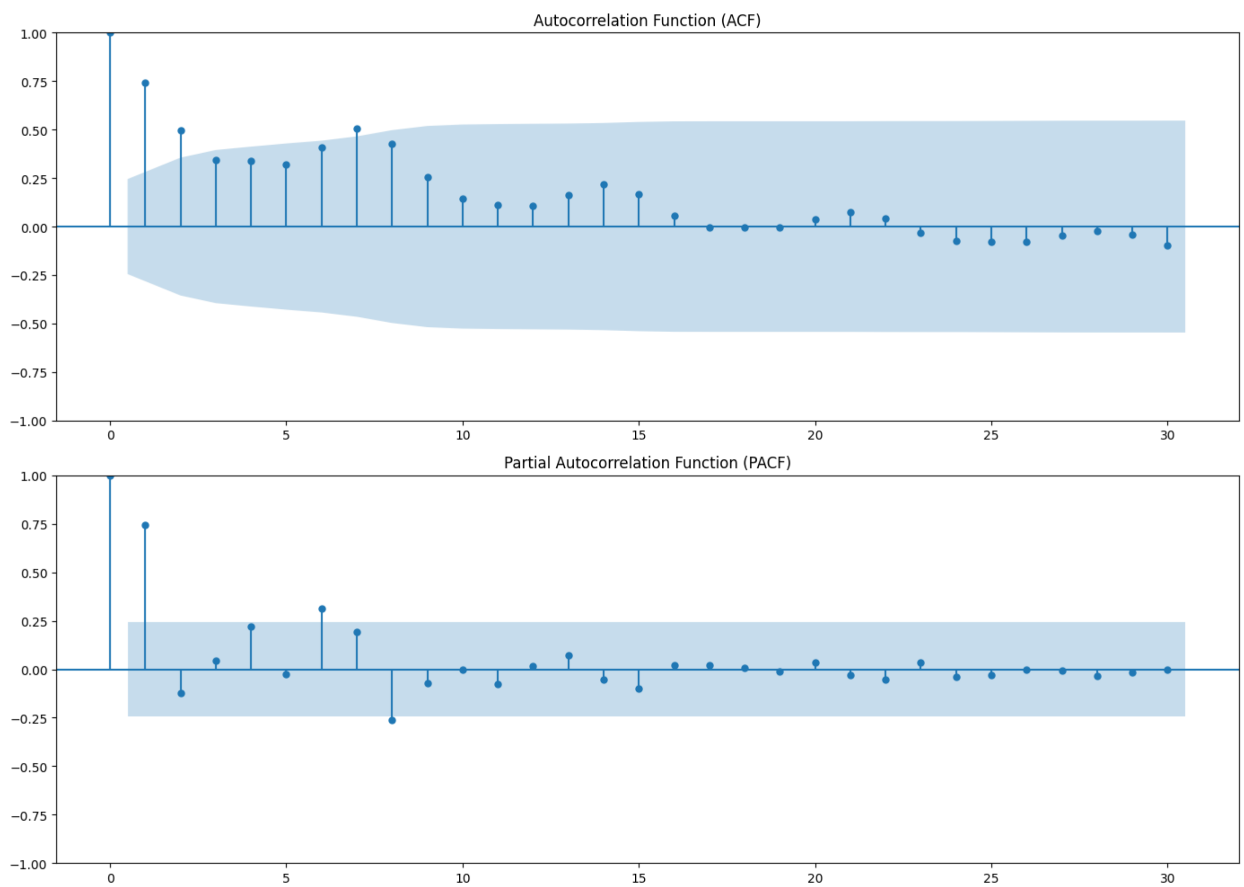
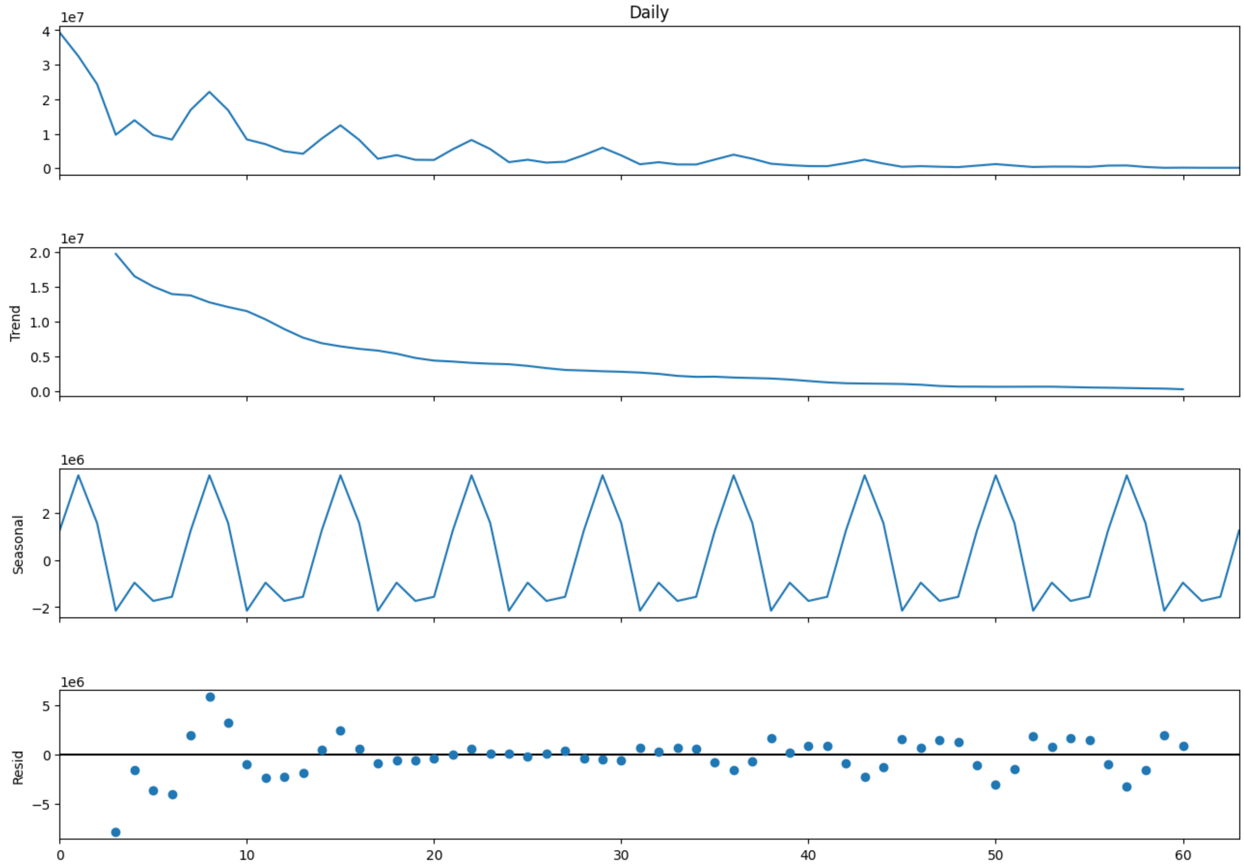


Figure 73

Seasonal Decomposition of the Time Series



As shown in Figure 73, the seasonal decomposition of the time series breaks down the daily revenues into trend, seasonal, and residual components. The trend component shows a clear downward trajectory, aligning with the overall decline observed in the time series plot. The seasonal component shows recurring weekly patterns that indicate possible weekly cyclical effects affecting daily revenues. In terms of the residual component, which captures the irregular fluctuations not explained by the trend or seasonal components, appears to be relatively stable. This means that the primary variations are captured by the trend and seasonal components. According to the seasonal decomposition results, the seasonal order parameters can be defined as: (P,D,Q,s)=(1,1,1,7).

After the seasonal decomposition, the Augmented Dickey-Fuller (ADF) test was conducted to assess the stationarity of the time series after the first-order differencing step. The results of the ADF test are as shown in Table 35.

Table 35

ADF Test Results

ADF Statistic	*-4.7415*
p-value	0.0001
Critical Values	
1%	-3.5602
5%	-2.9179
10%	-2.5968

The ADF test results indicate that the null hypothesis of non-stationarity can be rejected at the 1%, 5%, and 10% significance levels. The ADF statistic is significantly lower than the critical values and the p-value is considerably smaller than 0.05, suggesting that the time series is stationary. This finding is essential for time series modelling, as stationarity is a prerequisite for many forecasting models, including SARIMA. According to the results from the stationary test, the appropriate SARIMA model parameters are as follows:

- Non-seasonal parameters: (p,d,q)=(1,1,1) or (2,1,2) based on the significance of initial lags in the ACF and PACF.
- Seasonal parameters: (P,D,Q,s)=(1,1,1,7)

7.3.4.3 Results Interpretation

The Seasonal Autoregressive Integrated Moving Average with eXogenous regressors (SARIMAX) model results provide a detailed view of the relationship between various independent social media metrics (social network metrics and sentiment) and the daily box office revenue. The detailed results of the SARIMAX(1, 1, 1)x(1, 1, 1, 7) model are shown in Table 36.

Table 36

SARIMAX Results

	coef	*P>|z|*	*Effect Size z |r|*

total_nodes	-1.11E+04	0.0000	0.360
total_edges	1.12E+04	0.0000	0.390
average_degree_centrality	1.00E+14	0.0000	0.062
average_closeness	-1.36E+08	0.0000	0.088
average_betweenness	1.17E+10	0.0000	0.016
average_edge_betweenness	2.50E+08	0.0000	0.120
average_katz	-8.66E+06	0.0000	0.170
clustering_coefficient	-4.78E+08	0.0000	0.076
density	-2.01E+14	0.0000	0.062
sentiment	5.36E+05	0.0000	0.040
ar.L1	0.8879	0.0000	
ma.L1	-0.9886	0.0000	
ar.S.L7	0.2313	0.2700	
ma.S.L7	-0.0717	0.7190	
sigma2	1.60E+12	0.0000	

The coefficient for *total_nodes* is negative (coef. = -1.11E+04, p-value = 0.00 <0.05), indicating that an increase in the total number of nodes in the social network is associated with a decrease in daily box office revenues. This implies that a larger network might lead to more fragmented or less engaged audiences. When many users are talking about the movie without significant interaction, it may dilute the overall impact, leading to less effective word-of-mouth marketing. In contrast, the coefficient for *total_edges* is positive (coef. = 1.12E+04, p-value = 0.00 <0.05), which indicates that as the number of total edges increases, the daily box office revenue increases. More edges indicate stronger and more frequent interactions among users. This suggests that an engaged audience, actively discussing and sharing content about the movie, positively influences others to watch the movie, thus boosting revenue.

