Exploring Emoji Sentiment Roles in Arabic Textual Content on Digital Social Networks

By

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World Emoji Day ()

celebrated annually on July 17.

— **Emojipedia.org**

ABSTRACT

In today's digital landscape, emoji have risen as pivotal elements in articulating sentiment, especially within the intricacies of the Arabic language. This thesis examines the various roles that emoji can play in expressing sentiment in Arabic texts, highlighting their relevance both in academic and real-world contexts. Beginning with foundational insights, our investigation retraces the history of emoji as important non-verbal communicative tools in human interaction. Then, we explore the distinct challenges of sentiment analysis in Arabic and refer to a thorough review of previous studies to frame our method, identifying both established techniques and unexplored opportunities. At the heart of our research is the understanding that, depending on the context, an emoji can adopt a wide variety of sentiment roles. These range from acting as an *indicator*, *mitigator*, *emphasizer*, *reverser*, *releaser*, or *trigger* of either negative or positive sentiment. Additionally, there are instances where an emoji simply maintains a *neutral effect* on the sentiment of the accompanying text. To achieve this, we gathered a large dataset, mainly from Twitter, and developed lexicons of words and emoji tailored for sentiment analysis in Arabic. These lexicons were the basis of our analysis model. By leveraging the insights gained from the emoji-roles sentiment lexicon and combining them with our established knowledge of the sentiment roles associated with specific emoji patterns, we make a significant improvement in the conventional sentiment classifier based on the emoji lexicon. Traditional methods often assign a static sentiment score to an emoji, failing to consider its varying roles in different textual contexts. Our refined approach corrects this oversight. Instead of considering a singular unchanging sentiment score for each emoji, the classifier dynamically retrieves sentiment scores based on the specific role the emoji plays within a given sentence. In conclusion, we compare our method with other Arabic sentiment analysis tools, demonstrating the value of our approach, especially within nuanced linguistic phenomena such as sarcasm and humour. This thesis sets the foundation for future Arabic research in this expanding domain.

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Acronyms

Arab-ESL Arabic Emoji Sentiment Lexicon.

ArSenL Large Scale Standard Arabic Sentiment Lexicon.

ASCII American Standard Code for Information Interchange.

BERT Bidirectional Encoder Representations from Transformers.

Bi-GRU Bidirectional Gated Recurrent Unit.

Bi-LSTM Bidirectional Long Short-Term Memory.

BOW Bag-of-Words.

CAE Correlation-Attribute Evaluator.

CBOW Continuous Bag-of-Words.

CF-Arab-ESL Context-Free Arabic Emoji Sentiment Lexicon.

CNN Convolutional Neural Network.

EFL English as a Foreign Language.

ESR Emoji Sentiment Ranking.

Euro-ESL European Emoji Sentiment Lexicon.

F2F Face-to-Face.

GMM Gaussian Mixture Models.

GPT Generative Pre-trained Transformer.

GRU Gated Recurrent Unit.

L2 Euclidean Distance.

LDA Latent Dirichlet Allocation.

LEED Lisbon Emoji and Emoticon Database.

LM Language Model.

LR Logistic Regression.

LSA Latent Semantic Analysis.

LSTM Long Short-Term Memory.

mBERT Multilingual Bidirectional Encoder Representations from Transformers.

MLE Maximum Likelihood Estimation.

MLEmoji Multidimensional Lexicon of Emoji.

MNB Multi-Nomial Naive Bayes.

MSA Modern Standard Arabic.

MSE Mean Squared Error.

NB Naive Bayes.

NER Named Entity Recognition.

NLP Natural Language Processing.

POS Parts Of Speech.

PR Precision-Recall.

RF Random Forests.

RIPPER Repeated Incremental Pruning to Produce Error Reduction.

RMSE Root Mean Squared Error.

RNN Recurrent Neural Network.

SGD Stochastic Gradient Descent.

SMO-SVM Sequential Minimal Optimization-based Support Vectors Machine.

SMOTE Synthetic Minority Oversampling Technique.

ST Source Task.

SVM Support Vector Machine.

TF-IDF Term Frequency-Inverse Document Frequency.

TT Target Task.

UTF Unicode Transformation Format.

XLM-R Cross-lingual Language Model - RoBERTa.

ZWJ Zero Width Joiner.

Chapter 1

Introduction

This chapter introduces our investigation into sentiment analysis, with a specific emphasis on the Arabic language and the nuanced roles of emoji. Here, we establish the context and core research questions driving our investigation. We also briefly delve into the methodology, highlight potential challenges in the domain, and outline the subsequent chapters. By the conclusion of this introduction, readers will possess a comprehensive overview of our research journey and its relevance in today's digital landscape.

1.1 Research Overview

Communication is an essential aspect of human interaction that has evolved over time. With the advent of technology, communication has become increasingly digital, textual communication being the most common form [4]–[6]. However, despite its convenience, textual communication lacks the non-verbal cues present in face-to-face communication. When dealing with this issue in their text messages, people tend to use many types of text-based surrogates, such as nonstandard/multiple punctuations (e.g., **...** or **!!!**); lexical surrogates (e.g., **hmmm**, or **yummm**); asterisks (e.g., ***hug*** and ***grin***); emoticons (e.g., **:)** and **:(**); and lately emoji (e.g., 🙂 and 😕). Carey [7] categorised these non-verbal cues in text-based communication into five types: vocal spelling, lexical surrogates, spatial arrays, manipulation of grammatical markers, and minus features. Among these categories, emoji be considered as an example of spatial arrays [8]–[10]. Spatial arrays, in the context of text-based communication, refer to the arrangement of symbols or characters in a specific spatial pattern to convey meaning, feeling, or attitude [7]. It involves using visual elements within the text to enhance or complement the message being conveyed [11]–[13].

In recent years, emoji have become an increasingly popular feature in textual communication. These are small pictorial symbols (i.e., pictographs) that are used to convey emotions, reactions, concepts, and opinions in textual content [14]. In English, the word "emoji" can be used as singular and plural [1], which is what we follow in this thesis. Linguistically, emoji were defined as a form of developed punctuation, which is the way of encoding non-verbal prosody cues in writing systems, which supplement the written language to facilitate writers to articulate their emotions in text-based communication [8]. These pictographs can provide additional context to textual communication and provide insight into the underlying sentiment. Therefore, the incorporation of emoji into the analysis in various aspects,

[1] According to Cambridge (https://dictionary.cambridge.org/dictionary/english/emoji) and Merriam-Webster (https://www.merriam-webster.com/dictionary/emoji) English dictionaries.

including emotional and sentimental analysis, has become an active area of research [15]–[18].

The transition of human communication to digital platforms requires a re-evaluation of our methods for applying sentiment analysis. Sentiment analysis is a subfield of natural language processing (NLP) that involves the use of algorithms and computer technologies to identify, extract, and classify subjective information and affective states expressed in text [19], [20]. This includes opinions, attitudes, and emotions related to a service, product, person, or topic. Sentiments are often expressed in terms of polarity, such as positive/negative or good/bad, although neutral sentiment is also possible. The goal of sentiment analysis is to detect and extract subjective polarity in language, revealing sentiments and their strengths in words, sentences, and texts [21]. It focusses on identifying the subjectivity, polarity, and semantic orientation of the language when evaluating entities or individuals [22]–[24]. It is important to note that sentiment analysis is broader in scope than emotion analysis, which delves into specific emotions such as anger, anxiety, disgust, fear, joy, and sadness in more detail [25], [26]. This thesis focusses on understanding the nuanced role of emoji in relation to broader sentiment categories (i.e., negative, neutral and positive).

In the context of Arabic research, the analysis of emoji in textual content is still a relatively new field. Recent studies have shown that the use of emoji in Arabic communication is increasing, particularly among younger generations [27]–[29]. Therefore, understanding the role of emoji in Arabic communication is essential for developing effective sentiment analysis techniques that can meet the needs of these Arabic users.

1.2 Research Motivations and Objectives

Despite the increasing popularity of emoji in written communication, there is a noticeable research gap in the analysis of emoji specifically in the Arabic language. Existing research on emoji analysis has focused primarily on English and other languages such as French, Ger-

man, Chinese, and Japanese [1], [30]–[32]. However, these studies and the models and tools produced may not adequately capture the subtleties and cultural nuances inherent in Arabic communication. This lack of research on emoji analysis in the Arabic language hinders the development of effective sentiment analysis techniques and tools for Arabic textual content.

In fact, analysing sentiment in the Arabic language poses a complex challenge that requires careful attention to multiple factors. For instance, unlike Latin languages, Arabic lacks uppercase or lowercase letters and instead consists of 28 letters, including 25 consonants and only 3 vowels. To indicate pronunciation and disambiguate word meanings, the Arabic script utilises diacritical marks as short vowels that are placed above or below the letters. Although proficient speakers can comprehend texts without diacritical marks, most accessible texts, whether in Modern Standard Arabic (MSA) or dialects, are written without them [33]. This absence of diacritical marks in most texts presents a challenge for automated analysis models, leading to lexical ambiguity [34], [35]. For example, the undiacritized word "جد" can have multiple meanings such as "جَد grandfather", "جِد studiousness" or "جُد seriousness". Furthermore, the absence of capitalisation in Arabic proper nouns adds complexity to the identification of named entities in Arabic texts. Consequently, the implementation of a robust Named Entity Recognition system becomes essential in effectively analysing Arabic texts and accurately distinguishing between entity names and sentiment words [33]. For example, the word "أنهار Anhar" can serve as a proper noun, conveying a neutral sentiment as a female name, or expressing a positive sentiment when referring to "rivers". This word can also function as a verb, meaning "to collapse", which carries a negative sentiment. More challenges of the Arabic language in sentiment analysis will be discussed in Section 2.4 in the background chapter.

The complexity of interpreting emoji in sentiment analysis, particularly in the Arabic language, adds another level of challenge for Arabic researchers. The relationship between emoji and text plays a crucial role in shaping the emotive functions of emoji. Emoji can reinforce or modify the sentiment impact of a text, providing context, emphasis, or even

subverting the intended meaning. Thus, the interpretation of an emoji is deeply connected to the surrounding textual context, as it can influence how the emoji is understood and the emotional response it elicits. The same emoji used in different textual contexts can evoke a range of emotions or convey contrasting sentiments. Furthermore, the association between a specific group of emoji and certain words or phrases in popular usage can shape the collective understanding and emotional connotation attached to those emoji. Understanding the complex interaction between emoji and text is essential for comprehending the full emotional potential and functions of emoji in communication.

Consequently, more research is necessary to evaluate the effectiveness and limitations of current approaches and explore alternative strategies to integrate emoji into the sentiment analysis for Arabic. Therefore, the main objectives of this research are to investigate the consistency of sentiment labels assigned to individual emoji within and out of textual contexts in the Arabic language; explore the diverse roles of emoji in altering the overall sentiment of Arabic written messages; examine how variations in emoji sentiment roles contribute to differentiating sarcasm and humour in Arabic texts; and highlight the importance of identifying emoji sentiment roles to optimise sentiment classification performance. These objectives collectively aim to improve our understanding of the nuanced ways in which emoji influence sentiment interpretation in Arabic, contributing to more accurate and contextually relevant sentiment analysis within this linguistic and cultural context.

1.3 Research Premise and Key Questions

The core argument of this research is based on the belief that although emoji play a crucial emotional function, their true impact on sentiment becomes more pronounced in certain linguistically challenging scenarios, such as offensive language, hate speech, bullying, humour, and sarcasm. In such cases, a single emoji can pivot the sentiment's tone, and its absence

might result in a misinterpretation of the message's intent. These cases might be in the minority, but their impact is undeniable. Adding to that, our in-depth review of the literature reveals that despite their advancements, current Arabic sentiment analysis models often miss the subtle role of emoji in conveying sentiments. This drives the central question of our research: How can sentiment analysis be refined to interpret emoji more effectively within the Arabic-specific cultural and linguistic context? Several key questions will guide this exploration.

RQ1: To what extent is the sentiment interpretation of an individual emoji consistent within the Arabic language?

In addressing this question, we aim to examine the consistency of sentiment labels assigned to individual emoji both within and without the Arabic textual context.

RQ2: What are the potential emoji roles in altering the sentiment of Arabic written messages?

Answering this question, we seek to explore how individual emoji can change the overall sentiment of Arabic text by indicating, triggering, emphasising, mitigating, or reversing the sentiment tone of the message.

RQ3: How do alterations in emoji sentiment roles aid in discerning embedded sarcasm and humour in Arabic texts; and how does this enhance the accuracy of sentiment classification within these texts?

The response to this question will illustrate how the emoji sentiment roles can differentiate between the positive undertones of humour and the negative nuances of sarcasm. Furthermore, it will emphasise the importance of identifying emoji sentiment roles in optimising sentiment classification performance.

1.4 Research Contributions

The central objective of this thesis is to examine the sentimental behaviour of emoji in informal Arabic short texts. Our investigation began by exploring how emoji and sentiments coexist within these narratives. Taking into account the cultural backdrop of Arabic users, we pinpointed sentiment shifts in texts with and without emoji. By mapping these sentiment shifts to the inherent sentiments of each emoji, we outlined **thirteen** distinct roles that the emoji embody within Arabic texts. This insight spearheaded the construction of an emoji-role sentiment lexicon and the corresponding emoji-roles sentiment analysis model, marking a significant milestone in this research. Employing this lexicon not only enhanced the accuracy of Arabic texts' sentiment labelling, but also facilitated the unveiling of subtle linguistic phenomena, such as irony. As a culmination of our detailed study, we have developed and partially published four Arabic-centric emoji sentiment lexicons: context-sensitive, context-free, static, and sentiment-role-based. Anchored in meticulous sentiment annotation methodologies, these lexicons stand as highly reliable resources. Furthermore, we have compiled and published the **ArSarcasMoji**[2] dataset [36], tailored to analyse emoji in ironic Arabic textual contexts.