The variable *average_degree_centrality* has a significant positive coefficient (coef. = 1.00E+14, p-value = 0.00 <0.05). This indicates that higher average degree centrality(where nodes have more connections) within the network strongly correlates with higher daily revenues. When key influencers or well-connected individuals talk about the movie, their influence spreads widely, driving more people to theatres. However, the *average_closeness* has a negative coefficient (coef. = -1.36E+08, p-value = 0.00 < 0.05), meaning that higher average closeness is linked to lower daily revenues. This means that when nodes are closer to each other in terms of shortest path lengths, box office revenues tend to decrease. This might imply that in networks where information spreads too quickly and uniformly, the impact might be less effective in driving sustained box office performance.

The coefficient for *average_betweenness* is positive (coef. = 1.17E+10, p-value = 0.00 <0.05), indicating a positive relationship with daily revenues. Higher average betweenness centrality, which reflects nodes acting as bridges or intermediaries in the network, is associated with higher daily revenues. This highlights the role of nodes that connect different parts of the network, facilitating information flow and potentially increasing movie attendance. Similarly, *average_edge_betweenness* has a positive and significant coefficient (coef. = 2.50E+08, p-value = 0.00 <0.05). This suggests that key connections within the network ensure that promotional content reaches various segments of the audience, thereby increasing box office revenue. In contrast, *average_katz* has a negative coefficient (coef. = -8.66E+06, p-value = 0.00 <0.05), indicating that higher average Katz centrality, which measures the influence of nodes considering the entire network, might not be beneficial for box office revenues. In this context, it might indicate overexposure or negative sentiment if influential nodes spread unfavourable opinions, thereby reducing ticket sales.

The coefficient for *clustering_coefficient* is negative (coef. = -4.78E+08, p-value = 0.00 <0.05), suggesting that higher clustering within the network, where nodes form tightly knit groups, is associated with lower daily revenues. This could mean that highly clustered networks might lead to echo chambers, where the same information is circulated within small groups without reaching a broader audience, limiting the overall impact. Similarly, the variable *density* shows a high and significant negative coefficient (coef. = -2.01E+14, p-value = 0.00 <0.05). This indicates that denser networks, where nodes have a higher proportion of possible connections, are associated with lower daily revenues. This suggests that overly dense networks might lead to redundancy in information flow that fails to excite or attract new audiences.

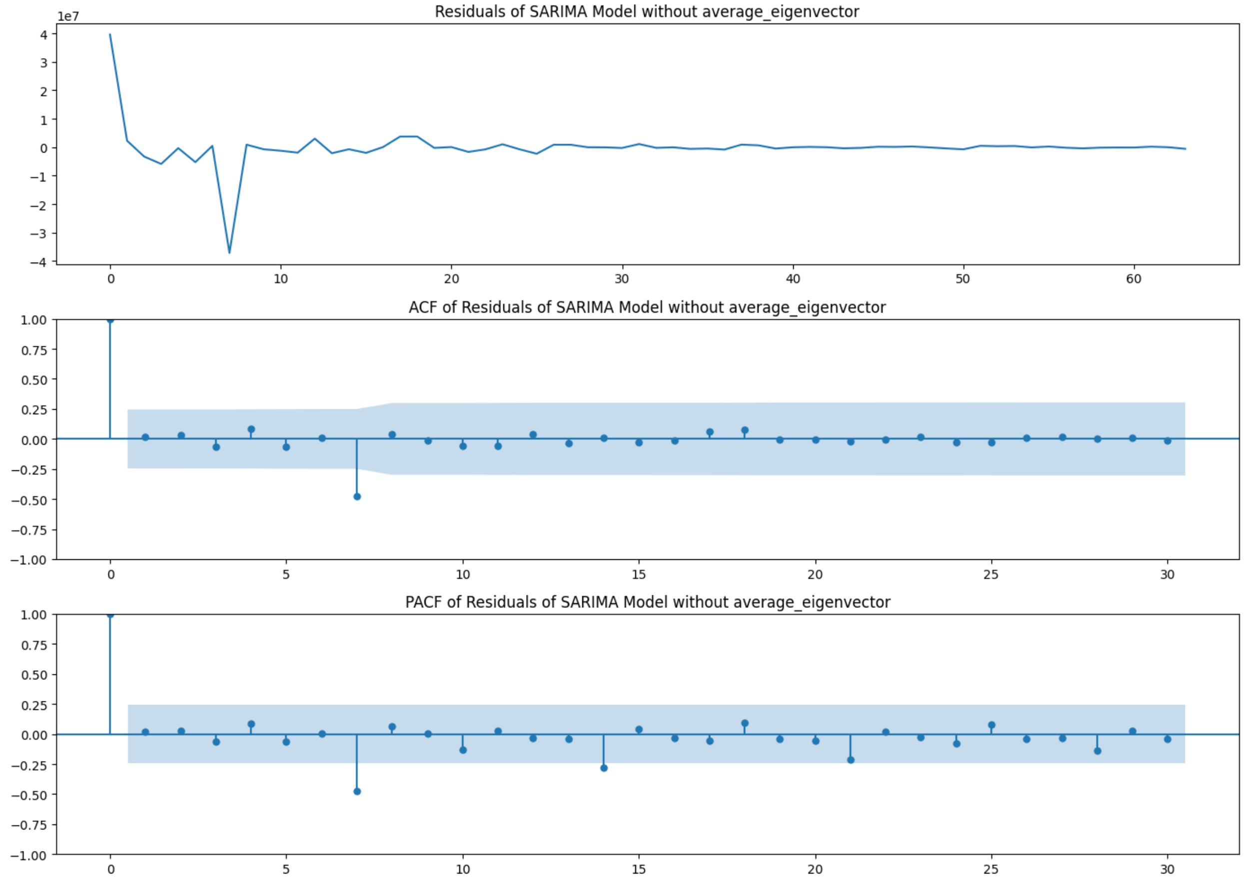
Finally, the coefficient for *sentiment* is positive (coef. = 5.36E+05, p-value = 0.00 <0.05), indicating a positive relationship with daily box office revenues. The positive sentiment reflects favourable opinions and excitement about the movie. When users express positive emotions and reviews, it encourages others to watch the movie, thus boosting ticket sales. In addition, the lag 1 autoregressive term, ar.L1 (coef. = 0.8879, p-value = 0.00 <0.05), is significant and positive, indicating a strong positive correlation with the previous period. Therefore, Hypothesis 2 is validated.

In addition to the coefficients presented in the SARIMAX model, Pearson's r was employed as a measure of effect size to quantify the strength of the relationships (Cohen, 1988; Wilkinson, 1999; Brydges, 2019) between various social media metrics and daily box office revenue. The effect sizes indicated in Table 36 reveal patterns of correlation that enhance our understanding of each metric's influence on box office performance. Among the metrics analysed, total_edges stands out with the highest absolute Pearson's r value of 0.390, indicating a strong positive relationship with daily revenue. This suggests that as user interactions increase, box office sales also rise significantly, emphasising the critical role of an engaged audience in promoting films effectively. In contrast, total_nodes exhibits a substantial negative correlation (r = 0.360), implying that a greater number of users discussing the movie may lead to reduced engagement. This result suggests that a larger, less cohesive audience could fragment discussions, thereby diminishing the impact of word-of-mouth marketing. Other metrics present a spectrum of influence: average_katz has a weak negative correlation (r = 0.170), indicating that while high centrality within the network is important, it may not yield positive revenue outcomes. This could reflect the potential for overexposure or negative sentiment among influential nodes. In comparison, average_degree_centrality, despite its large coefficient (coef. = 1.00E+14), shows a low absolute r value of 0.062, suggesting that while connectivity matters, its direct effect on revenue is relatively weak compared to total_edges. The sentiment metric shows an even weaker correlation (r = 0.040), implying that while positive sentiments can have a slight beneficial effect on box office revenue, this influence is minor when compared to the structural metrics. This comparative analysis underscores the varying degrees of influence that each metric exerts on box office performance, enhancing our interpretation of the findings.

7.3.4.4 Residual Analysis

Figure 74

Residuals Plot



The residuals plot shows the difference between the observed and predicted values of daily box office revenues over time. Initially, there is significant fluctuation, with a large negative spike around observation 10, followed by stabilisation around zero for the remaining observations. The residuals are centred around zero without clear patterns or trends. This suggests that the model has captured most of the systematic patterns in the data. The ACF and PACF plots of the residuals show that most of the autocorrelations and partial autocorrelations lie within the 95% confidence intervals, respectively. This indicates that there is no significant autocorrelation in the residuals. There are a few minor spikes, but none exceed the critical limits, which further supports the adequacy of the model. This confirms that the model is well-fitted and that the assumptions of the SARIMA model are met.

7.3.5 Discussion of the Results

This study applied a dual framework, integrating SA, network analysis, and additional statistical analyses, to understand the impact of social media discourse on the box office performance of the movie 'Joker'. The findings reveal several key insights.

The size and connectivity of the user network decreased significantly over the nine weeks. The number of nodes dropped from 31,995 in week 1 to 226 in week 9, showing a decline in user engagement over time. Low clustering coefficients and short network diameters suggest sparse local clustering and extensive but shallow interactions. The user network analysis successfully identified key influencers for each week with the use of out-degree and outward closeness centrality, as well as information disseminators by in-degree and Katz centrality. In addition to the user networks, the dual framework also analysed the semantic networks based on the co-occurrence of the bigrams. By using community detection techniques using node embedding and hierarchical clustering, the specific topics moviegoers were talking about during the period of nine weeks were identified, namely *Character Analysis, General Reactions and Mixed Reviews, Joaquin Phoenix's Performance, Mental Health Awareness and Its Portrayal in the Movie, Misrepresentation of Mental Health, Quotes, Viewing Experience, and Social Media and Blogging.* Throughout the nine weeks, Joaquin Phoenix's performance has been a consistent highlight, receiving high praise for its depth, intensity and emotional impact. This acclaim has had a steady positive impact on the movie's overall word-of-mouth. Artistic elements of the movie, such as cinematography and storytelling, were also consistently appreciated, although the initial excitement faded, and the intensity of positive reactions waned over time. Neutral ratings steadily increased over the weeks, suggesting a more balanced and reflective audience engagement. As viewers had more time to digest the movie, discussions became more nuanced, acknowledging both the movie's strengths and controversial aspects. This trend of increased neutrality suggests that viewers' evaluations became more mature and thoughtful as initial emotional reactions gave way to more analytical perspectives. From week 3 onwards, there was a noticeable increase in negativity, particularly in relation to the movie's portrayal of mental health issues. Criticism centred on concerns about distortion, potential harm and reinforcement of negative stereotypes. The tense and disturbing nature of the movie also contributed to negative reactions, with viewers expressing discomfort and concern about its social impact. The growing criticism highlighted the polarising effect of the movie and the importance of sensitive and accurate portrayals of mental health in the media.