1.5 Thesis Publications

As a result of this intensive investigation, we published six peer-reviewed papers, which are listed as follows:

1. S. A. A. Hakami, R. Hendley, and P. Smith (2020). Emoji as sentiment indicators: An investigative case study in Arabic text. In Proceedings of the 6th International Conference on Human and Social Analytics (HUSO 2020) (pp. 1-7). Porto, Portugal (Virtual): October 2020. [37].

[2] **ArSarcasMoji** Dataset: https://github.com/ShathaHakami/ArSarcasMoji-Dataset

2. S. A. A. Hakami, R. Hendley, and P. Smith (2021). Arabic Emoji Sentiment Lexicon (Arab-ESL): A Comparison between Arabic and European Emoji Sentiment Lexicons. In Proceedings of the 6th Arabic Natural Language Processing Workshop (WANLP) (pp. 60-71). Association for Computational Linguistics. Kyiv, Ukraine (Virtual): April 2021. [2].

3. S. A. A. Hakami, R. Hendley, and P. Smith (2022). A Context-free Arabic Emoji Sentiment Lexicon (CF-Arab-ESL). In Proceedings of the 5th Workshop on Open-Source Arabic Corpora and Processing Tools with Shared Tasks on Qur'an QA and Fine-Grained Hate Speech Detection (pp. 51-59). European Language Resources Association. Marseille, France (Hybrid): June 2022. [38].

4. S. A. A. Hakami, R. Hendley, and P. Smith (2022). Gender Impact on Emoji Sentiment Analysis Among Arabic Users in Digital Networks. Proceedings of the 14th International Conference on Computational Intelligence and Communication Networks (CICN) (pp. 199-203). Al-Khobar, Saudi Arabia (Hybrid): December 2022. [39].

5. S. A. A. Hakami, R. Hendley, and P. Smith (2022). Emoji Sentiment Roles for Sentiment Analysis: A Case Study in Arabic Texts. In Proceedings of the 7th Arabic Natural Language Processing Workshop (WANLP) (pp. 346-355). Association for Computational Linguistics. Abu Dhabi, United Arab Emirates (Hybrid): December 2022. [40].

6. S. A. A. Hakami, R. Hendley, and P. Smith (2023). ArSarcasMoji: The Emoji Sentiment Roles in Arabic Ironic Contexts. In Proceedings of the 1st Arabic Natural Language Processing Conference (ArabicNLP) (pp. 208-217). Association for Computational Linguistics. Singapore (Hybrid): December 2023. [36].

1.6 Thesis Structure

Through this thesis, we embark on a comprehensive journey to unravel the intricate web of sentimental roles that emoji play in Arabic texts. This quest is not just academic; it has real-world implications, especially in an era where digital communication is paramount. As we navigate through subsequent chapters, each segment will critically dissect the various aspects of this topic, from the foundational principles to evaluative methodologies and, ultimately, to potential future work. This is described below.

Chapter 2 sets the background and theoretical foundation for the thesis, delving into human communication distinctions, and charting the historical evolution of emoji and their roles in mirroring non-verbal cues. It also provides insight into sentiment analysis techniques, spotlighting the nuances and inherent challenges of the Arabic language.

Chapter 3 reviews the extensive body of literature in the burgeoning field of emoji-based sentiment analysis. Prioritising a comprehension of the Arabic linguistic context, this chapter traverses both applied and theoretical facets presented in the literature. Through a critical lens, it evaluates the methodologies and resources previously employed, takes stock of state-of-the-art learning models, and pinpoints gaps in knowledge, setting the stage for further exploration in the domain.

Chapter 4 delves into the overview of the methodology used in the study of emoji's role in sentiment analysis of Arabic texts. It begins by presenting the problem statement, contextualised within the broader discussion of emoji as communication tools. The chapter then expounds on the analytical model used, highlighting the influence of emoji on sentiment interpretation in Arabic texts. Furthermore, it offers information on the structure, requirements, and limits of the research framework, ensuring a thorough understanding of the methodological foundation for subsequent analyses.

Chapter 5 discusses the acquisition of a large Arabic dataset with emoji-centric texts,

primarily from Twitter, and presents a tailored preprocessing method for these nonstandard Arabic tweets. Additionally, it addresses the use of already existing Arabic sentiment classifiers to annotate the data, preparing them for further sentiment analysis.

Chapter 6 details the creation of sentiment lexicons attuned to Arabic nuances and dialects. It encompasses the formulation of two types of Arabic emoji sentiment lexicons, context-sensitive and context-free, and investigates their alignment, leading to the "*Static*" emoji sentiment lexicon. This addresses the key research question, "**RQ1: To what extent is the sentiment interpretation of an individual emoji consistent within the Arabic language?**". In addition, a sentiment lexicon for dialectical Arabic words is introduced, serving as a foundation for our lexicon-based sentiment classifier.

Chapter 7 uses our prepared dataset, lexicons, and sentiment classifier to examine the roles of emoji in the sentiment of Arabic texts. It introduces an enhanced emoji sentiment lexicon detailing thirteen sentiment roles for each emoji, helping to refine the Arabic text sentiment classification. This addresses the key research question, "**RQ2: What are the potential emoji roles in altering the sentiment of Arabic written messages?**".

Chapter 8 examines our sentiment analyser based on the emoji-role lexicon, with a special emphasis on Arabic texts containing irony. It addresses the key research question, "**RQ3: How do alterations in emoji sentiment roles help in discerning embedded sarcasm and humour in Arabic texts; and how does this enhance the accuracy of sentiment classification within these texts?**". Through quantitative metrics, qualitative assessments, and comparisons with five renowned Arabic sentiment analysers, readers will gain clarity on the model's performance and potential refinements.

Chapter 9 concludes the research, summarising the main objectives and findings. It relates the results to the main research questions and compares them with current studies. The chapter highlights the practical, theoretical, and conceptual impacts of the study, discusses its limitations, and offers suggestions for future research.

1.7 Chapter Conclusion

This research seeks to better grasp and use the varied roles of emoji to improve sentiment analysis in informal Arabic digital messages, making sure they accurately reflect the depth of the Arabic language and culture. The next chapter will discuss aspects of communication, define emoji, explain sentiment analysis, and discuss the primary features of the Arabic language.

Chapter 2

Background

This chapter sets the stage for our exploration of the dynamic world of emoji within the context of Arabic sentiment analysis. At the heart of our discussion lies an understanding of the core principles of human communication, with special emphasis on distinguishing between face-to-face and text-based interactions. We embark on a historical journey, tracing the evolution of emoji and delving into their intrinsic characteristics. These foundations enable us to dissect the complexities of visual and vocal non-verbal cues, and how emoji, in their myriad definitions, serve as reflective tools within texts. In addition, we provide a window into the sentiment analysis techniques tailored for Arabic, highlighting the nuances of this rich language and the challenges it presents in analysis.

2.1 Human Communication

Communication is a fundamental aspect of human interaction, which facilitates the exchange of information, emotions, and intentions. Traditionally, face-to-face communication has been the main mode of interaction, enabling people to convey messages through verbal and non-verbal signals. Verbal cues consist of spoken words, while non-verbal cues encompass visible or auditory behaviours that can be associated with or detached from the verbal message. With the advent of digital communication platforms, text-based communication has become increasingly prevalent, presenting new challenges due to the absence of non-verbal cues. This section reviews the characteristics of face-to-face and text-based communication, explores the significance of verbal and non-verbal cues in each mode, and investigates how emoji serve as a means to mitigate the limitations of lacking non-verbal cues in text-based communication within social media networking.

2.1.1 Face-to-Face Communication

Rapid advances in technology have transformed the landscape of face-to-face interactions, revolutionising the way people interact with each other. The emergence of new technologies has led to a shift in synchronous communication, enabling immediate and real-time exchanges. Platforms such as Skype, Zoom, and Google Meet have redefined video calls, creating virtual face-to-face settings where people can see and hear each other, regardless of physical distance. These tools facilitate synchronous communication, bridging gaps and offering an immersive experience akin to traditional in-person conversations. In addition, applications such as WhatsApp or Snapchat have introduced voice messaging capabilities that allow users to send audio messages that can be instantly played back by the recipient. This form of communication adds a personal touch and immediacy, closely resembling the experience of speaking directly to someone. The transformative impact of these technological

advances extends beyond the expansion of communication possibilities, as they have fundamentally redefined the concept of face-to-face interaction in the digital era. In the realm of effective interpersonal interaction, both verbal and non-verbal cues play indispensable roles, as follows.

Verbal Cues and Human Language

Verbal interactions encompass a range of informal and formal interactions, from friendly chats over coffee or in the office kitchen to scheduled meetings. In these interactions, spoken language or speech serves as the primary medium for exchanging information, emotions, and thoughts. In general, any natural human language may contain several basic components, including phonology, lexicon, syntax, semantics, pragmatics, and discourse [41]. The process of effective verbal communication extends beyond just words, encompassing the quality and complexity of language usage to convey a comprehensive message [41]–[43].

In order to better comprehend verbal communication and its various functions, Jakobson's model, also known as the "*Jakobson's Functions of Language*" [42], offers a comprehensive framework. This model identifies six fundamental functions or purposes of language, which encompass different facets of language that play a crucial role in conveying meaning. These functions include referential, expressive/emotional, conative, metalinguistic phatic, and poetic [ibid.]. By identifying these functions, the model improves understanding of the complexities involved in interpreting and analysing intentions, meanings, and effects in verbal communication.

In addition, the performative dimensions of language are also significant within verbal communication, as explored through the "*Speech Act Theory*". Developed by Austin [43], this theory delves into how language is utilised to achieve specific objectives and take actions within communication. It distinguishes between different types of speech acts, including locutionary acts, illocutionary acts, and perlocutionary acts [43]. These categories help to

analyse and understand the different functions and effects of speech acts. It highlights that speech acts not only convey information but also have the power to perform actions, influence others, and create certain effects in communication.

In addition, an influential aspect of verbal communication is the use of the "*Contextual Valence Shifters*" [44], [45], which hold the power to shape the evaluative stance and attitude expressed in an articulated message. Through the strategic use of various linguistic factors such as lexical choices, presuppositions, and organisational structures, speakers can influence the perceived positivity or negativity of their evaluation [44]. These valence changes are achieved by incorporating adverbs or modifiers that introduce negative or positive connotations or imply a discrepancy between expected and actual results [ibid.]. For example, certain adverbs such as "exceptionally" can amplify the valence of evaluative terms. Comparing phrases like "It is good" and "It is exceptionally good", the inclusion of "exceptionally" introduces an emphasised positive connotation. The strategic placement of valence shifters within the speech further enhances their impact on the listener's interpretation. Understanding the role of contextual valence shifters provides valuable insights into how language is employed to convey evaluative stances, evoke emotional responses, and shape the listener's understanding of the speaker's viewpoint.

Non-verbal Cues and The Visible Acts of Meaning

Non-verbal cues are an integral part of communication that enhances the understanding and interpretation of messages. According to Mehrabian [46], communication is composed of three elements: verbal, vocal, and visual. Each of these elements contributes differently to the overall understanding and impact of a message.

Visual non-verbal cues are perceived through sight. This includes the movement of facial muscles (i.e., facial expressions), including the eyebrows, eyes, nose, mouth, and cheeks, that help to communicate the emotional and cognitive state of an individual. Body

language is another vital visual cue that involves postures, gestures, and movements. It encompasses hand movements, arm crosses, head nods, and body orientation, among others [47]. Body language can communicate various messages, including openness, dominance, attention, relaxation, and confidence. Eye contact, a fundamental visual cue, establishes a visual connection between individuals and can indicate interest, attention, trust, and engagement [ibid.]. It serves as a powerful non-verbal signal during communication, conveying important social signals and establishing rapport [ibid.]. Furthermore, proxemics, the use of personal space and physical distance during communication, can convey intimacy, formality, or social status. It is important to note that the interpretation of eye contact, body language, and facial expressions can vary between different cultures and social contexts. Additionally, different cultures have varying norms regarding acceptable distances for different types of interaction, influencing non-verbal communication.

Vocal cues, on the other hand, are non-verbal signals conveyed through the tone, pitch, volume, and other vocal characteristics of speech. The tone of voice refers to the emotional quality conveyed by the pitch, inflection, and intonation of speech [ibid.]. It can express happiness, sadness, anger, sarcasm, enthusiasm, or boredom, adding emotional depth and context to the verbal message. The pitch, the highness or lowness of the voice, is another important vocal cue. It can convey various meanings, such as excitement, surprise, authority, or uncertainty. Volume, or the loudness or softness of the voice, is of significance in communication. It can indicate confidence, assertiveness, or a need for attention [ibid.]. The rate of speech, or the speed at which a person speaks, also contributes to vocal cues. A fast speech rate may indicate urgency, nervousness, or excitement, while a slower rate can convey calmness or thoughtfulness [ibid.]. Furthermore, voice quality, which encompasses the unique characteristics of an individual's voice, such as hoarseness, smoothness, nasality, or breathiness, adds further nuance and personality to the spoken message [ibid.].

According to Bavelas and Chovil [47], these signals can convey subtleties of emotion and personality traits. They proposed that face-to-face communication involves "*visible*

acts of meaning" that are both audible and visible. These acts are different from other non-verbal signals based on four key criteria. **Firstly**, they are sensitive to the sender-receiver relationship and are less likely to occur when the speaker is alone. This excludes involuntary or reflexive acts such as breathing, sneezing, or sleeping, as well as voluntary acts that serve purposes that are not related to communication such as scratching a bite. Static features such as physical appearance or resting positions are also not considered. **Secondly**, these acts function as analogically encoded symbols, similar to how words and phrases can serve multiple functions simultaneously. Gestures, for instance, can convey both intrapersonal and interpersonal meanings, while facial displays can express emotions and contribute to the overall message. **Thirdly**, the meaning of these acts can be understood and demonstrated within the specific context of the communication. In face-to-face dialogue, visible behaviours complement spoken words by emphasising, specifying, enhancing, or even replacing them through facial displays, gestures, and other depictions. **Lastly**, these acts are fully integrated with the accompanying words, whether they provide redundancy or offer additional meaning. These visible acts of meaning are inseparable from the spoken words at the moment, forming an integrated message. It is important to note that these acts of meaning are not derived solely from physical sources. Instead, they propose an integrated message model that considers audible and visible communicative acts as a unified whole, recognising their interconnection in real-time communication.

Together, visual and vocal cues work in tandem with verbal communication, enriching the overall communication process. They improve understanding, provide emotional context, and convey nuanced messages that may not be explicitly expressed through words alone. Non-verbal cues add depth and texture to interpersonal interactions, enabling individuals to gauge others' emotional states, intentions, and attitudes. Understanding and effectively using non-verbal cues are essential skills for successful communication, as they contribute to the overall meaning and impact of messages exchanged.

2.1.2 Text-based Non-verbal Cues

Text-based communication, commonly used in written mediums such as email, instant messaging, and social networks, offers numerous advantages in terms of convenience, time efficiency, and both synchronous and asynchronous communication. On social media platforms, text-based communication can take on synchronous and asynchronous forms, depending on the specific interaction and the platform utilised [48]. For example, individuals can participate in live chat sessions on platforms such as Facebook Messenger or Twitter, engaging in real-time conversations with individuals or groups. Conversely, users also have the flexibility to compose and respond to written content at their own pace when sending/receiving emails, sharing/commenting on posts, or sending text messages. Some platforms may even offer a combination of synchronous and asynchronous features, allowing users to engage in real-time conversations, while also permitting delayed responses.

However, text-based communication lacks many of the non-verbal cues that play a significant role in face-to-face communication. In this mode, verbal cues become the primary means of conveying information, relying solely on written words to communicate messages. This limitation increases the potential for misinterpretation, as the absence of vocal intonation and facial expressions can lead to ambiguity or misinterpretation. Recognising the importance of non-verbal cues in textual communication, people engaged in internet-based textual communication often use various types of text-based surrogates to compensate for the absence of non-verbal cues. Yus [49] refereed to such a behaviour as "text deformation". This includes creative use of punctuation marks, repetition of letters, or strategic use of capitalisation and emoticons/emoji. Text deformation is typical in Internet-mediated communication in both asynchronous and synchronous text-based interactions. According to Carey [7], the categorisation of non-verbal textual signals can be classified into the following five types:

- **Vocal Spelling:** This type involves the use of non-standard spellings that draw atten-

tion to sound qualities. It may indicate a regional accent or an idiosyncratic manner of speech. Often, this involves the repetition of a vowel or final consonant to emphasise sound qualities, as seen in examples like "**Soooo much**" or "**breakkk**".

- **Lexical Surrogates:** In this type, users use specific words to describe their intended "tone of voice" or "physical attitudes" in the message. Examples include vocal surrogates like **uh**, **huh**, or **yuk**, as well as physical surrogates like ***hug*** or ***grin***.

- **Minus Feature:** This type occurs when users intentionally leave spelling errors uncorrected or neglect capitalisation. These practises are used to indicate a relaxed tone of familiarity with the receiver or a fast pace of communication, particularly when the sender is busy.

- **Spatial Arrays:** Users employing this type of non-verbal cue treat the page space as a canvas for expression. They may utilise various formatting techniques, such as leaving spaces between words, skipping lines, or paraphrasing each new sentence. Some spatial arrays even go beyond words, employing actual graphics created with letters to convey intended meanings or behaviours. Examples include using white spaces to indicate pausing or merging words together to create an onomatopoeic effect.

- **Patterning of Features:** This type involves the combination of multiple types of written non-verbal cues to clarify the sender's attitude or tone. Users may employ vocal spelling along with varying numbers of periods or question marks to indicate different degrees of pause or perplexity, for instance.

These five types of textual non-verbal cues contribute to the richness and effectiveness of text-based communication, enhancing the communication experience and helping convey meaning beyond the words themselves.

2.2 Emoji Overview

2.2.1 Emoji Definition

To address the absence of non-verbal cues in textual messages, internet communicators had used emoticons (i.e., typographic characters) prior to the invention of emoji (i.e., graphic characters). In 1982, Professor Scott E. Fahlman used the first known smiley face emoticon in a post on Carnegie Mellon University's computer science general board [50]. Emoticons refer to a series of text characters (i.e., punctuation, numbers, letters, or special characters) that are used to primarily resemble gestures or facial expressions textually. They can be formed not only by ASCII characters but also by Unicode characters, such as U+203F (‿), U+FE35 (︵), U+25C9 (◉) and U+0CA0 (ಠ)[1] [51]. As shown below, emoticons can be written vertically (Western style) and horizontally (East Asian style) depending on cultural conventions, personal preference, or the platform or medium of communication [52].

:) (vertical) 8((vertical) <3 (vertical) ^_^ (horizontal) ◉‿◉ (horizontal) ಠ‿ಠ (horizontal)

Emoji, on the other hand, are the new generation of emoticons on smart devices. In 1999, Shigetaka Kurita, a Japanese designer, introduced emoji for the first time to the public through the first Japanese mobile Internet system "i-mode" [53]. Therefore, the word emoji comes from the Japanese language: 絵 ("e" means picture) 文 ("mo" means writing) and 字 ("ji" means character) and can be used appropriately in written English as singular and plural [12].

In practise, emoji are textual graphical characters that are used in various digital communication platforms, including WhatsApp, Twitter, Facebook, and Instagram. They appear alongside text and are similar in size. These symbols rely on the Unicode standard, the universal foundation for text in today's writing systems. Within Unicode, specific code-

[1] http://unicode.org/reports/tr51/

Table 2.1: Different Rendering of Eight Emoji Across Seven Platforms.

Emoji Unicode Name	Apple	Facebook	Google	Microsoft	Samsung	Twitter	WhatsApp
Person with Headscarf							
Grinning Face with Smiling Eyes							
Grinning Face with Star Eyes							
Pistol							
Angry Face with Horns							
Person Facepalming							
Face Screaming in Fear							
Credit Card							

points define each emoji. These codepoints are processed using the Unicode Transformation Format (UTF), ensuring machine compatibility. Three primary UTFs encode emoji codepoints: UTF-8, UTF-16, and UTF-32. As of September 13, 2022, there were 3,664 emoji in the latest list published by the writing of this thesis (i.e., Emoji 15.0) [2]. Every emoji in the Unicode system has both a UTF codepoint and a designated name. For example, the emoji (😂) is identified by the codepoint "U+1F602" and named "*Face with Tears of Joy*". However, Unicode provides only the reference for the emoji, not its visual design. Similar to how Unicode recognises the Latin capital letter '*A*' as "U+0041" without dictating its font style. The actual visual representation, whether it is a letter or emoji, is handled by a rendering mechanism. Consequently, tech giants such as Apple, Microsoft, and Google offer their own emoji designs. This means that an emoji can appear differently across platforms, as illustrated in Table 2.1. Sometimes, users choose emoji for their design rather than their intended meaning. Wiseman and Gould [54] referred to this phenomenon as *"visual affordance"* of emoji.

In addition, emoji are categorised into various groups, each representing a different thematic category or concept. This includes smileys and people; animals and nature; food

[2] https://emojipedia.org/emoji-15.0/

and drinks; activities and hobbies; travel and places; objects and symbols; and flags of different countries. With such diverse categories, emoji offer a comprehensive and expressive visual language to enrich digital conversations.

2.2.2 Emoji Sequence

In addition to their globally accessible, non-verbal, colourful, context-sensitive, and user-friendly nature, emoji possess a notable characteristic known as an "*emoji sequence*". According to Emojipedia[3], there are five types of *emoji sequences*[4] as follows.

- **Emoji Modifier Sequence:** An emoji *Modifier Sequence* is created automatically when a modifier character (i.e., gender-based or skin-tone-based) is inserted after a supported base emoji character, resulting in a single emoji with a skin tone or a gender representation. For example: (👍 + 🟫 = 👍🏾) and (👴 + ♀ = 👵). Many emoji with skin tones are Emoji ZWJ Sequences, due to the presence of additional characters for gender, multiple people, or a combination of people and objects.

- **Emoji ZWJ Sequence:** An emoji *ZWJ Sequence* is a combination of multiple emoji displayed as a single emoji on supported platforms. These sequences are joined with a Zero Width Joiner (ZWJ) character. ZWJ is an invisible Unicode character with a "U+200D" codepoint that enables the joining of multiple emoji together to create a new visual representation. For example: (👨 + (U+200D) + 👩 + (U+200D) + 👦 = 👨‍👩‍👦).

- **Emoji Flag Sequence:** An emoji *Flag Sequence* is a mechanism in which an emoji is created using a combination of two Regional Indicator characters. Unlike the *Emoji ZWJ Sequences*, *Flag Sequences* do not use a ZWJ character. When two Regional Indicator characters are inserted in sequence, certain pairs automatically create a grapheme

[3]Emojipedia is a comprehensive database and guide to emoji, providing information on their meanings, variations, usage, and history. https://emojipedia.org/

[4]https://emojipedia.org/emoji-sequence

(i.e., combinations of letters) cluster on supported platforms. For example, the Saudi Arabia flag emoji () is a flag sequence combining the *Regional Indicator Symbol Letter S* and the *Regional Indicator Symbol Letter A*.

- **Emoji Tag Sequence:** Emoji *Tag Sequence* is a mechanism that allows a series of characters to describe or create a new format of emoji. These tags are composed of a *Black Flag* emoji followed by a series of *Tag* characters forming regional flags. *Tag Sequence* is currently only used for subdivision flag support to support subregions or subdivisions specified under ISO 3166-2 [5]. For example, the Jizan flag (i.e., one of the thirteen main subregions in the Kingdom of Saudi Arabia) **Flag for Jizan (SA-09)** emoji is a *Tag Sequence* combining *Black Flag*, *Tag Latin Small Letter S*, *Tag Latin Small Letter a*, *Tag Digit Zero*, *Tag Digit Nine* and *Cancel Tag*. These are displayed as a single flag emoji on supported platforms [6].

- **Emoji Keycap Sequence:** An emoji *Keycap Sequence* is a sequence which combines a keycap character with another character to create an emoji with a keycap appearance (e.g., ). Not all keycap emoji use a keycap sequence.

The various forms of emoji sequences exemplify the immense creative potential and versatility inherent in emoji. They enable users to communicate nuanced meanings and depict intricate concepts by skilfully arranging and combining different emoji. This flexibility in emoji usage enables people to go beyond simple representations and craft visual compositions that capture the depth and complexity of their intended messages. Through the thoughtful combination of emoji, users can elevate their communication to a more expressive and imaginative level.

[5] https://emojipedia.org/emoji-tag-sequence/

[6] https://emojipedia.org/flag-for-jizan-sa09/

2.2.3 Emoji Meaning

The existing body of emoji literature, such as the studies listed in Table 2.2, predominantly focusses on exploring the meanings, functions, and social uses of individual emoji within different contexts. This emphasis comes from the inherent complexity of comprehending emoji and their intended purposes when used in textual communication. Understanding these characters requires examining them from various perspectives, including their classification as icons, symbols or indexes; their status as pictograms, ideograms, or logograms; their role as words or punctuation marks; and their potential as vocal or visual non-verbal cues. In the following subsections, we will dive into these viewpoints and explore how scholars have tried to enhance the understanding of emoji by applying relevant theories and principles.

Table 2.2: Examples of Research on Specific Emoji.

#	Reference	Year	Studied Emoji	Study Focus
1	[55]	2016	*Face with Tears of Joy* emoji (i.e., 😂)	Cross-cultural usage differences.
2	[56]	2018	*Winking Face* emoji (i.e., 😉)	Irony indication by emoji.
3	[57]	2018	*Smiling Face with Smiling Eyes and Hand Covering Mouth* emoji (i.e., 🤭)	Emoji communicative action.
4	[58]	2019	*Toilet* emoji (i.e., 🚽)	Discourse meaning-making.
5	[59]	2019	*Peach* and *Eggplant* emoji (i.e., 🍑 and 🍆)	The context effect on emoji interpretations.
6	[60]	2020	*Pile of Poop* emoji (i.e., 💩)	Emoji emotional function.
7	[61]	2020	*Hand Gestures* emoji (i.e., 👌, 👍 and ✌)	Emoji pragmatic function.
8	[62]	2020	*Smiling Face with Smiling Eyes* emoji (i.e., 😊)	Emoji and customer relationship management.
9	[63]	2021	Hearts emoji (e.g., ❤️, 💚 and 💜)	Examining emoji color spaces.
10	[64]	2021	*Person with Folded Hands* emoji (i.e., 🙏)	Non-facial emoji communicative function.
11	[65]	2022	Kissing emoji (e.g., 😘, 😙, 😽 and 💏)	Cross-cultural usage differences.
12	[66]	2022	Flags emoji (e.g., 🇪🇺, 🇩🇪, 🇺🇸 and 🇫🇷)	Online political communication.
13	[67]	2022	*Doge The Shiba* emoji on Weibo platform (i.e., 🐶)	Emoji pragmatic function.
14	[68]	2022	*Slightly Smiling Face* emoji (i.e., 🙂)	Sarcasm indication by emoji.