Finally, the proposed dual framework employed time series analysis for this case to explore the relationship between social network metrics, sentiment, and daily box office revenue for the movie 'Joker'. Key findings include the importance of engagement quality, the influence of key nodes, and the need to avoid over-connection within social networks. First of all, the results indicate a clear distinction between the quantity of users and the quality of their engagement. The positive influence of the total number of edges (total_edges) and average degree centrality on daily box office revenue emphasises the importance of active and meaningful interactions. These results support the conclusion of De Oliveira Santini et al. (2020), who found that customer interactions on social media significantly enhance firm performance. They also support Castillo et al. (2021) and Feng et al.'s (2020) research, which focused specifically on movie prediction. Conversely, the total number of nodes in the network negatively impacts daily box office revenue, suggesting that merely having a larger audience is not sufficient. This negative impact highlights that a high number of users without substantial interaction may dilute the overall effect, leading to less effective word-of-mouth marketing. This observation aligns with the findings of Wies et al. (2023), who noted that while a larger follower count can increase reach, it often results in weaker relationships and lower engagement levels. This study adds depth by showing that the quality of the interaction has a more significant impact than the quantity of customers on box office performance. Secondly, the analysis highlights the critical role of well-connected and influential nodes within the social network. Metrics such as average degree centrality and average betweenness indicate that higher centrality measures are associated with higher daily revenues. Average degree centrality indicates that nodes with more connections can spread their influence widely, driving more people to the theatres. Similarly, nodes and edges with high betweenness centrality connect different parts of the network, facilitating the flow of information and potentially increasing movie attendance. In contrast, average Katz centrality has a negative impact on box office revenues. This might indicate that nodes considered highly influential across the entire network could spread negative sentiment or lead to overexposure, thus reducing ticket sales. For example, the influencer with the highest Katz centrality in Week 8, *Hello_Tailor*, posted a tweet criticising the Joker movie for framing the character through a specific mental health diagnosis, suggesting that it oversimplified his nature as an unpredictable, chaotic figure. Although *Hello_Tailor* does have the largest direct following, their critique resonated with other influential users, who amplified the message through retweets and discussions. This broad dissemination of negative sentiment demonstrates how indirect influence can shape public discourse and potentially decrease box office revenues. This finding aligns well with existing research on the influence of social media influencers. In particular, according to the studies of Ki et al. (2020), Sánchez-Fernández & Jiménez-Castillo (2021), and Masuda et al. (2022), influencers build emotional attachments with their followers, and their attractiveness and trustworthiness enhance purchase intentions; in this case, increased movie attendance. Thirdly, while engagement and the influence of key nodes are beneficial, the analysis also reveals the pitfalls of over-connection within the network. High clustering coefficient, network density, and average closeness centrality all negatively impact daily box office revenue. High clustering indicates that nodes form tightly knit groups, which can lead to echo chambers where information circulates within a limited audience without reaching a broader network (Kitchens et al., 2020; Tokita et al., 2021). Similarly, high network density suggests that many connections exist, which can result in redundant messaging and a lack of diverse information (Buskens, 2020). Additionally, a negative average closeness centrality suggests that when nodes are closer to each other in terms of shortest path lengths, the spread of information might be too rapid and uniform, leading to less effective and potentially overwhelming promotional efforts. This over-connection can stifle the spread of fresh and varied content, ultimately reducing the overall impact of the promotional efforts. Finally, positive sentiment significantly increases daily box office revenue. This indicates that favourable opinions and excitement about the movie drive higher ticket sales. Maintaining and fostering positive sentiment is crucial for boosting box office performance. This finding contrasts with Lipizzi et al.'s (2016) research, which argues that sentiment as a determinant factor is overstated. However, it aligns with several recent studies on box office evaluation (Ahmad, Bakar, & Yaakub, 2020; Bogaert et al., 2021; Yang et al., 2023; Zhang et al., 2022). In addition, the present study provides a new perspective that considers the online sentiment from a more real-time perspective. It specifically tests the lagged impact of online sentiment on movie performance, thereby providing insight into how changes in sentiment over time affect box office revenues.

The findings from this study offer several actionable strategies for marketing professionals in the entertainment industry. It is crucial to prioritise engagement quality over sheer quantity. Firstly, marketing efforts should focus on fostering active and meaningful interactions rather than simply increasing the number of participants. This can be achieved through interactive campaigns, engaging content, and direct audience engagement, which enhance the quality of interactions and lead to more effective word-of-mouth marketing. Secondly, identifying and collaborating with key influencers is vital. These influencers can significantly amplify the reach and effectiveness of promotional efforts by spreading positive sentiment and information about the movie. Their role is crucial in generating discussions and shaping audience perceptions, making them valuable assets in marketing strategies. Thirdly, balancing network connectivity is also important. Over-connection can create echo chambers and spread redundant information, which diminishes the effectiveness of marketing messages. Therefore, marketing strategies should aim to ensure that information reaches a wide and diverse audience without becoming trapped in tightly knit clusters. Avoiding over-connection within networks can help maintain the effectiveness of promotional efforts by preventing the spread of repetitive messages and fostering the dissemination of fresh and varied content. By implementing these strategies, entertainment industry professionals can effectively use social media to drive higher engagement and improve box office outcomes.

In addition, this study significantly advances the theoretical understanding of SMA by validating the efficacy of a dual framework that integrates SA and network analysis. This methodology is instrumental in developing comprehensive models for understanding market performance based on consumer engagement, thereby enriching theoretical frameworks that examine the influence of social media on business outcomes. The findings reveal intricate dynamics within social networks, illustrating that while engagement and influencer activity are beneficial, over-connection can negatively impact information dissemination. This insight adds complexity to existing network theories, suggesting that optimal dissemination requires a balance between connectivity and the diversity of message reach. This finding challenges traditional views that more connections always result in better outcomes, emphasising instead the quality and strategic spread of information. The study also expands the theoretical discourse by emphasising the role of key influencers and the strategic dissemination of information. By identifying metrics such as degree centrality and betweenness centrality, as well as sentiment, which indicates the impact of moviegoers' online reviews on potential viewers' choices to watch the movie, as significant factors of box office success, the research emphasises the importance of targeted influencer engagement within social networks. This adds a new dimension to social media marketing theories, suggesting that strategic influencer partnerships can amplify positive sentiment and enhance market performance.

As shown in the above discussion, the proposed dual framework has proven to be highly effective in understanding movie box office performance based on social media discourse. This framework's effectiveness lies in its comprehensive ability to capture both the emotional tone and the structural dynamics of social media interactions, offering a holistic view of audience engagement and its impact on economic outcomes.

7.4 Summary

This study explored the effectiveness of the proposed dual framework, integrating SA and network analysis, to understand the impact of social media discourse on the box office performance of the movie 'Joker'. The findings demonstrate that active and positive social media engagement, driven by meaningful interactions and influential users, significantly enhances box office revenues. However, overly dense networks can reduce the effectiveness of information spread, highlighting the need for balanced connectivity.

The practical implications suggest strategies for leveraging social media in marketing, while the theoretical contributions enrich models that explore the interplay between social media and market performance. Overall, this dual framework provides a robust tool for investigating and optimising movie success in the entertainment industry.

Chapter 8 Effectiveness of the Proposed SMA Framework

8.1 Introduction

By integrating multiple analytical perspectives, including sentiment, network, and semantic analysis, the framework aims to provide a comprehensive understanding of social media discourse. It captures the structural relationships between users, uncovers latent topics, and identifies the emotional tone of the content to inform decision-making processes across various domains. This chapter evaluates the effectiveness of the framework by examining its comprehensiveness, accuracy, robustness, and practical utility. These four criteria were selected based on the five key attributes of existing SMA, namely activity, what, where, how, and why (Holsapple, 2018).

Firstly, comprehensiveness is a criterion chosen to evaluate the activity and what attributes of a high-quality SMA framework. According to Holsapple (2018), the activity attribute refers to the range of objectives within the SMA exercise, such as data collection, monitoring, analysis, summarisation, and visualisation, while the what attribute defines specific targets for these activities, like posts, conversations, sentiment, and emerging topics. These attributes reflect SMA's multidisciplinary nature and objective of providing a holistic view of social discourse (Stieglitz et al., 2014; Ayele & Juell-Skielse, 2017). By examining comprehensiveness, this study assesses whether the framework captures a wide range of insights across various social media data points, enabling a complete view of interactions, topics, and sentiments.

Secondly, accuracy and robustness were chosen as criteria to evaluate Holsapple's how attribute, which refers to the procedural aspects of analytics (Holsapple, 2018). Since the framework is developed on big data techniques, accuracy and robustness are essential for reliably managing the volume and variability of social media data (Manure & Bengani, 2023). The criterion of accuracy was assessed by comparing the framework's outputs with corresponding know results from reliable benchmarks (Borenstein, 1998), like surveys, existing literature, or market reports, to confirm its credibility and precision. Robustness, meanwhile, confirms that the framework performs consistently across diverse datasets and changing contexts, a quality emphasised in the study by Bollen, Mao, & Zeng (2011), who demonstrate the importance of reliable insights in social contexts. By focusing on accuracy and robustness, the framework's reliance on big data techniques is thoroughly evaluated, ensuring it can process complex data while yielding reliable and trustworthy insights.

Finally, practical utility is used to assess the why attribute, which Holsapple (2018) defines as the larger purpose of an analytics exercise. This criterion evaluates the framework's real-world applicability in guiding decisions across domains like policymaking, marketing, and crisis management. Practical utility ensures that the framework not only captures social dynamics effectively but also translates them into timely and actionable insights. Choi et al. (2020) and Kumar & Nanda (2019) emphasise that SMA's goal is to inform decision-making by generating specific types of knowledge. Thus, by evaluating practical utility, the framework's capacity to fulfil SMA's purpose, supporting responsive, data-driven actions, is fully assessed.

The last attribute, where, refers to the specific social media type(s) that host(s) the required target(s). Due to limitations in access rates on other platforms during data collection and the time constraints of this project, the proposed framework was validated only on data from Twitter. In future research, additional social media platforms will be included to further validate the effectiveness of the dual framework.

8.2 Effectiveness Evaluation

8.2.1 Comprehensiveness

Comprehensiveness measures the framework's ability to capture a wide range of relevant data points and provide holistic insights. The framework demonstrates comprehensiveness by offering multi-dimensional insights that combine different analytical perspectives into a cohesive understanding of social media discourse. It successfully identifies the key influencers and contextualises their impact through sentiment trends, offering comprehensive insights into public anticipation and reactions to certain events, such as the cost of living crisis in the UK and movie box office performance evaluation. Additionally, the framework successfully identifies and analyses a diverse set of topics across different social contexts. In the cost of living crisis case study, topics such as payment adequacy, eligibility issues, and government communication were prevalent. In the movie performance evaluation case study, themes included character analysis, general reactions, Joaquin Phoenix's performance, mental health portrayal, and social impact. This breadth of topic coverage indicates the framework's ability to provide a comprehensive analysis of social media discourse. Furthermore, the framework evaluates the lagged impact of social media discourse through temporal analysis, analysing how early interactions and sentiments influence later outcomes. This capability is crucial for predicting long-term trends and outcomes, such as the sustained impact of an influencer's endorsement or a major event on public opinion. The lagged impact analysis in the second case study demonstrated how initial social media buzz translated into box office performance over time. This multi-dimensional approach ensures that most relevant aspects of the data are considered, providing a comprehensive understanding of how public sentiment is shaped and spread. The combination of these methods in both case studies illustrates the framework's ability to deliver a well-rounded analysis.