Emoji as Icons, Symbols and Indexes

Peirce's theory of signs [69], also known as semiotics or semiotic theory, is a framework that explores how signs function and convey meaning within human communication. According to Peirce, a sign is a triadic relationship consisting of three elements: the sign itself (representative), the object to which it refers (object), and the interpretant (the understanding or meaning produced in the mind of the interpreter). These three components work together to generate meaning and communication. Accordingly, Peirce classified signs into icons, indexes, and symbols.

This theory has significantly impacted the definition of emoji and the understanding of their meaning. As argued by Wallenhorst [70], emoji are not merely iconic characters that visually resemble the objects they represent, but possess symbolic and indexical dimensions within textual contexts. Peirce defines **icons** as signs that directly refer to their objects based on intrinsic characteristics, such as visual similarity [69]. For example, a road sign depicting a camel (i.e., ) serves as an iconic sign, as it evokes the similarity and familiarity associated with an actual camel, even though a camel may not be physically present on the road. Similarly, many emoji are naturally iconic, such as (🍦) which means (ice cream), (🌷) which means (flower) and (🌞) which means (sun). In addition, emoji can be used as an "*image of word*" [54]. For example, emoji can be used as a direct translation of a "pet name" (e.g., penguin (🐧) and chocolate (🍫)). However, according to Wiseman and Gould [54], it was discovered that certain emoji were repurposed by users in textual communication as icons, specifically coded as "*Avatars*" to represent a particular person or place. For example, users used animal emoji to represent themselves or used specific emoji to refer to their partners on certain websites. Utilising emoji as avatars allowed users to convey personal identities while maintaining anonymity.

In contrast, **indexes** establish a tangible connection with the objects they denote. This connection can be established through various means, including causality, contiguity,

or attentional orientation. For example, smoke is an indexical sign of fire, since its presence is causally linked to the existence of fire. Similarly, pointing gestures (👈, 👆, 👉), eye movements (🙄 and 🫤), and arrows (↖️, ⬆️, ↘️) emoji are indexes by drawing attention to specific objects, guiding the interpretive process within a given context. More creatively, internet users can use emoji to refer to a shared incident at a particular time. Wiseman and Gould [54] coded the type of emoji used for this purpose as *historical* emoji. For example, family members may translate a shared awkward moment in real life into a commonly written shorthand represented by an emoji within their WhatsApp chatting group. '*Evocative*' emoji, as referred to by Wiseman and Gould [ibid.], are another indexical sign representing a shared metaphor between two people. These emoji refer to a common understanding that is "*evoking*" a particular feeling or opinion. For example, adding *Multiple Musical Notes* emoji (🎶) to a written line from the lyrics of a song evokes the original melody of that line of the song in the reader's mind. Similarly, Wiseman and Gould [ibid.] reported that partners might use a shared love of food to evoke feelings towards each other by using emoji like *Pizza* (🍕) and *Cheese Wedge* (🧀).

Lastly, **symbols**, according to Peirce, lack any inherent connection to the objects they represent [69]. Their meaning is established solely through conventional usage and agreed-upon associations. Flags are prime examples of symbols representing nations, regions, or organisations. They do not have a direct visual resemblance to the entities they symbolise, but their meaning is established through widely recognised conventions and associations. Humans have demonstrated remarkable creativity and ingenuity in utilising emoji as symbolic representations of a wide range of things, concepts, and ideas. Emoji provide a visual shorthand that allows individuals to convey nuanced meanings and complex messages in a concise and accessible manner. Their versatility as symbols extends beyond conventional usage and opens new avenues of communication. For example, research investigating human-sex-trafficking advertisements [71] has shed light on how emoji can be repurposed to convey hidden meanings. In this context, a seemingly innocuous *Rose* (🌹) emoji may indicate a

price, while a *Growing Heart* (💗) emoji can signify young girls. Likewise, the *Thinking Face* (🤔) emoji can be interpreted as lesbian, as the position of the thumb and forefinger on the chin denotes "lesbian" in American Sign Language [54]. These subtle repurposing and reinterpretations of emoji in specific contexts illustrate the adaptability of symbols and how they can be harnessed to communicate covert messages.

In sum, icons rely on visual resemblance and similarity; indexes establish spatial, temporal, or emotional connections and associations; and symbols depend on conventions and agreed-upon meanings. It is important to recognise that emoji can simultaneously embody all three dimensions, showcasing their versatility and the multifaceted nature of their communicative potential.

Emoji as Pictograms, Ideograms, and Logograms

The use of emoji is usually studied as elements in a grammatical structure (e.g., words and punctuation) or to indicate abstractive phenomena (e.g., sarcasm and metaphors). This is in accordance with the users' first language, the emoji positions and quantity within messages, or their ability to form a "*syntagm*", for example. *Syntagm* is a sequentially grouped symbol that together conforms to a new concept or idea (e.g., a birthday party = 🎈🎂🎉) [72]. In this context, emoji can be pictograms, ideograms, and logograms, each representing a distinct aspect of their nature and function within communication.

Pictograms are visual symbols that directly represent objects or actions. With their colourful and expressive images, emoji visually represent various objects, emotions, activities, and non-verbal facial expressions and gestures [73]. They serve as pictorial representations that enable quick and intuitive understanding across language and cultural barriers. For example, a smiley face emoji (e.g., 😊) can universally convey happiness or positivity without an explicit textual explanation.

Ideograms, however, are symbols that represent ideas or concepts, often without a direct visual resemblance to their referents. Emoji go beyond mere visual representation and convey abstract concepts or emotions. For instance, the *Breast-Feeding* (🤱) emoji represents motherhood, the *Face with a Zipper Mouth* (🤐) emoji indicates silence, and the *No Entry Sign* (🚫) signifies prohibition. These ideographic aspects of emoji allow for concise and efficient communication of complex ideas or sentiments in a visually concise manner.

Logograms are symbols that represent words or morphemes. While emoji are not directly linked to specific words, they can function as logograms when combined with text. In digital communication, emoji are frequently used to enhance or supplement textual content, providing additional layers of meaning or emotional context. For example, combining a *Breast-Feeding* emoji (🤱) and the word '*mother*' creates a more vibrant and expressive message.

To put it simply, emoji visually represent objects and actions (pictograms), convey abstract ideas and emotions (ideograms), and can supplement or represent words in combination with text (logograms). This multidimensional nature of emoji contributes to their widespread popularity and effectiveness as a communication tool in today's digital world. Emoji possess the key attribute of communicative potential, allowing social media users to be more emotionally expressive.

Emoji as Developed Punctuation (Vocal Textual Cues)

Punctuation has historically served as a way to convey non-verbal signals in writing. Chafe [74] suggested that when people write or read, they mentally simulate auditory attributes, termed "*Covert Prosody*". These encompass nuances like emphasis, pauses, rhythms, and tone. He believed that punctuation is a writer's primary tool to render this *covert prosody* explicit. In this context, emoji have emerged as an advanced punctuation form, enriching the digital written language by adding emotional dimensions [8]. For example, a statement

such as "*I just finished my first exam*" paired with a crying emoji (😭) would likely elicit sympathies. However, when the same statement is coupled with a smiley face (😊) or even non-facial emoji like clapping hands (👏), it prompts positive reactions, with responses like "*Congratulations!*" or "*Great job!*". Thus, emoji provide nuanced commentary, assisting writers in conveying the intended emotional undertones, and guiding readers on the sentiment and emotional depth of a message. Their role in online communication is crucial, enabling richer and more effective emotional expression alongside written words.

Emoji as Visible Acts of Meaning (Visual Textual Cues)

In line with Carey's [7] insights, emoji have been considered under the *Spatial Arrays* type of textual non-verbal cues [75]. Just as spatial arrays (i.e., the textual formatting techniques) utilise the page space for expressive purposes, emoji visually represent attitudes and play crucial roles as non-verbal features in text-based interactions. Consequently, Miller, Kluver, Thebault-Spieker, et al. [76] considered emoji as "visible acts of meaning". Emoji are iconic, symbolic, and indexical visual representations that function analogically as pictograms, ideograms and logograms to enhance the conveyed message. Like the face-to-face visible acts of meaning, emoji in texts are sensitive to the sender-receiver relationship, have contextual meaning, and are fully integrated with the accompanying words. They provide a visual complement to written text, conveying emotions, actions, and ideas and forming an integrated message that combines visual and verbal elements.

2.2.4 Emoji General Functions

Emoji have become integral to online communication, adding a visual and expressive dimension to text-based interactions. Beyond their colourful and playful appearance, emoji serve many functions, allowing individuals to convey emotions, enhance linguistic elements,

foster social interaction, and inject humour into digital conversations. Scholars have made significant efforts to classify and categorise emoji functions based on various criteria and research perspectives. In this context, we explored the themes that emerge from the collective work of researchers to understand the pragmatic functions of emoji. By analysing and organising the findings of multiple studies, listed in Tables 2.3, 2.4, 2.5, 2.6, 2.7, we could gain insight into the diverse general roles that emoji play in shaping online communication. The following paragraphs will delve into the seven main themes that have emerged from these classifications, shedding light on how emoji contribute to the dynamics and richness of digital conversations.

Theme 1: Emotional Expression Function

Emoji serve as nuanced tools to capture and convey the complex spectrum of human emotions in the digital realm. From depicting overt feelings to establishing moods, they act as a bridge between textual content and emotional intent. By doing so, they help to ensure that the sender's emotional state or reactions are accurately conveyed to the recipient [27], [49], [77]–[85].

Theme 2: Communicative Function

Beyond emotion, emoji have the power to fortify messages, regulate interactions, and even guide the conversational tone. They can provide clarity, amplify the intensity of messages, and function as pivotal elements in shaping the trajectory of digital interactions [27], [48], [72], [78], [80], [82], [84]–[86]

Theme 3: Linguistic Function

Emoji complement the text, enriching its linguistic fabric. They can underscore the verbal component, act as syntactic markers, or even function as standalone lexical units. In this capacity, they are instrumental in ensuring that the nuances of messages, which might be evident in spoken interactions, are not lost in textual form [72], [81], [82], [87].

Theme 4: Ironic and Playfulness Function

Emoji have been seamlessly woven into the fabric of digital humour and irony. Through them, users can convey playfulness and jest, and even use them as tools for sarcastic undertones. They are not just about adding a light-hearted touch, but also serve as devices for multilayered expression in the digital discourse [49], [81], [82], [84], [85].

Theme 5: Social and Cultural (Pragmatic) Function

In digital interactions, emoji serve a broader social and pragmatic role. From expressing politeness and marking social rituals to fostering rapport in interactions, they reflect the evolving social and cultural dynamics of the digital age [27], [29], [78], [82], [87], [88].

Theme 6: Stylistic and Aesthetic Function

Emoji also contribute to the visual appeal and stylistic richness of digital conversations. By making messages visually prominent, they not only capture attention, but also underscore the aesthetic creativity of the sender, making digital interactions more dynamic and vivid [29], [72], [79], [86].

Theme 7: Miscellaneous Function (Ambiguous or Multifunctional)

Although many emoji functions can be grouped under well-defined categories, some of their roles remain multifaceted, versatile, and sometimes ambiguous. This theme acknowledges the diverse and evolving nature of emoji use, which may not always fit neatly into predefined boxes [11], [83].

Table 2.3: Emoji General Functions Taxonomy (Part I)

#	Reference	Year	Perspective	Data Source	Examined Language	Emoji Functions
1	[79]	2007	Linguistics: pragmatic	Instant Messenger	Singaporean (unspecified)	1. Accentuating or emphasizing a tone or meaning of the message. 2. Establishing the current mood or impression of the sender. 3. Making the conversation creative and visually salient.
2	[77]	2007	Linguistics: syntactic	Website Message Boards	English	1. Functioning as a standalone message (i.e., Naked emoticons). 2. Emoticons placed at the beginning or end of the message. 3. Emoticons inside the message, qualifying the text.
3	[80]	2008	Linguistics: pragmatic	Questionnaire Items	English	1. Expressing emotion. 2. Strengthening the message. 3. Regulating the interaction. 4. Putting into perspective.
4	[88]	2009	Linguistics: pragmatic and semantic	Internet Relay Chat System	English	1. Adding an evaluative dimension to the meaning of an utterance. 2. Expressing politeness and friendliness. 3. Back-channelling device. 4. Introducing pragmatic complexity (vague or ambiguous meaning).
5	[81]	2010	Linguistics: pragmatic and semantic	Instant Messaging System	Taiwanese (unspecified)	1. Enhancing Positive Emotions. 2. Reducing Negative Emotions. 3. Enhancing Tasks Coordination. 4. Signalling Common Knowledge. 5. Facilitating Expressions.
6	[82]	2010	Linguistics: pragmatic	Weblogs	Japanese and English	1. Devices of modesty. 2. Hedging devices. 3. Softening requests. 4. Positive politeness strategies. 5. Rapport building. 6. Humour device. 7. Conveying emotion. 8. Emphatic use. 9. Lexical use.