8.2.2 Accuracy

In this context, accuracy refers to the precision and correctness of the results or findings generated by the proposed SMA framework. Specifically, accuracy can be evaluated by comparing the results obtained from the framework with established or reliable external data sources, such as government surveys, market performance metrics, or existing studies to determine how closely the framework's outputs align with these benchmarks.

To evaluate the accuracy of the framework in the context of the UK's cost of living crisis, this thesis compared the results obtained from the proposed framework with the findings from a survey conducted by the DWP and the Work and Pensions Committee report. Firstly, the framework successfully identified key public concerns through semantic network analysis regarding payment adequacy, eligibility issues, timing of payment distribution, and the complexity of government communication. These findings were consistent with the report from the Work and Pensions Committee, which highlighted similar issues based on qualitative data and structured surveys. For instance, the framework detected that many people were unaware of the payment methods or found the government communication vague and ineffective. This concern was also noted in the Work and Pensions Committee's report, validating the accuracy of the framework's outputs in capturing public sentiment and identifying critical issues. Secondly, the SA component of the framework showed predominantly negative sentiments during the announcement and initial distribution phases, which shifted to more mixed sentiments post-distribution. This trend matched the general sentiment trends observed in the DWP survey, where initial responses were largely critical but became more varied as people started receiving payments. This alignment further supports the accuracy of the SA conducted by the framework.

For the movie box office case study, the accuracy of the framework is evaluated by comparing the results with existing literature. The framework identified several key factors, namely the quality of engagement over quantity, the influence of key nodes, the impact of over-connection, and the role of sentiment, as significant in affecting box office performance. These findings were validated by existing studies in the field of movie box office prediction (De Oliveira Santini et al., 2020; Feng et al., 2020; Wies et al., 2023; Sánchez-Fernández & Jiménez-Castillo, 2021; Masuda et al., 2022; Kitchens et al., 2020; Tokita et al., 2021; Ahmad, Bakar, & Yaakub, 2020; Bogaert et al., 2021; Yang et al., 2023; Zhang et al., 2022). Among these results, the findings regarding the quality of customer engagement and the impact of over-connection are particularly noteworthy as they were validated by research from other domains or from the use of entirely different methods. This further underscores the effectiveness of the proposed dual framework. The model's ability to capture the latent and diverse nature of social media discussions and translate them into actionable insights highlights its potential for informing strategic decisions in the entertainment industry.

8.2.3 Robustness

Robustness refers to the consistency and reliability of the proposed SMA framework, despite changes in data or context. The robustness of the framework is evidenced through its consistent performance in two cases, namely the UK's cost of living crisis and the movie box office analysis for 'Joker'. In both scenarios, the framework accurately translated social media data into valuable information for relevant stakeholders to make decisions. For instance, during the analysis of the cost of living crisis, the framework successfully identified key public concerns and sentiment trends despite the complexity and variability of the social media discourse surrounding this issue. Similarly, in the movie box office analysis, the framework effectively analysed social media data to evaluate economic outcomes, demonstrating its reliability across different contexts. Adaptability to different data structures further highlights the framework's robustness. It successfully handled various types of social media content required by the various analytical components of the framework, such as hashtags, mentions, and emojis for initial analysis, relational data for network analysis, posts for SA, and co-occurrences of terms within posts for semantic analysis. The framework's scalability, managing large volumes of data from social media platforms, also highlights its robustness in handling diverse data structures. The framework's stability over time is another critical aspect of its robustness. It effectively tracks changes in sentiment, network structure, and topic prevalence over extended periods, highlighting its temporal stability. For example, in the movie box office analysis, the framework analysed social media discussions over several weeks, capturing the evolving sentiment and engagement patterns that influenced box office performance. The framework's ability to handle dynamic data, providing accurate and timely information for decision-making despite the volatility in the social media environment, further demonstrates its robustness.

8.2.4 Practical Utility

In this section, practical utility refers to the effectiveness of the proposed SMA framework in real-world scenarios. This is evaluated by examining how effectively the framework's insights can inform decision-making and drive actions across various contexts.

One significant area where the framework demonstrates practical utility is in shaping policy and public communication strategies. During the UK's cost of living crisis, by identifying issues such as payment adequacy, eligibility, and communication complexities, the framework's findings guide policymakers in refining their approaches to public support and communication. The framework also proves its utility in the business domain, particularly in shaping marketing strategies and predicting economic outcomes. In the case study evaluating the box office performance of 'Joker', the analysis using the proposed framework highlighted the importance of engagement quality over quantity and the impact of key influencers on public sentiment. These insights can help businesses tailor their marketing campaigns, focusing on influential figures and fostering meaningful interactions to drive better market outcomes. The framework's practical utility extends to crisis management, where timely and accurate insights are critical. In the context of the UK's cost of living crisis, the framework was able to quickly identify and analyse public sentiment and key issues, leading to more responsive and informed decision-making. By analysing social media discourse in a timely manner, the framework enabled policymakers to dynamically adapt strategies and communications to ensure that the most pressing public concerns were effectively addressed. This capability is essential in managing crises where public sentiment and information dissemination can rapidly evolve.

Another important aspect of the utility of the framework is its efficiency compared to traditional survey methods. Conducting a survey involves developing questions, deciding on the method of administration, waiting for responses, and ensuring that there is a sufficient number of useful responses to make the data reliable. This process can be expensive in terms of time and resources. Delays in data collection or processing can also lead to outdated results, reducing the timeliness and relevance of analyses. In contrast, the framework directly utilises data from social media platforms, which are publicly available and voluntarily expressed by users. This approach avoids lengthy survey administration processes and allows for immediate data collection and analysis. As a result, the framework conducts an analysis and provides results in a timely manner, without the delays associated with traditional survey methods.

In addition, the framework's integrated analytical capabilities make it an invaluable tool for strategic planning and forecasting across industries. The dual framework combines sentiment and network analysis, offering a robust mechanism to understand long-term trends and potential future scenarios. For example, a company can project market trends by analysing changes in social media discourse using the framework, thereby creating more informed strategic planning. Similarly, policymakers can use the framework to predict public reactions to upcoming policy changes and take measures to minimise the negative impacts.

8.3 Challenges and Limitations

While the proposed SMA framework offers significant advantages and demonstrates strong applicability across various contexts, it is essential to acknowledge the challenges and limitations associated with its use. Understanding these limitations will help guide future improvements and contextualise the framework's findings.

One of the primary challenges in implementing the dual framework is data quality and availability. Social media sources are often noisy and filled with irrelevant or generally low-quality posts, which can influence the accuracy of the analysis. The presence of spam, bots, and fake accounts may further distort the data and lead to misleading results. Additionally, access to social media data is often subject to platform policies, which can limit the amount and type of data available for analysis. For example, the deactivation of scholarly accounts after Twitter became Platform X affected the continuity and comprehensiveness of data collection for this project, shortening the analysis window. Consequently, the amount of data available for later use in predictive modelling, such as for movie box office performance, was insufficient.

Applying quantitative data analytics methods for textual analysis presents several challenges. Language is complex and context-dependent, which can pose difficulties for accurate SA and topic detection. While the proposed framework accounts for informal language use on social media platforms, specifically the use of emojis, and targets specific aims of SA for certain cases, variations in language use, slang, and sarcasm can affect the interpretation of social media content. The framework, while robust overall, may struggle with these nuances, potentially leading to misinterpretations of sentiment or themes in the data. In this regard, there is a need to continually update the SA model to reflect changing language usage. Considering that social media language evolves rapidly with the invention of new slang, abbreviations, and trends, updating them within the model remains crucial for its correctness and relevance. This requires continuous monitoring and upgrading of the NLP algorithms to adopt to these changes.

Scalability and computational demands present additional limitations. Handling large volumes of social media data demands a large amount of computation resources, such as processing power, memory, and storage. In the case studies, the proposed dual framework demonstrated its capability to manage significant data volumes, processing thousands of tweets over several weeks. However, the data size in these studies is very small compared to what would be needed in practical applications, necessitating more processing power and advanced data management techniques. Ensuring the framework can scale efficiently to handle big data while maintaining performance and accuracy is a significant challenge. The need for high-performance computing infrastructure and advanced data management techniques can also increase operational costs and complexity.

8.4 Summary

The evaluation of the proposed SMA framework through the lens of comprehensiveness, accuracy, robustness, and practical utility demonstrates its significant potential in analysing social media discourse. The framework's ability to integrate sentiment, network, and semantic analysis allows for a multi-dimensional understanding of social media interactions. It successfully identified key influencers, analysed diverse topics, and evaluated the lagged impact of social media discourse, proving its comprehensiveness. The accuracy of the framework was validated by comparing its outputs with established external data sources, such as government surveys and market performance metrics, showcasing its precision in capturing public sentiment and evaluating outcomes. The framework's robustness was evident in its consistent performance across different contexts and its ability to handle various data structures and large volumes of social media content. Its stability over time further emphasised its reliability. Additionally, the framework demonstrated significant practical utility by informing policymaking, business strategies, and crisis management. Its efficiency compared to traditional survey methods and its comprehensive analysis capabilities make it a valuable tool for strategic planning and forecasting in various sectors.

However, the framework also faces challenges and limitations, including data quality and availability issues, the complexity of language and context, and scalability and computational resource demands. Addressing these challenges through continuous updates and improvements is crucial for maintaining the framework's effectiveness and ensuring it provides reliable insights in diverse real-world scenarios.

Chapter 9 Conclusion

9.1 Overview

This thesis aimed to develop and validate a comprehensive SMA framework for capturing and analysing social media discourse, thereby gaining insights into socio-political and economic issues. This chapter discusses the findings of the thesis in order to answer the research questions. It will also discuss the significance of the framework, highlighting both its theoretical contributions and practical applications. Finally, the chapter will explore the future directions.

9.2 Summary of Findings

9.2.1 Development of the Framework

The proposed SMA framework was designed to incorporate SA, network analysis, and semantic analysis. The integration of these methodologies resulted in a robust tool capable of systematically analysing and interpreting social media data. The framework effectively identified key influencers, prominent topics, and sentiment trends, providing comprehensive insights into public opinion and emotional responses to various issues.

9.2.2 Case Studies and Practical Applications

The framework's applicability was demonstrated through two case studies: the UK's cost of living crisis and movie box office predictions. In the UK's cost of living crisis case, the framework successfully identified public concerns, key influencers, and sentiment trends, which closely aligned with findings from government surveys and reports. This demonstrated the framework's accuracy and practical utility in real-world policy analysis and public sentiment tracking. For the movie box office predictions, the framework's predictive accuracy was validated through a comparison with actual box office data. The results highlighted the importance of engagement quality, the impact of key influencers, and sentiment trends in predicting economic outcomes, showcasing the framework's utility in business and economic forecasting. These outcomes show the framework’s ability to provide deep insights into public opinion and emotional responses that traditional methods might overlook.

9.3 Significance and Evaluation of the Framework

The findings of this thesis contribute significantly to the field of SMA by demonstrating the effectiveness of the proposed dual framework through four aspects: comprehensiveness, accuracy, robustness, and practical utility.

Firstly, the comprehensiveness of the framework was evident in its ability to provide multi-dimensional insights by combining sentiment and network analysis on users and words. It effectively captured a wide range of data points, offering a holistic view of social media discourse. The breadth of topic coverage and the ability to analyse the temporal impact of social media interactions further validated its comprehensive nature. Secondly, accuracy was assessed by comparing the framework's outputs with established external data sources. The framework consistently produced results that aligned with qualitative data and structured surveys, demonstrating its precision in capturing public sentiment and identifying critical issues. The accurate prediction of movie box office performance further validated the framework's predictive capabilities. Thirdly, the framework demonstrated robustness through its consistent performance across diverse contexts and its adaptability to different data structures and large volumes of social media content. It maintained stability over time, effectively tracking changes in sentiment and network structure, which is crucial for predicting long-term trends and outcomes. Finally, the practical utility of the framework was highlighted by its effectiveness in informing policy decisions, shaping marketing strategies, and managing crises. Its efficiency in analysing social media data compared to traditional survey methods provided timely and actionable insights, proving to be invaluable for strategic planning and forecasting in various sectors.

9.4 Contributions to the Field

The theoretical contributions of this thesis are rooted in the innovative advancements made in network analysis, SA, and their integration, which collectively enhance the understanding and analysis of social media discourse.

Firstly, this thesis makes contributions to network analysis by improving methods for community detection and clustering. By implementing robust community detection algorithms, the framework can identify and analyse user communities with greater precision. Clustering techniques, such as node embedding and hierarchical clustering, capture complex relationships and structural properties within the network, providing a nuanced understanding of how users interact and form communities. Additionally, semantic network analysis adds another layer of depth by visualising and analysing the co-occurrence patterns of words in tweets. Combined with topic modelling, this approach effectively extracts latent topics and themes from social media discussions, revealing the underlying topics that drive user engagement. A rule-based methodology for tweet assignment ensures precise content analysis and accurate identification of community-specific themes, thereby enhancing the reliability and validity of the network analysis.

Secondly, in terms of SA, the thesis extends the theoretical understanding by proposing a novel multi-view learning approach. This approach treats text and emojis as distinct but valuable sources of sentiment information, demonstrating that incorporating emojis into SA models improves their performance. This innovation highlights the importance of non-verbal cues in online communications, offering a more comprehensive analysis of user sentiments. The framework's enhanced efficiency, requiring minimal preprocessing of social media posts, allows it to process large volumes of data efficiently. This efficiency is crucial for practical applications in high-stakes environments such as business and public policy, where timely and accurate insights are essential.

Thirdly, the integration of network analysis and SA represents a major theoretical innovation, combining advancements in machine learning, NLP, and network theory. This dual-framework approach leverages the strengths of both methodologies to provide a holistic understanding of social media interactions. Network analysis identifies the structure of online communities, key influencers, latent topics, and information dissemination pathways. In contract, SA examines the emotional content of communications, offering insights into public sentiments and perceptions on various topics. Transforming these analytical results into quantitative social media metrics, such as average degree centrality, average closeness, and betweenness, as well as daily sentiments, allows for the evaluation of their impact on business performance. This integration not only enhances the accuracy and depth of social media analysis but also provides a valuable tool for strategic planning and decision-making across various sectors.

In summary, the theoretical contributions of this thesis lie in the innovative methodologies developed for network and SA and their integration for a richer and more nuanced analysis of social media discourse. These methodologies provide a foundation for a more robust framework for analysing complex user engagement online and are essential for further research and practical applications in the domain of SMA. The practical applications demonstrated through the case studies emphasise the framework's utility and effectiveness in various contexts.

In terms of practical contributions, the dual framework can provide valuable information for marketing, public relations (PR), and crisis management. Businesses can now develop their strategies based on identifying the most critical influencers, structuring the online community, and pinpointing key discussion topics to which they can map their product benefits. This targeted approach could enhance the reach and impact of marketing campaigns, thereby improving customer engagement and conversion rates. With a good understanding of social media dynamics, PR professionals can also help identify potential crises early and enable proper management of brand reputation through proactive actions.

In the realm of public policy, the framework can help track fluctuations in public engagement and sentiment over time, informing policymakers about public opinion on various issues. This dynamic tracking allows for timely adjustments to policies and communication strategies, ensuring they align with public sentiment. For example, during public health emergencies, such as a pandemic, public health officials might monitor ongoing social media conversations to evaluate the level of public concern, correct misperceptions, and conduct targeted messaging to enhance compliance with health recommendations.

In commercial sectors, this framework can predict business performance by analysing social media buzz and public sentiment. By transforming network and SA results into quantitative social media metrics, stakeholders can make data-driven decisions to optimise marketing strategies, allocate resources effectively, and anticipate market trends.

The efficiency and adaptability of the framework, which requires minimal preprocessing of social media posts, make it particularly valuable in high-stakes environments where timely insights are essential. Unlike traditional survey methods, which often involve lengthy preparation, data collection, and analysis phases, this framework can process large volumes of data quickly and efficiently. Traditional surveys also tend to suffer from biases such as non-response and self-reporting errors, whereas social media analysis captures spontaneous, real-time reactions from a broad and diverse user base. The framework's ability to handle extensive data sets without significant preprocessing ensures it remains relevant and effective in the rapidly evolving social media landscape. This adaptability also allows for the integration of new analytical techniques that may emerge to ensure continuous improvement in actionable insights. By leveraging this immediacy and breadth of information, the framework offers a more dynamic and responsive tool for understanding public sentiment and behaviour than traditional survey methods.

In addition, this study analyses economic performance by demonstrating how the quality of engagement, influence of key influencers, and sentiment trends can be used. These contributions will improve academic knowledge and offer practical tools useful for policymakers, businesses, and researchers for understanding and using social media data.

9.5 Future Research Directions

Future SMA research will greatly benefit from the richness of multimodal information and cross-platform analysis. In addition to text and emojis, the inclusion of images, videos, and audio content from various social media platforms, such as Instagram and TikTok, can provide a better perspective on user interactions and the emotions presented in the content. These platforms are visually driven, and incorporating such data modalities will help in understanding how users express themselves and engage with content. By developing methods to analyse these heterogeneous data types, researchers may be able to discover patterns or trends that are not pronounced through text analysis alone, hence leading to an even more in-depth investigation of social media dynamics.

Another key area for future research is improving real-time analytics and predictive modelling. By upgrading the system to gather and analyse live data, it will be possible to quickly understand current events and respond more rapidly to new trends or crises. In high-pressure situations, such as public health emergencies or political campaigns, real-time analytics are particularly important, where quick decisions can have significant impacts. Integrating predictive modelling into a real-time framework makes it possible for stakeholders to anticipate future trends based on current data and helps them to be proactive in managing potential problems that arise and take advantage of new opportunities.

Another promising area for future research lies in longitudinal studies and analyses of trends. Research that investigates how social media discourse itself evolves offers insights into persistent trends and shifting patterns of public sentiment. This will help in the understanding of the life cycle of social issues, brand reputation, and sustained marketing campaigns. Developing ways to track and analyse these long-term shifts helps businesses and policymakers realign their strategies with up-to-date historical data and foresee future developments.

More contributions could be made by further exploring the application of the framework across various fields. Although this thesis has already demonstrated its applicability in marketing, public policy, and crisis management, the framework can also be applied to other areas such as healthcare, education, politics, and tourism. Each domain presents unique challenges and opportunities, and customising the framework to meet specific needs can increase its usefulness. For instance, within healthcare, analysis of social media data might track disease spread and monitor public health sentiment, or even support improvements in patient engagement. In education, it could highlight student experiences and influence policy. In political science, it could analyse voter sentiment to predict election outcomes. In addition, the framework can be applied to the travel and tourism industry to understand travellers' experiences, preferences and concerns. Tourism boards and travel companies can use this data to improve services, develop targeted promotions and increase customer engagement. By broadening its scope, the framework could provide an even more powerful tool for leveraging social media data across sectors.

In addition to these directions, future research could also explore enhanced user behaviour modelling. There are a variety of user interactions on social media platforms, such as retweets, quotes and replies on Twitter/X. By focusing on different types of interaction networks and their impacts, the dual framework can provide a deeper understanding of how information is disseminated and how different types of engagement affect sentiment and community formation. Whilst this framework provides valuable insights into social media discourse, it is important to recognise the potential limitations associated with data source bias. As this study relies on Twitter data, the sample is inherently biased towards those who are more active on social media platforms. This includes younger users as well as frequent digital media users. As a result, the findings may not adequately reflect the perspectives of older populations and individuals with less internet access. This limitation suggests that conclusions drawn from Twitter data may be less applicable to populations with lower levels of social media engagement. Future research could address this issue by incorporating data from more diverse sources, including surveys or traditional media, to provide a more balanced picture of public sentiment and discourse.

In summary, future research directions in SMA should focus on integrating multimodal data, developing real-time analytics, conducting longitudinal studies, and exploring diverse applications.

These advancements will enhance the framework's capability to provide deeper, more actionable insights, thereby driving innovation and effectiveness in utilising social media data.

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Appendix A: Algorithms for Emoji Feature-Incorporated Multi-view Sentiment Classifier

This appendix details the various algorithms used in the proposed E-BiLSTM-CNN used for SA. Algorithm A.1. first describes the algorithms for calculating emoji scores in comments, explaining the process of calculating emoji scores based on sequences of emoji in tweets. Next, Algorithm A.2. describes the process of creating a combined word and emoji embedding matrix using GloVe and Emoji2Vec embeddings and provides steps for labelling tweets and integrating embeddings. Following this, there is a description of the Algorithm A.3. Sentiment Polarity Prediction Model. It details how BiLSTM and Conv1D layers can be used to predict the sentiment polarity of comments. Finally, Algorithm A.4. plots positional interpretations of SA results using LimeTextExplainer, focusing on how to interpret and visualise the model's predictions for headline text.