Table 2.4: Emoji General Functions Taxonomy (Part II)

#	Reference	Year	Perspective	Data Source	Examined Language	Emoji Functions
7	[87]	2012	Linguistics: lexical, pragmatic, syntactic and semantic	Instant Messaging System	French	1. Additions of para-verbal elements to the message. 2. Expressing redundancy. 3. Contradicting or nullifying the expressed meaning. 4. Functioning as a standalone message. 5. Functioning as syntactic markers (often as punctuation).
8	[83]	2014	Linguistics: pragmatic	Unspecified	Unspecified	1. Emotion indicators (mapped directly onto facial expression). 2. Non-emotional indicators of meanings. 3. Illocutionary force indicators.
9	[49]	2014	Linguistics: pragmatic	Unspecified	Spanish	1. Signalling attitude/emotion. 2. Enhancing attitude/emotion intensity. 3. Modifying illocutionary force. 4. Indicating humor. 5. Indicating irony. 6. Signalling parallel emotions.
10	[89]	2015	Computer science: Human-Computer Interaction	Interview Data	English	1. Expressing emotions. 2. Keeping a conversational connection. 3. Creating a space for playful interaction. 4. Creating shared and secret uniqueness.
11	[90]	2016	Linguistics: lexical and pragmatic	Facebook	English	1. Addition of information. 2. Expressing emotion. 3. Situational context. 4. Changing tone. 5. Engagement & relationship. 6. Engaging the recipient. 7. Social & convers. Norms. 8. Relationship maintenance.

Table 2.5: Emoji General Functions Taxonomy (Part III)

#	Reference	Year	Perspective	Data Source	Examined Language	Emoji Functions
12	[48]	2017	Linguistics: pragmatic	Facebook	English	1. Mention. 2. Reaction. 3. Tone modification. 4. Riffing. 5. Action. 6. Narrative sequence. 7. Other. 8. Ambiguous.
13	[85]	2017	Linguistics: semantic and pragmatic	Twitter	Unspecified	1. Expressing Sentiment. 2. Strengthening the Expressions. 3. Adjusting Tone. 4. Describing Content. 5. Expressing Humour. 6. Expressing Intimacy. 7. Expressing Irony.
14	[84]	2018	Linguistics: pragmatic	Twitter	Chinese	1. Signalling attitude/emotion. 2. Enhancing attitude/emotion intensity. 3. Modifying illocutionary force. 4. Indicating humour. 5. Indicating irony. 6. Signalling parallel emotions. 7. Turn-taking/giving device. 8. Backchannelling device.
15	[27]	2018	Linguistics: pragmatic	WhatsApp	Arabic	1. Indication of Celebration. 2. Approval of Others' Messages. 3. Responses to Thanks and Compliments. 4. Conversational Openings and Closings. 5. Linking Devices. 6. Indication of Task Fulfilment.

Table 2.6: Emoji General Functions Taxonomy (Part IV)

#	Reference	Year	Perspective	Data Source	Examined Language	Emoji Functions
16	[54]	2018	Computer science: Human-Computer Interaction	Questionnaire Items	English	1. Expressing romantic/platonic love and affection. 2. Used in place of a specific person or animal. 3. Expressing emotions. 4. Repurposing emoji for simple conversational words. 5. Referring to a place or plan. 6. Referring to sex. 7. Expressing humour. 8. Expressing opinion. 9. Showing solidarity or power.
17	[78]	2019	Linguistics: pragmatic	Unspecified	Unspecified	1. Emotive Function. 2. Social Function. 3. Beat Gestures. 4. Assessing Personality.
18	[86]	2019	Linguistics: pragmatic	WhatsApp	Spanish	1. Illocutionary. 2. Discursive. 3. Stylistic.
19	[72]	2019	Linguistics: lexical, pragmatic, syntactic and semantic	Twitter	English	1. Illustrative. 2. Metaphoric. 3. Pointing. 4. Beat. 5. Illocutionary. 6. Backchannelling.
20	[91]	2020	Computer Science: Natural Language Processing	YouTube Comments Section	Uzbek	1. Expressing emotion. 2. Expressing opinion.
21	[92]	2021	Linguistics: pragmatic	Weibo	Chinese	1. Perform Speech Acts. 2. Highlight Subjective Interpretations. 3. Enhance Informality. 4. Substitute, Reinforce, and Complement Meanings.

Table 2.7: Emoji General Functions Taxonomy (Part V)

#	Reference	Year	Perspective	Data Source	Examined Language	Emoji Functions
22	[93]	2021	Linguistics: pragmatic	Weibo and Twitter	Chinese	1. Emphasis on text. 2. Text complementary. 3. Adding information. 4. Tone modification. 5. Text embellishment.
23	[94]	2021	Linguistics: semantic and pragmatic	Unspecified	English and Russian	1. Illocutionary Acts. 2. Semantic and Pragmatic Potential. 3. Terminological Variability. 4. Structural and Content Potential. 5. Use in Internet Culture. 6. Differentiation and Characterization. 7. Field Approach and Thematic Thesaurus. 8. Structural and Semantic Features. 9. Inclusion in Internet Spheres.
24	[28]	2021	Linguistics: pragmatic	Twitter	Arabic	1. Communicating facial expressions. 2. Used as punctuation. 3. Reflecting the para-linguistic prosodic features. 4. Expressing emotional states. 5. Representing culture-specific gestures.
25	[95]	2022	Linguistics: pragmatic	Facebook	Arabic	Nineteen multiple illocutionary acts.
26	[29]	2023	Linguistics: pragmatic	Twitter	Arabic	1. Multiple functions. 2. Reaction. 3. Action. 4. Decoration. 5. Physical action. 6. Softening. 7. Tone modification.
27	[96]	2023	Linguistics: lexical, pragmatic, syntactic and semantic	The Emoji Movie	Kurdish	1. Reducing ambiguity. 2. Representing specific cultural background. 3. Earning new meanings. 4. Replacing words. 5. Context-sensitive interpretations.

2.3 Sentiment Analysis

2.3.1 Sentiment Analysis Definition

Sentiment analysis, also known as opinion mining, is a subfield of NLP that involves the automated extraction and classification of subjective information from the text to determine the emotion or sentiment expressed [19], [20], [23]. It aims to understand the underlying attitudes, opinions, and emotions of individuals or groups toward a particular topic, product, service, or entity. Frequently, the results of this analysis determine whether a given text conveys a positive, negative, or neutral sentiment. Accomplishing this involves analysing textual content, including words, phrases, and linguistic patterns, to infer the polarity and intensity of the sentiment. Sentiment analysis can be performed at various levels, such as document level (analysing the sentiment of an entire document or article), sentence level (analysing the sentiment of individual sentences), or even aspect level (analysing the sentiment associated with specific aspects or features mentioned in the text) [20], [22], [23], [97].

Sentiment analysis is applicable in various domains, including business / finance, politics, healthcare / medicine, entertainment, customer reviews, social media, product feedback, education, travel and hospitality, and news and media [20], [22], [98]. It involves assessing and understanding public sentiments and opinions in various contexts, providing valuable information for decision-making and analysis in each domain.

2.3.2 Sentiment Analysis Approaches

Sentiment analysis is an active area of research and new approaches and techniques are constantly being developed to improve its accuracy and performance. However, there are several main approaches to sentiment analysis, including:

Lexicon-based approaches: These approaches use sentiment lexicons or dictionaries containing words or phrases annotated with their associated sentiment polarity (positive, negative or neutral) [21]–[23], [99]. The sentiment of a given text is calculated based on the presence or frequency of sentiment-bearing words in the lexicon.

Machine learning approaches: These approaches employ various machine learning algorithms to train models on labelled datasets. Common techniques include:

- **Supervised learning:** Training models using labelled datasets where each text is assigned a sentiment label. Algorithms such as Naive Bayes, Support Vector Machines (SVM), and Random Forests are commonly used [20], [97].
- **Unsupervised learning:** Clustering techniques such as K-means or hierarchical clustering can be used to group texts into sentiment categories based on their similarity. Latent Dirichlet Allocation (LDA) and Gaussian Mixture Models (GMM) are also used to identify sentiment clusters [20], [97].
- **Deep learning:** Deep learning models, such as recurring neural networks (RNN), convolutional neural networks (CNN), and transformer models (e.g. BERT), have shown significant success in sentiment analysis. These models can learn intricate patterns and dependencies from text data [100], [101].

Rule-based approaches: Rule-based methods involve defining rules or patterns that capture sentiment-related information. These rules range from simple heuristics to more complex linguistic rules based on syntactic or semantic structures. Regular expressions and grammatical parsers are often used in this approach [97].

Hybrid approaches: Hybrid approaches combine multiple techniques to improve the performance of sentiment analysis. For example, a lexicon-based approach can be combined with machine learning algorithms to take advantage of the coverage of the lexicon and the ability of the model to learn from the data [ibid.].

Aspect-based sentiment analysis: This approach focusses on identifying sentiment at the document or sentence level and at a more granular level considering specific aspects or characteristics of a product, service, or entity. It aims to extract sentiments associated with different aspects mentioned in the text [97].

Emotion detection: Sentiment analysis can be extended to detect specific emotions expressed in text, such as joy, anger, sadness, or surprise. Emotion detection approaches often involve training models on labelled datasets that associate specific emotions with textual signals or patterns [ibid.].

2.4 Arabic Language

Arabic is one of the official languages of the United Nations and serves as the primary language in 27 countries. More than 422 million people speak it in the Arab world, making it the fourth most popular online language [102]. The language has three variants: Classical Arabic, the language of the Qur'an; Modern Standard Arabic (MSA), used formally in writing and speech; and dialectical Arabic, which is conversational and varies between regions [35], [102].

2.4.1 Arabic Language Characteristics

Arabic scripts move from right to left, without making any distinction between uppercase and lowercase. The alphabet comprises 28 letters, with 25 consonants and 3 vowels. However, short vowels, known as diacritical marks, are placed above or below letters for accurate pronunciation. Although many MSA texts omit these, they are common in resources for learners (e.g., children and non-Arabic speakers) [35], [102], [103]. Their absence can cause lexical ambiguity, as the same word might have different meanings. For example, the undia-

critized word "جد" can have multiple meanings such as "جَد grandfather", "جِد studiousness" or "جُد seriousness". Additionally, some punctuation marks in Arabic have orientations opposite to those in English [103]. For example, the question mark in English (?) is represented as (؟) in Arabic. Similarly, the commas (,) and semicolon (;) in English correspond to (،) and (؛) in Arabic, respectively.

Moreover, the Arabic language possesses a nuanced and sophisticated morphology, where even a single word can convey significant details [102], [103]. Within its space-delimited structure, Arabic words highlight various morphological facets, such as *derivation*, *inflection*, and *agglutination* [102]. In the *derivational morphology*, Arabic relies on a root-and-pattern system, with words built upon a sequence of consonants or "root" that holds the core meaning [ibid.]. Different patterns of vowels and consonants shape-related words. For example, the root "Shaara شَعَرَ" (means "feel") can produce multiple words with distinct meanings based on the pattern. This includes "Sha'ir شَاعِر" (a poet) and "Istish'ar اِسْتِشْعَار" (perception or realisation). In the *inflectional morphology*, Arabic words vary to convey similar meanings in different grammatical contexts [ibid.]. Arabic words can reflect seven aspects: tense (past and present), person (1st, 2nd, and 3rd), number (singular, dual, and plural), gender (feminine and masculine), case (nominative, accusative, and genitive), mood (indicative, imperative, subjunctive, jussive, and energetic), and voice (active and passive) [ibid.]. In the *agglutinative morphology*, Arabic words can be attached to multiple affixes. This can result in many derivatives from a single stem [ibid.].

The complex nature of Arabic word formation presents a primary challenge for researchers in Arabic sentiment analysis. The following section will list the primary obstacles encountered when trying to establish a system for Arabic.

2.4.2 Arabic Language Challenges in Sentiment Analysis

Arabic sentiment analysis has gained more attention in recent years. However, the unique complexities of the Arabic language, characterised by its rich grammar, expansive lexicon, and various dialects, introduce numerous challenges for sentiment analysis. This includes the following.

1. **Morphological Complexity:** Sentiment analysis in Arabic deeply depends on morphological analysis to dissect words into their constituent morphemes and assign relevant morphological details like stems, roots, and parts-of-speech (POS) [35], [102]. Because of the complex nature of Arabic morphology, there is an urgent demand for systems skilled in tasks like tokenization, spell-checking, stemming, lemmatisation, and pattern identification. Although multiple Arabic morphological tools are available, they often struggle with uncertainties caused by missing diacritics, the language's adaptable sentence construction, or missing personal pronouns.

2. **Dialectal Variations:** For everyday communication, speakers often choose colloquial Arabic, which differs considerably from MSA. Given that there are approximately 30 primary dialects, each with unique phonetic, structural, and lexical features [35], [102], [103]. The use of MSA-focused sentiment tools in these dialects leads to reduced effectiveness models. Despite recent efforts to create parsers for individual dialects, these tools still fail to provide accurate results.

3. **Romanised Arabic (Arabizi):** Arabizi, which represents Arabic sentences using Latin characters, is commonly used on social networks [35], [102]. Although some research efforts focus on identifying and translating Arabizi back to Arabic, the majority of sentiment analysis works tend to bypass this issue, usually removing such Romanised Arabic sentences in the initial processing stages.

4. **Named Entity Recognition (NER):** Because Arabic does not capitalise proper nouns, it is difficult to differentiate between Arabic names linked with positive adjec-

tives and actual sentiment terms, like "Farah فرح" (happiness) [102]. This distinction is even more pertinent considering that many Arabs have names derived from emblematic animals that signify attributes such as bravery (e.g., "Fahad فهد" (Cheetah), "Dheeb ذيب" (Wolf) and "Saqar صقر" (Eagle)) or beauty (e.g., "Reem ريم" and "Maha مها" (Arabian Oryx)).

5. **Orthographic Challenges:** Arabic script's unique characteristics pose several orthographic challenges. For instance, users might introduce spelling errors by omitting or incorrectly placing diacritical marks, or resorting to informal or phonetic spellings which deviate from the standard. Additionally, Arabic has a significant number of homographs, words that are spelt identically, but carry different meanings [35], [102]. This is more challenging when it comes to differentiating between an MSA word and a dialectal word. For example, the Arabic word 'هم' is an MSA noun meaning (worry); an MSA pronoun meaning (them); or an adverb meaning (also) in the Gulf dialect. Deciphering the intended sentiment in such contexts demands nuanced analysis and sophisticated preprocessing, more so than many other languages.

6. **Language Detection:** Arabic script is shared among various languages such as Persian, Urdu, and Azerbaijani [104]. Existing Web data-gathering tools struggle to discern the specific language of a script. Such language confusion can mislead Arabic sentiment classifiers, resulting in arbitrary results.

7. **Idiomatic Expressions:** Idioms in Arabic often carry inherent sentiments [102], [103]. For example, the idiom "حسبي الله ونعم الوكيل" (*Allah is sufficient for me, and he is the best trustee*) has a negative indication, while it is full of positive vocabularies (i.e., *Allah*, *sufficient* and *best trustee*). Recognising and correctly interpreting these expressions is essential.

8. **Negation Handling:** Handling negation in NLP, particularly in the context of dialectical Arabic, presents a unique set of challenges. Each dialect might employ unique

negation expressions. Challenges include the frequent use of double negation for emphasis, determining the precise scope of negation in a sentence, implicit negations, and morphology-based negation through prefixes or suffixes [102]. Furthermore, the dynamic interaction of negation with verb mood and tense, frequent code-switching in informal contexts, and the scarcity of annotated dialectical datasets complicate the task [ibid.]. The presence of idiomatic expressions in dialects, which often carry nuanced or implicit negation, adds another layer of complexity [35], [102].

9. **Pidginization:** Pidgin Arabic emerges when non-Semitic migrants interact with native Arabic speakers [103]. This variant of language is often used humorously or mimicking non-Arabs on social media (e.g., "انت مافي شوف (*You no see*)", "انا مافي معلوم (*I no know*)" and "هو يجي الهين (*He come now*)"), poses another layer of complexity in Arabic sentiment analysis.

2.4.3 Sentiment Analysis Tools for Arabic Language

Mazajak Sentiment Classifier

Mazajak [105] is the first Arabic online sentiment analyser, it is based on a deep learning model built on a CNN followed by Long-Short-Term memory (LSTM). This analyser provides different functionalities for Arabic sentiment analysis, including two modes for raw text processing: batch mode and online API [7], which is what we used. The annotation result of this classifier is one of the sentiment labels: positive, negative, or neutral.

[7] http://mazajak.inf.ed.ac.uk:8000/

CAMeL Sentiment Tool

The Computational Approaches to Modelling Language (CAMeL) tools [106] represent a refined compilation of utilities meticulously designed to address the intricacies inherent in Arabic text processing. This toolkit emerges as an authoritative solution in response to the multifaceted challenges posed by the Arabic linguistic landscape. It offers an array of open-source instruments tailored for Arabic NLP, encapsulated in Python, delivering functionalities that span a wide array of NLP tasks[8].

Among its core tools is the *morphological analyser*, adept at understanding the intricate combinations of roots, stems, prefixes and suffixes, capturing the morphological essence of Arabic. The *named entity recognition* (NER) plays a crucial role in classifying specific terms such as the names of individuals, locations, and organisations embedded within textual data. *Dialect identification*, another hallmark of CAMeL tools, acknowledges the vast tapestry of Arabic dialects, pinpointing with accuracy the regional nuance that a particular text embodies. On the *transliteration* front, the toolkit shines by effortlessly converting Arabic script into its Latin representation, an invaluable utility for systems less familiar with the Arabic script. The script utility feature is meticulously designed, offering services from diacritic removal to normalisation, ensuring that the Arabic text remains consistent and machine-friendly.

More importantly, the sentiment analysis functionality, refined through extensive research, penetrates the text to extract underlying opinions and emotions with impressive precision. The system has two sentiment analysis models. One was generated by fine-tuning the AraBERT language model [107] and it is the default sentiment model in the system. The other sentiment model was generated by fine-tuning the multilingual BERT (mBERT) language model [108]. These models take an Arabic text as input and give one of the three sentiment labels: positive, negative, or neutral as output.

[8] https://camel-tools.readthedocs.io/en/latest/api.html

ASAD Sentiment Classifier

Arabic Social Media Analysis and unDerstanding (ASAD) toolkit [109] is an online tool with seven individual modules, one of which is for sentiment analysis. For the sentiment analysis task, the toolkit utilises the ArSAS dataset, which consists of 21K tweets labelled Positive, Negative, Mixed, or Neutral [110]. Although many modern techniques employ intricate Deep Neural Network (DNN) models, ASAD aims for models that are both compact and effective. The performance of fine-tuned BERT models was evaluated against several SVM models that used character n-gram vectors, weighted by the term frequency-inverse document frequency (TF-IDF) as features. In particular, the SVM models were highly competitive with the state-of-the-art DNN models, especially in the sentiment analysis task. When compared to the BERT models, ASAD used a fine-tuned version of AraBERT [107]. The results demonstrated that the SVM models trained on Twitter data were particularly effective (are 2% away), possibly due to their training on this specific type of informal text, as opposed to BERT's training on more formal content. This toolkit is made available through a Web API and a Web interface where users can enter text or upload files [9]. In our analysis, we used the sentiment web API via the Python programming language. Similar to the previous tools, this model annotates Arabic texts with sentiment labels: positive, negative, or neutral.

The Reported Classification Performance

In the original studies, ArSAS [110] was employed as a benchmark to evaluate the performance of the previously discussed Arabic sentiment classifiers. Mazajak [105] and CAMeL (AraBERT and mBERT) [106] were specifically evaluated on negative and positive tweets, while ASAD [109] was evaluated in the three categories: negative, positive, and neutral. The reported $F1$ scores for these classifiers are presented in Table 2.8.

[9] https://asad.qcri.org/about

Table 2.8: The Reported $F1$ Scores for Sentiment Classification Performance of Three Arabic Tools.

Sentiment Classifiers	$F1$
CAMeL-AraBERT	0.92
CAMeL-mBERT	0.89
Mazajak	0.90
ASAD (SVM)	0.73.7
ASAD (BERT)	0.75.8

2.5 Chapter Conclusion

In this chapter, we started by delving into the core principles of human communication, underscoring the distinct differences between face-to-face and text-based interactions. As a foundational step, we provided an overview of the history of emoji, shedding light on their primary characteristics, and tracing their evolution. Using this foundation, we showed the intricacies of visual and vocal non-verbal cues. We demonstrated how emoji, defined in various ways such as icons, symbols, indexes, pictograms, ideograms, logograms, and punctuation, mirror these cues in both visual and vocal contexts within texts. We then proceeded to explore sentiment analysis techniques, highlighting the practical tools specifically crafted for Arabic. We also delved into the unique characteristics of the Arabic language, emphasising the challenges inherent in sentiment analysis efforts. As we move to the next chapter, we will probe deeper into scholarly perspectives, from both non-Arabic and Arabic viewpoints, regarding the use of emoji in sentiment analysis, while pinpointing the current gaps in Arabic-centric sentiment analysis research.

Chapter 3

Literature Review and Related Work

Emoji-based sentiment analysis has received notable attention in recent years, becoming a significant domain in NLP research. However, the exploration of this topic, especially within the context of the Arabic language, still presents numerous intricacies and nuances that await examination. This chapter endeavours to elucidate the current state of the art in emoji-based sentiment analysis, carefully examining its practical use in the Arabic context. Through this literature review, we will delve into existing resources, explore advanced learning models that leverage emoji for sentiment analysis in both non-Arabic and Arabic contexts, and identify gaps and areas of research opportunity. By the end of this chapter, the reader will have a strong understanding of the prevailing literature and be equipped with the knowledge necessary to appreciate the nuances and challenges in this field.

3.1 Emoji in Arabic Context

To understand how Arabic users use emoji to facilitate them in their daily lives, 16 Arabic studies (i.e., listed in Tables 3.1, 3.2, 3.3, 3.4 and 3.5) have been reviewed. These works used emoji as the main features in their analysis from three main domain perspectives: pragmatical linguistics, education, and computer science. We were careful to include most of the Arabic studies that are accessible and vary in their data sources (i.e., social media platforms, questionnaires and interviews); their participant's age and gender; and the examined Arabic region. Therefore, these studies covered texts from four main social media platforms (i.e., Facebook, Twitter, WhatsApp, and Telegram). They also covered four main Arabic regions: the Gulf (i.e., Saudi Arabia, Kuwait, United Arab Emirates, and Oman), Iraq, Egypt, and Levant (i.e. Jordan and Lebanon).

Pragmatic Usage of Emoji in Arabic Contexts

Emoji usage among Arabic users on social media platforms encompasses a range of pragmatic functions that contribute to various aspects of online communication. Multiple studies shed light on these functions, as outlined below.

Al Rashdi [27] focused on the usage of emoji in two gender-specific WhatsApp chat groups among Omani users. The study explores the various functions of emoji in these interactions, including their role in conveying emotions, constructing messages, establishing alignments, and structuring conversations. In the male group, participants predominantly use emoji such as the *Smiling Face* (😊), the *Sad Face with Teardrop* (😢) and the *Red Angry Face* (😡) emoji to express their emotional responses. These visually appealing emoji serve as concise tools to convey feelings effectively in the absence of paralinguistic cues. For example, the studies provided showed that the *Face Throwing Kissing* (😘) and the *Grinning Face* (😀) emoji were used to indicate sarcasm, soften criticism, and mitigate negative

feedback or any potential face-threatening act. On the contrary, the female group displays a broader range of emoji usage, incorporating emoji like *Woman Dancing* (💃) the *Confetti Ball* (🎊), the *Party Popper* (🎉) and *Red Balloon* (🎈) to celebrate and express affection. This diversification reflects a greater emphasis on joy, celebration, and interpersonal connections. Additionally, emoji serve as contextualisation cues, guiding message interpretation and fulfilling functions in initiating and closing conversations, indexing previous messages, and indicating approval. The *Thumbs Up* (👍) emoji is commonly used for agreement and support, while the *Loudspeaker* (📢) emoji visually represents speaking with a loud voice (i.e., as a vocal cue), compensating for the absence of capitalisation in Arabic. The study acknowledged that cultural norms and gender roles may influence emoji usage patterns, although common practises, such as emoji repetition for emphasis and the use of emotional emoji, can be observed between genders.

Mahzari [111] explored specific functions of emoji usage (i.e., for congratulating) among Saudi users on Facebook. The study reveals that Saudi users employ emoji as part of their congratulation strategies to express their appreciation, use them as gifts, celebrate occasions, express happiness, praise others, participate in joking, and emphasise prayer. For example, emoji such as the *Thumbs Up* (👍), the *OK Hand Sign* (👌) and *Clapping Hands* (👏) serve as non-verbal intensifiers, conveying approval and praise for achievements. In contrast, emoji, like *Face with Tears of Joy* (😂) and *Winking Face* (😉) add playfulness and humour; while the *Woman Dancing* (💃) emoji visually expresses joy and celebration.

Abbas and Ubeid [112] conducted a study on the usage of pragmatic emoji among Iraqi users in an educational-oriented Telegram chat group. The study analysed emoji functions based on Yus's eight-pronged pragmatic function taxonomy [49], which aligns with Relevance Theory. The findings revealed that emoji serve various purposes, including signalling emotions in parallel to communicative acts, indicating attitudes, modifying illocutionary force, conveying humour and irony, and intensifying emotions. According to relevance theory, the meaning of an emoji is aligned with the communicative act of the utterance, rather than its

content, ensuring that relevance is achieved when the emoji complements the overall communicative intention. For example, the *Smiling Face* (😊) emoji can guide the recipient in understanding the propositional attitude of the sender rather than the emotional tone of the message. On the contrary, the use of the *Person Facepalming* (🤦) emoji in a different context expresses dissatisfaction and disbelief, requiring cognitive effort for interpretation and guiding the recipient's understanding of the emotional stance. Other emoji, such as *Face with Rolling Eyes* (🙄) and *Face Without Mouth* (😶), can convey an underlying ironic meaning that diverges from the literal interpretation of the utterance. In a different study, Kadhim, Jasim, and Jasim [113] have confirmed that Iraqi students employ emoji as a communicative language in their text-based interactions.

Analysing Facebook posts, Alshboul and Rababah [114] and Hamdan [95] provided insights into the pragmatic functions of emoji usage among Jordanian users. These studies highlight various functions, such as expressing emotions, establishing or maintaining social connections, and enhancing the aesthetic appeal or poetic quality of messages. The details of these emoji functions are as follows. Drawing upon Austin's speech acts [43], the functions of various emoji were examined within the context of Jordanian communication [95]. The *Face with Tears of Joy* (😂) emoji was found to express extreme laughter, maintain contact, tease, soften tense situations, and conclude conversations. The *Red Heart* (❤️) emoji conveyed affection, admiration, respect, gratitude, and contentment. The enduring popularity of this emoji as a symbol of love can be attributed to cultural associations with the heart as a focal point of affection. Interestingly, some participants reported substituting the *Red Heart* emoji with the *Smiling Face with Heart-Eyes* (😍) emoji to express happiness, indicating a potential change in usage patterns. The *Slightly Smiling Face* (🙂) emoji conveyed disapproval, discontent, shock, and disinterest, while also serving as a vehicle for teasing, sarcasm, and contentment. However, the participants noted that this emoji may better represent happiness without negative connotations, suggesting the need for further investigation. The *Face Throwing a Kiss* (😘) emoji conveyed love, courtesy, closure of the

conversation, and even implied threats, deviating from its original intended purpose. Some users perceive this emoji as disingenuous and manipulative. Finally, the *Winking Face* (😉) emoji indicated agreement and also had an undertone of threat.