Algorithm A.1. Computing Emoji Scores of Reviews

Input: Tweet T_i **=**{w_1, w_2, ..., w_a, e_1, e_2, ..., e_b**}**

Output: emoji score of each review (es_{i})

1. Data preprocessing to obtain a cleaned version clean_ T_i
2. Extract emoji sequence EM for each clean_ T_i
3. **for** each emoji sequence**, do**
4. Obtain emoji scores for each emoji
   - emoji_scores = []
   - for emoji in EM:
   - es = compute_emoji_score(emoji) by $\mathrm{es}_{\mathrm{e_b}} = (N(e_{b+}) - N(e_{b-}))/N(e_b)$
   - emoji_scores.append(es)
   - end for
   Compute emoji score for the tweet
   - avg_emoji_score (es_{i}) $= (\sum_1^b \mathrm{es}_{\mathrm{e_b}})/b$
5. **end for**
6. Output the emoji score of each review (es_{i})

Algorithm A.2. Creation of the Word_Emoji_Embedding

Input: GloVe and Emoji2Vec embedding dictionaries, the dimensionality of embeddings, tweets

Output: Word_Emoji_Embedding matrix and padded sequences

1. Tokenise the tweets using a Tokeniser and build the vocabulary.
-tokeniser = Tokeniser()
-tokeniser.fit_on_texts(clean_T)
-sequences = tokeniser.texts_to_sequences(clean_T)
2. Pad the tokenised tweets to a fixed length using a padding function.
-padded_sequences = pad_sequences(sequences,
3 maxlen=max_tweet_length, padding='post')
4. Load the GloVe and Emoji2Vec embedding dictionaries.
5. Define the dimensionality of the embeddings (e.g. 300)
Initialise the embedding matrix with random values.
-num_words = len(tokeniser.word_index) + 1
6. -embedding_matrix = np.random.random((num_words, embedding_dim))
7. **for** each token in the vocabulary, **do**
8. Check if the token exists in the GloVe embedding dictionary or the
9. Emoji2Vec embedding dictionary.
If it does, use the corresponding embedding for this token in the embedding matrix.
If it doesn't, check if the token exists in the Emoji2Vec embedding dictionary.
-for word, i in tokeniser.word_index.items():
10. if word in glove_embeddings:
11. embedding_matrix[i] = glove_embeddings[word]
12. elif word in emoji_embeddings:
embedding_matrix[i] = emoji_embeddings[word]
end for
Output the embedding matrix and padded sequences.

Algorithm A.3. Sentiment Polarity Prediction model

Input: Word_Emoji_Embedding matrix and padded sequences, emoji scores

Output: The sentiment polarity of each review polarity (T_i)

1. **for** each sequence, **do**

2. The element (word and emoji) vector xt, is obtained by transforming the element e_i to vector x_t through the word_emoji embedding matrix W: $x_t = W_e e_t$
3. h_i = BiLSTM(x_i): pass x to BiLSTM layer and obtain the element vector $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$
4. a_i = Conv1D (h_i); pass h to 1D convolutional layer to extract higher-order features $a_i = f(F \circ h_{i:i+q-1} + b)$ and obtain a feature map $c = [a_1, a_2, \ldots, a_{n-l+1}]$
5. the maximum value m = max{c} is extracted by applying the max pooling operation to each feature map
6. Add emoji score feature to the features extracted by the CNN layer: $V_i = [m_i, es_i]$
7. The dropout rate of 0.3 to deal with the overfitting issue
8. end for
9. Using sigmoid activation function to compute the binary classification distribution
10. Predict sentiment polarity: polarity (T_i) = (p > best_thresh).astype
11. Output the sentiment polarity of each review polarity (T_i)

Algorithm A.4. Location Explanation Plotting Algorithm for Multi-View SA

Input: a processed headline text sample, and multi-view SA pipeline

Output: A plot of the location explanation for the given sample

1. Instantiate the LimeTextExplainer to explain how the SA model made its prediction for the headline
2. Use explain_instance() with appropriate parameters (text, predict_proba, num_features) to generate an explanation for the given text sample:
3. Extract the ordered dictionary of words and weights from the explanation
4. Plot a bar figure for the location explanation for the given sample
5. Output the location explanation figure

Appendix B: Sentiment Distribution of Themes in Case 1: Cost of Living Payment Discussions

This appendix presents data on the distribution of sentiment for the various topics discussed at different times in Case 1, that is the Cost of Living Payments discussions. The data is organised into tables that show the percentage of tweets expressing negative, neutral, and positive sentiments, along with the total percentage of tweets for each topic.

Table B.1

Thematic Sentiment Distribution of Case 1

Period	***Community***	***-1 (%)***	***0 (%)***	***1 (%)***	***% of Total Tweets***
Announcement Period	**Eligibility**	5.98	92.48	1.54	64.43
	Main Cost-of-Living Package	18.98	75.91	5.11	15.09
	Energy Bills	9.45	81.89	8.66	13.99
	Confirmation from DWP	41.67	58.33	-	1.32
	Support for Low-Income Households	8.51	89.36	2.13	5.18
	Grand Total	9.03	87.89	3.08	100.00
1st Payment Distribution	**DWP Payment**	27.12	72.88	-	15.86
	Communication and Execution of the Cost of Living Payment	37.04	50.00	12.96	14.52
	Cost of Living Payment	6.56	87.64	5.79	69.62
	Grand Total	14.25	79.84	5.91	100.00
After the 1st Payment	**Communication and Execution of the Cost of Living Payment**	18.95	49.47	31.58	73.08

	Employee Support/Benefits	16.00	56.00	28.00	19.23
	New Government Measures	10.00	80.00	10.00	7.69
	Grand Total	17.69	53.08	29.23	100.00
2nd Payment Distribution	**Impacts and Perceptions of Financial Relief Measures**	21.31	59.02	19.67	16.40
	Receipt of the Second Cost of Living Payment	8.90	85.17	5.93	63.44
	Availability of Financial Assistance and Criticism of Support Payment	36.00	46.67	17.33	20.16
	Grand Total	16.40	73.12	10.48	100.00
After the 2nd Payment	**Winter Fuel Payments and the Pensioner Cost of Living Payment**	21.33	77.33	1.33	84.27
	Contact Details	20.00	80.00	-	5.62
	Adjustments in Cost of Living Payments	-	88.89	11.11	10.11
	Grand Total	19.10	78.65	2.25	100.00

Appendix C: Entity Analysis of Weeks for Case 2: Movie Performance Evaluation

Table C.1

Hashtag Analysis Across Weeks of Case 2

Week	*No.*	*hashtag*	*abs_freq*	*wtd_freq*	*rel_value*
Week 1	1	#worldmentalhealthday	1187	586506	494

	2	#joaquinphoenix	325	19612	60
	3	#mentalhealth	223	14693	66
	4	#worldmentalhealthday2019	131	11860	91
	5	#mentalhealthawarenessday	123	11796	96
	6	#wmhd2019	95	11777	124
	7	#jokerquotes	89	7631	86
	8	#dv	66	7458	113
	9	#nojoke	21	743	35
	10	#gulmantips	19	741	39
Week 2	1	#worldmentalhealthday	309	130464	422
	2	#joaquinphoenix	99	3679	37
	3	#worldmentalhealthday2019	57	3040	53
	4	#mentalhealth	68	2010	30
	5	#mentalhealthawarenessday	22	1548	70
	6	#wmhd2019	12	1536	128
	7	#worldmentalhealthweek2019	38	1480	39
	8	#judgementallhaikya	38	1480	39
	9	#jokerquotes	21	1393	66
	10	#dv	12	1356	113
Week 3	1	#worldmentalhealthday	11	4275	389
	2	#batman	17	250	15
	3	#mentalillness	33	249	8
	4	#movies	13	242	19
	5	#moviereview	12	242	20
	6	#psychology	11	242	22
	7	#bestmovielineever	11	242	22
	8	#joaquinphoenix	29	232	8
	9	#mentalhealth	58	178	3
	10	#worldmentalhealthday2019	1	128	128
Week 4	1	#worldmentalhealthday	6	4271	712
	2	#mentalillness	19	144	8
	3	#batman	9	134	15
	4	#moviereview	8	132	16

	5	#psychology	6	132	22
	6	#bestmovielineever	6	132	22
	7	#movies	6	132	22
	8	#nstletter	11	116	11
	9	#mentalhealth	38	68	2
	10	#n5hruae	5	30	6
Week 5	1	#worldmentalhealthday	2	1996	998
	2	#mentalhealth	36	257	7
	3	#antidepressant	6	42	7
	4	#tweetnotes	5	20	4
	5	#guion	4	20	5
	6	#mentalhealthawareness	11	14	1
	7	#fanart	1	10	10
	8	#artistontwitter	1	10	10
	9	#artph	1	10	10
	10	#artshare	1	10	10
Week 6	1	#worldmentalhealthday	4	3992	998
	2	#jokerquotes	23	460	20
	3	#mentalhealthawareness	26	449	17
	4	#electronica	20	440	22
	5	#rockmusic	20	440	22
	6	#mentalhealth	25	55	2
	7	#jokerfilm	3	53	18
	8	#sendintheclowns	1	20	20
	9	#bloggersconnects	5	20	4
	10	#trjforbloggers	10	20	2
Week 7	1	#mentalhealth	7	98	14
	2	#batman	2	22	11
	3	#movies	2	22	11
	4	#moviereview	1	22	22
	5	#bestmovielineever	1	22	22
	6	#psychology	1	22	22
	7	#mentalillness	3	22	7
	8	#jokerquotes	3	17	6

	9	#mentalhealthawarenessweek	1	17	17
	10	#joaquinphoenix	8	15	2
Week 8	1	#mpkbaliw	17	323	19
	2	#deep	2	30	15
	3	#mvrp	1	9	9
	4	#anyrp	1	9	9
	5	#nonlewdrp	1	9	9
	6	#lewdrp	1	9	9
	7	#synicalwriter	1	9	9
	8	#healthcare	3	6	2
	9	#mentalhealth	6	6	1
	10	#amwatching	2	4	2
Week 9	1	#therapy	1	2	2
	2	#analysis	1	2	2
	3	#christhecounsellor	1	2	2
	4	#counselling	1	2	2
	5	#mentalhealth	2	2	1
	6	#batweek	2	1	0
	7	#jongho	1	1	1
	8	#mingi	1	1	1
	9	#leeknow	1	1	1
	10	#mina	1	1	1

Table C.2

Mention Analysis Across Weeks of Case 2

Week	*No.*	*mention*	*abs_freq*	*wtd_freq*	*rel_value*
Week 1	1	@rdzaminhat	128	36992	289
	2	@jokermovie	198	12298	62
	3	@allontheboard	99	11776	119
	4	@sayeffit	41	1722	42

	5	@adriandhy	28	1316	47
	6	@twitchyspoonie	25	646	26
	7	@lovealwaysiris	23	642	28
	8	@karleia	23	642	28
	9	@callieahlgrim	22	470	21
	10	@toofab	18	396	22
Week 2	1	@jokermovie	66	1726	26
	2	@allontheboard	12	1536	128
	3	@tuckerdalebooth	36	812	23
	4	@thr	52	508	10
	5	@joker_of_jokers	1	498	498
	6	@heatvisionblog	20	304	15
	7	@pennsas	9	243	27
	8	@vanityfair	9	243	27
	9	@keirwales	16	67	4
	10	@bdisgusting	4	56	14
Week 3	1	@pennsas	11	297	27
	2	@vanityfair	11	297	27
	3	@rdzaminhat	1	289	289
	4	@goodjobliz	17	240	14
	5	@keirwales	35	204	6
	6	@jokermovie	21	187	9
	7	@allontheboard	1	128	128
	8	@torontostar	8	80	10
	9	@guardian	23	79	3
	10	@fussybabybitch	7	63	9
Week 4	1	@jokermovie	51	1491	29
	2	@eriksoninst	13	76	6
	3	@independentaus	10	72	7
	4	@usatoday	8	60	8
	5	@bryalexand	6	60	10
	6	@pennsas	4	36	9
	7	@vanityfair	4	36	9
	8	@torontostar	5	30	6

	9	@heatvisionblog	1	19	19
	10	@thr	1	19	19
Week 5	1	@maddow	14	182	13
	2	@hardball	14	182	13
	3	@hardballchris	14	182	13
	4	@jokermovie	9	88	10
	5	@dataracer117	9	81	9
	6	@pennsas	1	27	27
	7	@vanityfair	1	27	27
	8	@chicagotribune	5	11	2
	9	@elsie2127	3	9	3
	10	@nealcurtis	3	9	3
Week 6	1	@thatninahastie	5	20	4
	2	@fortyshort	5	20	4
	3	@radio702	5	20	4
	4	@bloggerconnects	5	20	4
	5	@ukblogrt	5	20	4
	6	@bblogrt	4	12	3
	7	@teaandpost	4	12	3
	8	@cbeechat	4	12	3
	9	@allthoseblogs	4	12	3
	10	@bloggershare2	5	10	2
Week 7	1	@vanityfair	1	27	27
	2	@pennsas	1	27	27
	3	@joerocket28	2	2	1
	4	@sqnshn	1	1	1
	5	@itssfwed	1	1	1
	6	@killaclown73	1	1	1
	7	@robinbartlett16	1	1	1
	8	@aalizianta	1	1	1
	9	@d_angelous	1	1	1
	10	@janicefiamengo	1	1	1
Week 8	1	@ind1obattalion	17	323	19
	2	@youtube	6	16	3

	3	@arod1895	3	6	2
	4	@el_platan0	3	6	2
	5	@vuecinemas	4	4	1
	6	@bbeldn	3	3	1
	7	@tragiqpvp	2	2	1
	8	@mystic82683001	2	2	1
	9	@richtiganz	1	1	1
	10	@changingamerica	1	1	1
Week 9	1	@imdb	2	4	2
	2	@truthstreamnews	1	3	3
	3	@calvinevans_	2	2	1
	4	@fincherism	1	1	1
	5	@egirlsnailmail	1	1	1
	6	@jgonzo	1	0	0
	7	@lilithlovett	1	0	0
	8	@craigcrusader	1	0	0
	9	@noobde	1	0	0
	10	@kyle____elyk	1	0	0

Table C.3

Emoji Analysis Across Weeks of Case 2

Week	*No.*	*emoji*	*abs_freq*	*wtd_freq*	*rel_value*	*emoji_text*
Week 1	1	🔥	719	394311	548	fire
	2	👏🏼	209	116354	557	clapping hands: medium-light skin tone
	3	🥺	96	73347	764	pleading face
	4	🎬	158	33821	214	clapper board
	5	😔	170	31880	188	pensive face

	6	🤲🏻	117	28431	243	palms up together: light skin tone
	7	🃏	174	10703	62	joker
	8	☹️	72	6721	93	frowning face
	9	⭐	181	5638	31	star
	10	🖤	116	4275	37	black heart
Week 2	1	👏🏼	1724	1037475	602	clapping hands: medium-light skin tone
	2	🤦🏻‍♀️	119	29869	251	woman facepalming: light skin tone
	3	🔥	11	3476	316	fire
	4	🤦🏾‍♂️	33	1353	41	man facepalming: medium-dark skin tone
	5	🥺	38	1251	33	pleading face
	6	💯	28	630	22	hundred points
	7	🎬	25	443	18	clapper board
	8	❤️	27	181	7	red heart
	9	🃏	17	156	9	joker
	10	👏🏻	17	150	9	clapping hands: light skin tone
Week 3	1	👏🏼	26	9703	373	clapping hands: medium-light skin tone
	2	🔥	5	1737	347	fire
	3	🎬	2	466	233	clapper board
	4	⬅️	7	63	9	left arrow
	5	➡️	7	63	9	right arrow
	6	™	7	63	9	trade mark
	7	😟	2	55	28	worried face

	8	🤡	35	45	1	clown face
	9	❤️	4	32	8	red heart
	10	😳	32	32	1	flushed face
Week 4	1	🎬	1	233	233	clapper board
	2	😊	16	210	13	smiling face with smiling eyes
	3	☹️	1	105	105	frowning face
	4	🃏	11	56	5	joker
	5	💯	4	20	5	hundred points
	6	👍	10	18	2	thumbs up
	7	🤡	14	16	1	clown face
	8	🙂	5	12	2	slightly smiling face
	9	👇🏾	4	8	2	backhand index pointing down: medium-dark skin tone
	10	😂	15	4	0	face with tears of joy
Week 5	1	👏🏼	8	4848	606	clapping hands: medium-light skin tone
	2	⭐	5	225	45	star
	3	🃏	15	12	1	joker
	4	😊	1	10	10	smiling face with smiling eyes
	5	💯	1	5	5	hundred points
	6	🤡	10	3	0	clown face
	7	🤨	3	2	1	face with raised eyebrow
	8	🤯	2	2	1	exploding head
	9	🙂	6	2	0	slightly smiling face
	10	😒	2	2	1	unamused face

Week 6	1	😂	248	73904	298	face with tears of joy
	2	👏🏼	8	4848	606	clapping hands: medium-light skin tone
	3	🖤	40	880	22	black heart
	4	💛	26	446	17	yellow heart
	5	😪	20	440	22	sleepy face
	6	🃏	51	124	2	joker
	7	🎞	27	54	2	movie frames
	8	😊	8	6	1	smiling face with smiling eyes
	9	😅	3	6	2	grinning face with sweat
	10	🤡	18	6	0	clown face
Week 7	1	😂	12	3278	273	face with tears of joy
	2	🖤	18	442	25	black heart
	3	🤦🏻‍♀️	1	251	251	woman facepalming: light skin tone
	4	🙂	13	74	6	slightly smiling face
	5	😟	1	55	55	worried face
	6	😔	4	6	2	pensive face
	7	✨	4	4	1	sparkles
	8	🎨	2	2	1	artist palette
	9	👌	3	2	1	OK hand
	10	😍	2	2	1	smiling face with heart-eyes
Week 8	1	👌🏾	32	1120	35	OK hand: medium-dark skin tone
	2	👍🏾	32	1120	35	thumbs up: medium-dark skin tone
	3	🃏	6	54	9	joker

	4	💯	3	32	11	hundred points
	5	🤡	5	2	0	clown face
	6	🤔	3	2	1	thinking face
	7	🙂	5	2	0	slightly smiling face
	8	☺	1	0	0	smiling face
	9	😬	1	0	0	grimacing face
	10	🌻	1	0	0	sunflower
Week 9	1	☹️	2	2	1	frowning face
	2	😖	2	2	1	confounded face
	3	👍🏾	2	2	1	thumbs up: medium-dark skin tone
	4	🖤	2	0	0	black heart
	5	🎭	1	0	0	performing arts
	6	™	1	0	0	trade mark
	7	😒	1	0	0	unamused face
	8	🃏	1	0	0	joker
	9	💚	1	0	0	green heart
	10	📷	1	0	0	camera

Appendix D: Semantic Networks of Weeks for Case 2: Movie Performance Evaluation

This appendix contains the semantic network analyses of Case 2 (i.e., the evaluation of movie performance). For each week, the semantic network of all bigrams is shown in the first two subfigures. The left subfigure highlights the top 20 words with the highest degree centrality, while the middle subfigure highlights the top 100 words used to conduct the community analysis. The community results of the top 100 words with the highest degree centrality are also extracted and shown on the right-hand side of the figures.