In addition, based on Jakobson's functions of language [42], emoji in the Jordanian context were found to fulfil various pragmatic roles [114]. The *emotive function* was exemplified by emoji accompanied by text, such as the *Face with Tears of Joy* (😂), the *Winking Face* (😉), the *Face Throwing a Kiss* (😘) and the *Smiling Face with Heart-Eyes* (😍), conveying surprise, praise, and love. These emoji served as evidence of the speaker's emotional reaction, imbuing the message with an emotive tone. The *conative function* was observed through messages employing the *See-No-Evil Monkey* (🙈) and *Face with a Zipper Mouth* (🤐) emoji, urging action and indicating agreement or disagreement. The *phatic function* was evident in non-verbal communication using emoji like the *Grinning Face with Big Eyes* (😃), *Waving Hand* (👋), and *Person Raising Hand* (🙋), which facilitate social interaction in chat groups. The *poetic function* was observed in romantic dialogues, where emoji, like the *Rose* (🌹), the *Red Heart* (❤️), and the *Ring* (💍) conveyed emotions and intentions. The *referential function* was demonstrated during significant events such as Ramadan and Eid, with emoji, such as *Crescent Moon* (🌙) and *Mosque* (🕌) symbolising the two religious occasions and their celebrations. The *meta-lingual function* was apparent when emoji were used to express an attitude, clarify misunderstandings or express confusion, exemplified by emoji, like the *Thinking Face* (🤔), the *Weary Face* (😩) and the *Face Screaming in Fear* (😱). These emoji facilitated communication and negotiated meaning. The multifaceted nature of emoji reflects their role in augmenting and enriching online interactions, aligning with different functions of language.

Examining Twitter tweets, Etman and Elkareh [28] explored the pragmatic functions of emoji among Arabic users of different dialects. The findings revealed that the average length of the tweet was 69 characters, with an average of three emoji and eight words per tweet. In all dialects, the *Face with Tears of Joy* (😂) emoji was commonly used to convey

laughter, while the *Loudly Crying Face* (😭) emoji was second. Hand gestures were more prevalent in the Egyptian dialect, reflecting their usage in face-to-face conversations. Arabic users used emoji as punctuation marks, such as substituting the exclamation mark with the *Frowning Face with Open Mouth* (😦) emoji and the question mark with the *Thinking Face* (🤔) emoji. Furthermore, emoji were found to replace interjections, with examples including the *Grinning Face with Star Eyes* (🤩) emoji that replace the interjection "واو (wow)", the *Face with Open Mouth Vomiting* (🤮) and *Nauseated Face* (🤢) emoji replacing "يع (yuk)", the *Face with Head-Bandage* (🤕) emoji substituting "آخ (ouch)", and the *Face with Finger Covering Closed Lips* (🤫) emoji standing for "أصه (shush)". These findings demonstrate the adaptability of emoji in Arabic communication, which serve as substitutes for non-verbal cues and enhance expression.

Similarly, Alharbi and Mahzari [29] conducted a study examining the usage of emoji among multi-dialectic Arabic users on Twitter, utilising Herring and Dainas [48]'s emoji pragmatic function taxonomy. The findings revealed that emoji in Arabic tweets serve various functions, including indicating multiple meanings, reacting to previous statements, triggering actions, decorating messages, indicating physical actions, softening harmful messages, and modifying the tone of voice. For example, the *Broken Heart* (💔) or *Pleading Face* (🥺) emoji can convey sadness and alter the overall tone of a message, regardless of its positive context. Emoji are also used to soften statements or requests, such as using the *Face with Tears of Joy* (😂) emoji to lighten a comment and make it more acceptable, or the *Smiling Face with Sunglasses* (😎) emoji to add a courteous and friendly tone to a request. Examples highlighted the use of emoji for reactions, where the Red Heart (❤️) emoji was used to indicate the emotional response, often repeated to emphasise the intensity of the emotion. Similarly, the Face with Tears of Joy (😂) emoji was used to react to videos, expressing a strong and intense reaction. Emoji can also represent actions, such as the *Folded Hands* (🙏) emoji representing supplication or seeking prayers and the *Woman Dancing* (💃) emoji symbolising celebration or the realisation of a joyful event. Emoji like *Yawning Face* (🥱)

and *Face with Head-Bandage* (🤕) effectively convey physical actions or states experienced by users at the time of their comments. Moreover, emoji are used for decorative purposes, with the *White Heart* (🤍) and *Two Hearts* (💕) emoji enhancing the aesthetic appeal of comments without conveying specific meanings beyond their decorative function. It was also observed that an emoji can serve multiple functions. For example, the *Zany Face* (🤪) emoji can function as a reaction to a comment or as a virtual action of teasing, while the *Slightly Smiling Face* (🙂) emoji can be used to react to a video, softening criticism or as a virtual action of smiling. The study emphasised the cultural-specific usage of emoji, with examples demonstrating how specific emoji are commonly used in Arabic tweets, such as *Kaaba* (🕋), *Blue Heart* (💙), and *Yellow Heart* (💛), hold cultural significance and serve as cultural markers in Arabic user communication. For example, the *Kaaba* emoji represents the holy site in Islam and is of great importance to Arabic-speaking individuals. Similarly, *Blue Heart* and the *Yellow Heart* emoji may be used together (💙💛) to represent specific sports teams (i.e., Al Nassr Football Club[1]) or national colours that are culturally significant in Arabic speaking regions. These findings highlight how emoji are used in Arabic online communications to reflect cultural context, preferences, and specific cultural symbols.

Emoji in Arabic Educational Settings

Algharabali and Taqi [115] investigated the reasons and methods of the use of different emoji by Kuwaiti college students in academic settings. Their study aimed to address four objectives within the context of students' online communities: (a) to determine why emoji are considered an important feature of communication, (b) to examine whether different topics trigger specific types of emoji use during interaction, (c) to investigate potential differences in emoji use between male and female students, and (d) to explore whether the presence of a specific audience, such as professors or students from the opposite gender, influences the use of emoji. The findings revealed that emoji are of significance in online student communities,

[1] https://en.wikipedia.org/wiki/Al_Nassr_FC

as they serve as a tool for communication and expression, allowing for the clarification of messages, the transmission of emotions, and the creation of solidarity among peers. Emoji were observed to be used in response to various topics, with negative emoji employed to express compassion and convey intense feelings about academic challenges. Gender differences were apparent, as female students exhibited a higher frequency of emoji use, focussing on interactional clarification, while male students exhibited a preference for more playful use of emoji. The type of audience present also impacted emoji usage, with female students tending to limit their use of emoji to all-female audiences and expressing concerns about potential disrespect toward professors. On the contrary, male students demonstrated a more flexible approach, using emoji with professors while considering their selection to align with female preferences and avoid potential misunderstandings.

For that, Al Zoubi and Shamma [116] examined the use of emoji by Jordanian university instructors in distance learning environments during the COVID-19 pandemic. The findings revealed that Jordanian instructors moderately used emoji in their virtual lectures. They tended to use culturally and socially recognised emoji, with the aim of maintaining a formal tone in their communication with students. Jordanian instructors' most frequently used emoji was the *Thumb Up* (👍) emoji, which conveyed positivism, agreement, support, motivation, liking, and assurance. In addition, the *Red Heart* (❤️) emoji was used to reinforce the distinguished responses of the students. The study highlighted that Jordanian instructors, regardless of their gender, were cautious in their selection of emoji, avoiding those with potential negative interpretations or meanings that could be misunderstood in the context of distance learning.

Ghaban [117] investigated the understanding and interpretation of emoji among younger Saudi students (i.e., 9−11 years) and their Arabic female teachers (i.e., Saudis, Egyptians and Jordanians) in an online learning environment. The study targeted six different primary school students in Saudi Arabia when the schools were running remotely and all classes were conducted online using Zoom due to COVID-19 lockdowns. The research aimed to address

questions such as the popularity of emoji in online learning environments, the most common emoji used, and whether students and teachers interpret emoji in the same way. Ultimately, the goal was to improve the quality of communication in online learning by resolving any variations in emoji interpretation. The study findings revealed that teachers use emoji in online communication as a means to express approval, provide positive feedback, convey emotions, indicate prayer or belief, show affection or liking, and portray various other functions. They interpret emoji based on their intended meanings, such as interpreting *Victory Hand* (✌) as a sign of "*a good job*" and the *Crossed Fingers* (🤞) as a wish for "*good luck*". Similarly, students use emoji to express victory, attention, happiness, and a range of emotions. They also interpret emoji based on their own understanding, such as interpreting *Grimacing Face* (😬) as silliness or apologies and *Smiling Face With Heart-Eyes* (😍) as a representation of love or admiration. Although there is general agreement on the interpretation of emoji between teachers and students, there can be variations in certain emoji where individual perspectives differ. As a aresult of this work, a list of 43 sentiment-annotated emoji has been produced.

Regarding the study of English as a foreign language (EFL), Qunayeer and RahmtAllah [118] found that the coherence of the writing skill improved when a group of Saudi EFL female learners was taught in a teaching setting that included emoji. The researchers in the study used the scores obtained from the pre-test and post-test of writing to analyse their research questions. They compared the performance of the control group (taught without emoji) and the experimental group (taught with emoji) on these tests to assess the impact of using emoji on students' writing skills and coherence. The study recommends integrating authentic materials like emoji into writing instruction, encouraging EFL teachers to utilise emoji without fear of negative effects, providing training programmes for teachers to incorporate emoji in language teaching, and conducting additional research to explore the potential of emoji in enhancing various language skills and sub-skills. These recommendations aim to promote the effective use of emoji in language learning and advance understanding of their impact on language proficiency.

Consequently, Al-Garaady and Mahyoob [119] tested how to address the writing problems of Arabic learners of EFL using emoji. They distributed a survey-based questionnaire among EFL learners to collect data on their use of emoji in social media communication. Descriptive statistics and ANOVA were used to analyse the data obtained and draw conclusions about the impact of emoji on writing skills. As a result, the researchers found that EFL learners tend to substitute emoji for different parts of speech during social interaction. This means that instead of using words to express certain categories of language, such as verbs, adjectives, or nouns, participants opt to use emoji in their places. This suggests that relying heavily on emoji and informal language may negatively impact the development of standard writing skills among EFL learners. Ultimately, the effectiveness of emoji in the development of writing skills for EFL learners is a complex topic. While emoji can be a valuable tool for communication, it is essential for learners to maintain a balance between using emoji and developing proficiency in standard written language. Educators and students should be aware of the potential impact of emoji on writing skills and ensure that learners are equipped with the knowledge and strategies necessary to use emoji appropriately in the context of language learning and academic writing.

Emoji and Arabic Users of Social Media Platforms

Park and El Mimouni [52] analysed how Twitter users of different languages and cultural backgrounds manage the lack of contextual cues in their tweets. The researchers focused on Arabic, English, and Korean tweets and examined the strategies used by users to compensate for the constraints of the Twitter platform. The data for the study were collected from a corpus of 1,200 tweets, with 400 randomly selected tweets from each language. For the analysis, the researchers created a coding taxonomy through interactive processes, preceded by a literature review and preliminary analysis of a subset of 150 tweets. The coding taxonomy focused on identifying and isolating non-verbal communication devices and emoticons used in tweets. Their findings indicate that users employ common strategies and creative

approaches across the three languages to compensate for the limitations of the Twitter platform. However, the researchers also observed language-specific characteristics when using these devices. For example, based on the prediction of the Hall [120] and Hofstede [121] cultural dimension, a low context-based culture and a language such as English would use text more than graphical symbols. In contrast, a highly context-based culture like Arabic and Korean may trigger more prevalent indirect communication styles and visual communication such as emoji. Therefore, the dominant usage of emoji over texts (i.e., emoji repetition phenomena) [52] is probably found more in Arabic texts than in other languages. The study suggests that the communication mode, influenced by the restriction of 140 characters per tweet, leads to frequent usage of emoticons and emoji regardless of language differences. This finding highlights the impact of platform constraints on online social interaction. The results also have implications for the design of social media technologies, emphasising the importance of considering effective aspects of communication and language/culture-specific traits.

With that in mind, Hussein, Farouk, and Hemayed [122] identified the gender of the authors of 140,000 Arabic tweets through their usage of emoji. In this study, emoji play a role in the feature selection process for gender identification in Egyptian Arabic tweets. The researchers identified certain emoji that have a significant impact in discriminating between genders, and these selected emoji are incorporated as features in the text classification model. The role of emoji in this study is to provide discriminatory power to distinguish between male and female authors based on their usage patterns. The researchers conducted experiments and found that certain emoji significantly differ in occurrence between genders. Emoji that exhibit a 20% higher occurrence in one gender compared to the other are selected as features. By including emoji-based features in the feature vector, the model was able to capture the presence and frequency of specific emoji that are indicative of gender-related language usage. This proposed approach achieved high accuracy of gender identification on the datasets used.