Figure D.1

Semantic Network of Week 1 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

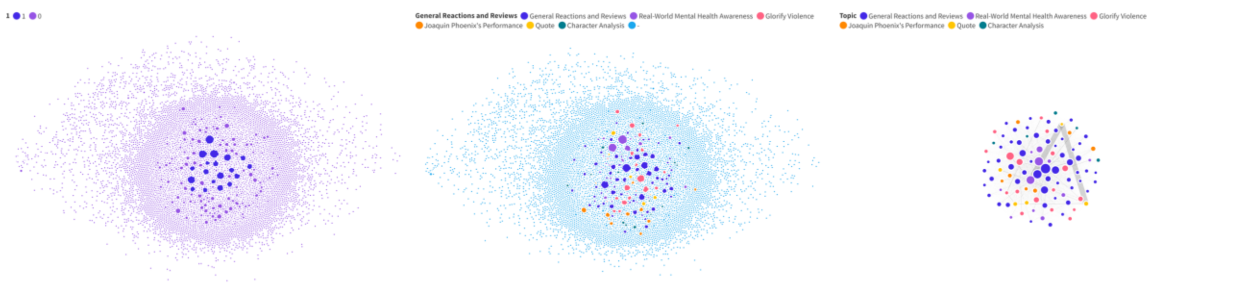


Figure D.2

Semantic Network of Week 2 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

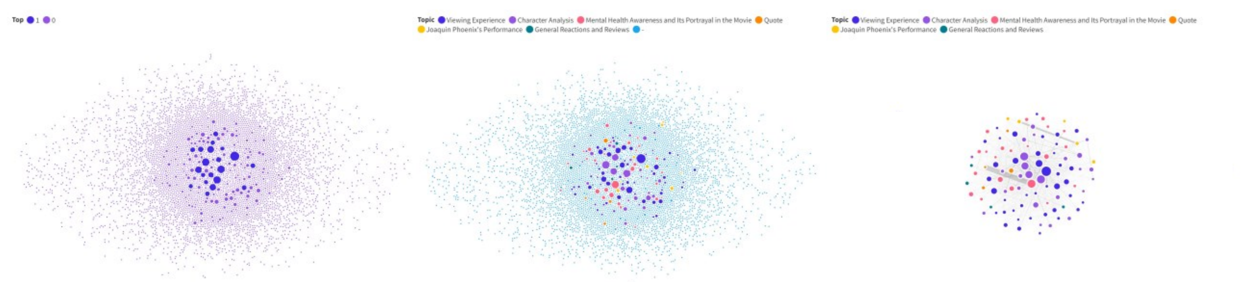


Figure D.3

Semantic Network of Week 3 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

Figure D.4

Semantic Network of Week 4 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

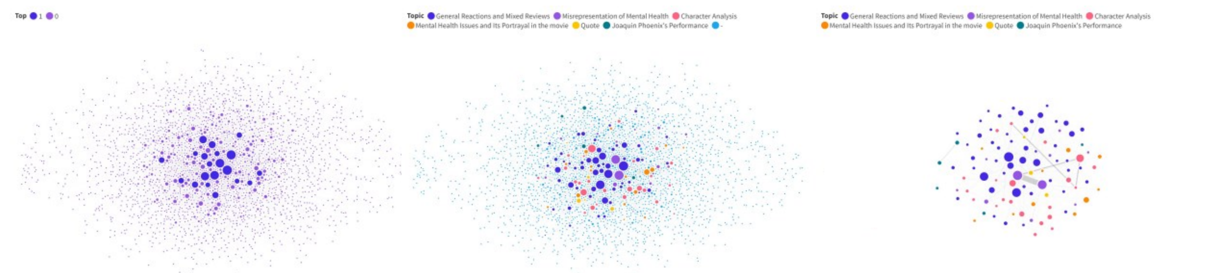


Figure D.5

Semantic Network of Week 5 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

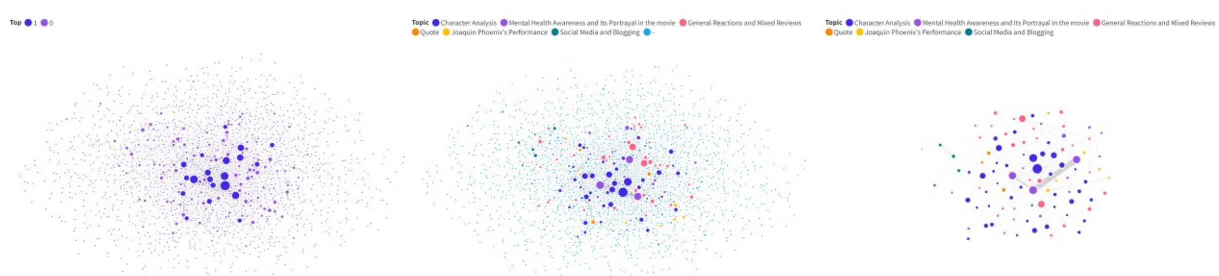


Figure D.6

Semantic Network of Week 6 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

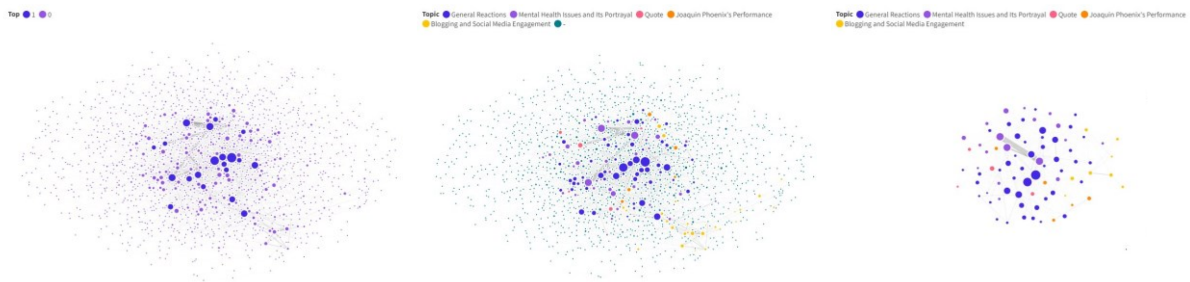


Figure D.7

Semantic Network of Week 7 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

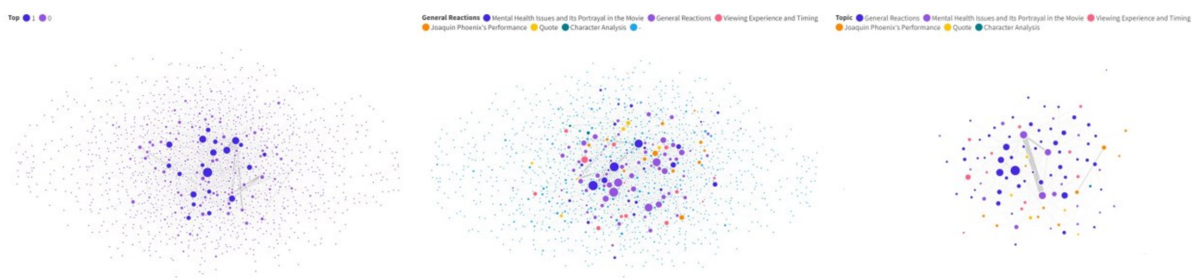
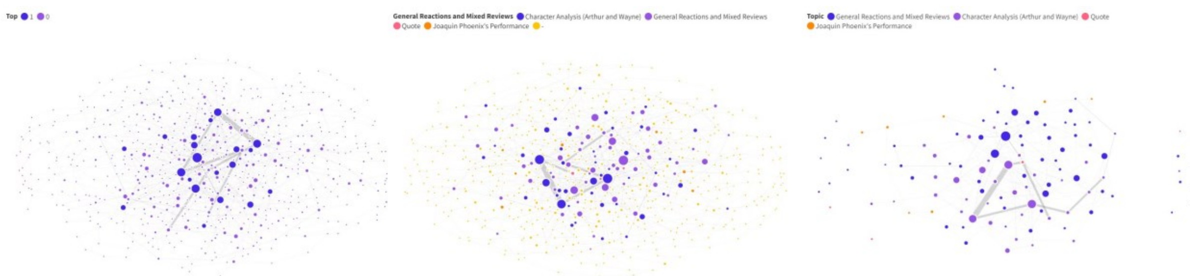


Figure D.8

Semantic Network of Week 8 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)

Figure D.9

Semantic Network of Week 9 with Top 20 Words Highlighted (left), Semantic Network of Week 1 with Top 100 Words Highlighted by Community (middle), Community Results on Top 100 Words (right)



Appendix E: Sentiment Distribution of Themes in Case 2: Movie Performance Evaluation

This appendix details the distribution of sentiment across the various topics discussed during different weeks of Case 2. The data is presented in tables that show the percentage of tweets expressing negative, neutral, and positive sentiments, along with the total percentage of tweets for each topic.

Table. E.1

Topic Sentiment Distribution of Case 2

Week	***Topic***	***0 (%)***	***1(%)***	***2(%)***	***% of Total Tweets***

W1	**Character Analysis**	14.06	20.31	65.63	1.98
	General Reactions and Reviews	14.83	22.07	63.10	54.32
	Glorify Violence	56.11	42.37	1.53	4.05
	Joaquin Phoenix's Performance	4.32	4.17	91.52	10.39
	Quote	0.55	88.97	10.49	19.77
	Mental Health Issues and Its Portrayal in the movie	7.67	19.58	72.76	9.48
	Grand Total	**11.89**	**33.98**	**54.12**	**100.00**
W2	**Character Analysis**	17.56	31.90	50.54	9.55
	General Reactions and Reviews	13.75	29.64	56.61	32.11
	Joaquin Phoenix's Performance	3.79	1.90	94.31	7.22
	Mental Health Issues and Its Portrayal in the movie	12.66	28.75	58.59	18.93
	Quote	0.65	79.87	19.48	15.82
	Viewing Experience	10.46	14.64	74.90	16.36
	Grand Total	10.58	33.17	56.25	100.00
W3	**Character Analysis**	28.36	22.39	49.25	3.88
	Joaquin Phoenix's Performance	9.40	15.38	75.21	6.77
	Mental Health Issues and Its Portrayal in the movie	34.04	13.68	52.28	19.05
	Misrepresentation of Mental Health	97.53	2.47		9.38
	General Reactions and Reviews	14.94	22.56	62.50	37.98
	Quote	3.10	73.79	23.10	16.79
	Viewing Experience	16.04	4.72	79.25	6.14
	Grand Total	24.55	26.00	49.45	100.00
W4	**Character Analysis**	13.89	36.81	49.31	19.49

	General Reactions and Reviews	10.55	28.52	60.94	34.64
	Joaquin Phoenix's Performance	10.91	7.27	81.82	7.44
	Mental Health Issues and Its Portrayal in the movie	23.93	27.61	48.47	22.06
	Misrepresentation of Mental Health	74.19	12.90	12.90	4.19
	Quote	-	81.11	18.89	12.18
	Grand Total	15.56	34.10	50.34	100.00
W5	**Character Analysis**	19.21	21.40	59.39	50.33
	General Reactions and Reviews	10.53	71.05	18.42	8.35
	Joaquin Phoenix's Performance	-	8.33	91.67	5.27
	Mental Health Issues and Its Portrayal in the movie	33.33	18.67	48.00	16.48
	Quote	-	86.89	13.11	13.41
	Blogging and Social Media Engagement	-	92.86	7.14	6.15
	Grand Total	16.04	37.58	46.37	100.00
W6	**Blogging and Social Media Engagement**	4.44	88.89	6.67	11.19
	General Reactions and Reviews	13.11	31.15	55.74	30.35
	Joaquin Phoenix's Performance	5.88	5.88	88.24	4.23
	Mental Health Issues and Its Portrayal in the movie	23.97	23.29	52.74	36.32
	Quote	-	88.89	11.11	17.91
	Grand Total	13.43	44.03	42.54	100.00
W7	**Character Analysis**	21.05	21.05	57.89	6.19
	General Reactions and Reviews	22.41	31.03	46.55	18.89

	Joaquin Phoenix's Performance	3.23	16.13	80.65	10.10
	Mental Health Issues and Its Portrayal in the movie	18.92	27.93	53.15	36.16
	Quote	4.00	88.00	8.00	16.29
	Viewing Experience	15.79	15.79	68.42	12.38
	Grand Total	15.31	35.18	49.51	100.00
W8	**General Reactions and Reviews**	22.41	32.76	44.83	35.80
	Joaquin Phoenix's Performance	6.45	32.26	61.29	19.14
	Mental Health Issues and Its Portrayal in the movie	44.23	23.08	32.69	32.10
	Quote	4.76	85.71	9.52	12.96
	Grand Total	24.07	36.42	39.51	100.00
W9	**Character Analysis**	26.67	33.33	40.00	12.20
	General Reactions and Reviews	35.48	35.48	29.03	25.20
	Joaquin Phoenix's Performance	-	41.30	58.70	37.40
	Quote	3.23	90.32	6.45	25.20
	Grand Total	13.01	51.22	35.77	100.00