Similarly, Aldihan, Gaizauskas, and Fitzmaurice [123] conducted a study that focused

on gendered language and emoji usage in mixed-gendered Kuwaiti Arabic WhatsApp chat groups. Several findings emerged regarding emoji usage patterns. Both males and females used emoji, although with some notable differences. Females displayed a more extensive and varied use of emoji, employing them for emotional expression, non-verbal cues, and social connection. They used various emoji in different categories, including heart and floral emoji, showcasing their emotional expressiveness and individuality. On the contrary, males demonstrated a more limited use of emoji, focussing on smileys, nature-related emoji, and male character emoji. Their emoji usage appeared to be less emotionally expressive compared to females. These findings suggest that emoji serve as important tools for communication, allowing people to convey emotions, enhance social connections, and personalise their messages, with females exhibit a more diverse and expressive repertoire of emoji.

Table 3.1: Emoji General Functions in Arabic Context (Part I)

#	Reference	Year	Domain	Data Source	Arabic Region	Emoji Size	Emoji Usage (Findings)
1	[111]	2017	Linguistics: pragmatic	Facebook	Saudi Arabia	42	**Saudi** users on Facebook employ emoji within their congratulation strategies for: 1. Expressing endearment. 2. Using as a gift. 3. Celebrating. 4. Expressing happiness. 5. Praising. 6. Joking. 7. Emphasizing prayer.
2	[27]	2018	Linguistics: pragmatic	WhatsApp	Oman	121	**Omani** users in gender-specific WhatsApp chatting groups use emoji for: 1. Indication of Celebration. 2. Approval of Others' Messages. 3. Responses to Thanks and Compliments. 4. Conversational Openings and Closings. 5. Linking Devices. 6. Joking. 7. Indication of Task Fulfilment.
3	[115]	2018	Education	Questionnaire Items and Interview Data	Kuwait	33	**Kuwaiti** students within online communications use emoji for: 1. Clarification. 2. Expressing emotions. 3. Solidarity and commiseration. 4. Playfulness and breaking the sombre mood. 5. Group identification and community building. 6. Context-dependent interpretation. 7. Safe expression and protection of anonymity. 8. Practicality and time-saving.
4	[122]	2019	Computer Science (NLP)	Twitter	Egypt	159	The emoji were used as a text-based discriminating feature for a gender identification (GI) task, based on their usage patterns by **Egyptian** authors of Arabic tweets, and had proven to be effective.

Table 3.2: Emoji General Functions in Arabic Context (Part II)

#	Reference	Year	Domain	Data Source	Arabic Region	Emoji Size	Emoji Usage (Findings)
5	[118]	2020	Education	92 Writing Test Scores	Saudi Arabia	Unspecified	The use of emoji in language learning, specifically in writing instruction, resulted in significant improvements in coherence skills among **Saudi** female EFL learners.
6	[52]	2020	Computer Science (HCI)	Twitter	Unspecified	91	**Arabic** tweeters employ emoticons and emoji as a creative mechanism to compensate for the character limitations of the tweets on the Twitter platform. This includes conveying various interpersonal and emotional stances, such as acknowledgements, expressions of gratitude, sympathy, and happiness.
7	[28]	2021	Linguistics: pragmatics	Twitter	Multi-dialects (i.e., Saudi Arabia, Egypt, Kuwait, United Arab Emirates, Iraq and Lebanon)	111	**Arabic** users on Twitter use emoji for: 1. Substituting Facial Expressions. 2. Substituting Hand Gestures. 3. Substituting Tone Voice and Prosodic Features. 4. Substituting Punctuation. 5. Substituting Vocal Expressions.
8	[119]	2021	Education	Questionnaire Items	Saudi Arabia	None	**Saudi** EFL learners tend to use emoji instead of English words in written communications to avoid spelling mistakes and connect the language with the meaning. This implies that the overreliance on emoji may compromise the accuracy and proficiency of their writing.
9	[112]	2021	Linguistics: pragmatics	Telegram	Iraq	Unspecified	**Iraqi** users on Telegram using emoji for: 1. Signalling a specific or multiple emotion in parallel to the communicative acts. 2. Signalling Attitude. 3. Modifying illocutionary force. 4. Indicating humour. 5. Indicating irony. 6. Enhancing emotion intensity.

Table 3.3: Emoji General Functions in Arabic Context (Part III)

#	Reference	Year	Domain	Data Source	Arabic Region	Emoji Size	Emoji Usage (Findings)
10	[116]	2021	Education	Questionnaire Items	Jordan	Unspecified	**Jordanian** instructors in distance learning environments use emoji for: 1. Expressing agreement. 2. Signifying support and motivation. 3. Reinforcing distinguished answers. 4. Providing clarity and tone. 5. Substituting facial expressions. 6. Avoiding misinterpretation. 7. Maintaining a formal tone.
11	[114]	2021	Linguistics: syntactic, semantic and pragmatic	Facebook	Jordan	Unspecified	**Jordanian** students on Facebook use emoji for: 1. Expressing emotions. 2. Establishing or maintaining social connections. 3. Enhancing the aesthetic appeal or poetic quality of messages. 4. Referring to specific objects, events, or concepts. 5. Ensuring sender-receiver mutual understanding.
12	[95]	2022	Linguistics: Pragmatic	Facebook	Jordan	5	**Jordanian** Facebook users employ emoji for: 1. Expressing extreme laughter. 2. Showing courtesy and maintaining contact. 3. Teasing and showing mockery. 4. Softening a tense situation. 5. Ending an ongoing conversation. 6. Expressing affection and admiration. 7. Showing respect. 8. Expressing gratitude. 9. Expressing content and happiness. 10. Expressing disapproval, discontent, shock, and disinterest. 11. Sending love. 12. Indicating a threat. 13. Showing agreement.
13	[113]	2022	Linguistics: Pragmatic	Questionnaire Items	Iraq	None	**Iraqi** students employ emoji in their text-based communications as a communicative language.

Table 3.4: Emoji General Functions in Arabic Context (Part IV)

#	Reference	Year	Domain	Data Source	Arabic Region	Emoji Size	Emoji Usage (Findings)
14	[117]	2022	Education	Questionnaire Items	Multi-dialects (i.e., Saudi Arabia, Jordan, Egypt)	31	Emoji used by **Arabic** teachers in online environments for: 1. Expressing approval and positive feedback. 2. Wishing a good luck. 3. Conveying happiness and positive emotions. 4. Indicating surprise or being startled. 5. Signifying prayer or a request. 6. Showing affection or liking. 7. Displaying sadness, disappointment, or apology. 8. Portraying various emotional states. 9. Indicating humour or a mix of emotions. 10. Expressing confusion or needing further explanation. 11. Encouraging hard work or effort. 12. Conveying restrictions or prohibition. 13. Signifying warnings or importance. 14. Providing information or notification. Emoji used by **Arabic** young students in online environments for: 1. Expressing approval, positive feedback, or success. 2. Conveying attention, focus, or happiness. 3. Displaying happiness, surprise, sadness, or confusion. 4. Signifying prayer, belief, hope, or luck. 5. Indicating love, admiration, or affection. 6. Conveying gratitude, apologies, or regret. 7. Portraying humour, laughter, or silliness. 8. Showing patience, waiting, or being patient. 9. Expressing exhaustion, tiredness, or not feeling well. 10. Representing mixed emotions of sadness and relief. 11. Conveying confusion, the need for explanation, or difficulty. 12. Indicating satisfaction, happiness, or liking. 13. Displaying approval, praise, or pride. 14. Conveying anger, displeasure, or frustration. 15. Signifying strength, accomplishment, or capability. 16. Portraying prohibition, restrictions, or importance. 17. Indicating the need for attention, warning, or stopping.

Table 3.5: Emoji General Functions in Arabic Context (Part V)

#	Reference	Year	Domain	Data Source	Arabic Region	Emoji Size	Emoji Usage (Findings)
15	[123]	2022	Computer Science (NLP)	WhatsApp	Kuwait	Avg. mean 67	**Kuwaiti** females use emoji in mixed-gender WhatsApp chatting groups for: 1. Expressing emotions through smiles, hearts, and floral emoji. 2. Approving and encouraging with positive hand gesture emoji. 3. Demonstrating stereotypical femininity using heels, nail polish, and dancing emoji. 4. Highlighting their attitude through specific patterns and combinations of emoji. **Kuwaiti** males use emoji in mixed-gender WhatsApp chatting groups for: 1. Conveying basic emotions or natural elements using smileys and a limited number of hearts and nature emoji. 2. Representing their masculinity through the inclusion of male character emoji.
16	[29]	2023	Linguistics: Pragmatic	Twitter	Multi-dialects (Unspecified)	102	**Arabic** users on Twitter use emoji for: 1. Indicating multiple meaning at once. 2. Reacting on what already has been stated. 3. Triggering an action. 4. Decorating their messages. 5. Indicating physical action. 6. Softening harmful messages. 7. Modifying tone of voice.

3.2 Emoji in Sentiment Analysis

Conventional sentiment analysis approaches have operated under the assumption that emoticons serve as reliable indicators of sentiment and can be evaluated independently of the accompanying text. In light of this assumption, researchers have initiated the analysis of texts with emoticons (and/or emoji) by employing basic models (e.g., rule-based and lexicon-based) and machine learning models. As a result, part of the earlier research focused on developing resources, such as lexicons, datasets, and tools, specifically for emoji-based textual sentiment analysis.

3.2.1 Emoji-based Resources

Kralj Novak, Smailović, Sluban, et al. [1] were the pioneers in creating an emoji sentiment lexicon with 751 emoji. The lexicon was constructed from over 70,000 tweets in 13 European languages, including English, Spanish, Polish, Russian, a union of tweets in Serbian, Croatian, and Bosnian; Hungarian, German, Swedish, Slovak, Slovenian, Portuguese, Bulgarian, and Albanian. This corpus was annotated for sentiment by 83 human annotators, each of whom was a native speaker of at least one of the languages. The sentiment of the emoji was computed from the sentiment of the tweets in which they occur and reflects the actual use of emoji in a context. The researchers of the work did not observe significant differences in the emoji sentiment rankings between the thirteen languages. Accordingly, they considered the constructed lexicon a generic European language-independent resource for automated sentiment analysis and made it freely accessible. For simplicity, we refer to this lexicon as the European Emoji Sentiment Lexicon (Euro-ESL).

The Lisbon Emoji and Emoticon Database (LEED)[2] [14] is another resource that can be used for sentiment analysis. It contains 238 symbols (i.e., 85 emoticons and 153 emoji)

[2] https://osf.io/nua4x/

collected from various platforms. The annotation process was manual, with 505 Portuguese participants. Each participant was asked to evaluate a random subset of 20 emoticons/emoji for seven dimensions; including aesthetic appeal, familiarity, visual complexity, concreteness, valence, arousal, and meaningfulness. The LEED provides quantitative descriptive results and a meaning analysis for each of the symbols, making it a valuable resource with potential applications in different research domains. However, it is important to note that the database only provides subjective norms of emoji and emoticons from everyday users and may not reflect the full range of possible interpretations of these symbols. Furthermore, since the database was only collected from Portuguese participants, it may not be fully representative of other cultures or languages.

Kimura and Katsurai [124] sought to automate the emoji sentiment lexicon construction process since they found the manual approach to be laborious. They began their approach by first extracting the sentiment words from WordNet-Affect [125] and then calculating the frequency of cooccurrence between each sentiment word and emoji. Based on the ratio of the number of occurrences of each emoji among the sentiment categories, they automatically obtained sentiment scores for 236 emoji. Besides being inaccessible, this lexicon is smaller than the Euro-ESL and LEED.

Fernández-Gavilanes, Juncal-Mart'inez, Garc'ia-M'endez, et al. [126] took a step further than just expanding the size of the included emoji. They exploited emoji definitions to automatically construct an emoji sentiment lexicon with 840 emoji. The researchers used an unsupervised sentiment analysis system based on the definitions provided by the emoji creators on Emojipedia[3]. Additionally, they created another text-based lexicon, considering the sentiment distribution of informal texts that accompanied the emoji, in both English and Spanish languages. Again, this lexicon is culturally specific in addition to being inaccessible.

Although these lexicons have simple implementations, their primary drawback is that

[3]https://emojipedia.org/

they assign a single fixed averaged sentiment score to each emoji, effectively treating the emoji as representative of that particular sentiment. Therefore, Godard and Holtzman [127] developed the multidimensional lexicon of emoji (MLEmoji). The emoji lexicon comprises 359 emoji labelled with eight emotions (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) and two sentiment norms (positivity and negativity). However, it does not account for the neutral sentiment norm of the featured emoji. Moreover, the size of the lexicon is relatively small, as it only covers 10% (359 of 3,664 emoji) of the emoji listed in the latest standard Unicode version 15.0. Additionally, it is an English-based emotional lexicon and may not be transferable to other languages.

Taking a different perspective, Wijeratne, Balasuriya, Sheth, et al. [128] built **EmojiNet**, a sensible tool that goes beyond sentimental/emotional labels. It enables systems to link emoji with their context-specific semantic meaning (i.e., as a noun, verb, or adjective). EmojiNet was created by integrating multiple emoji lexicographic resources from the Web (i.e., Unicode Consortium[4], Emojipedia, iEmoji[5] and The Emoji Dictionary[6]) with BabelNet[7], a comprehensive machine-readable sense inventory for words. The tool includes 12,904 sense labels for 2,389 emoji, but is limited to the English language.

In order to keep up with advancements in NLP, Eisner, Rocktäschel, Augenstein, et al. [129] introduced the **emoji2vec** model for emoji embeddings. The developers utilised a pre-existing word embedding model called word2vec [130], and applied it to emoji by associating them with their corresponding textual Unicode descriptions (i.e., their Unicode names). The generated emoji embeddings are now commonly used as a textual representation of emoji in various studies that implement advanced learning algorithms. However, emoji2vec is only applicable to the analysis of text written in English.

[4] https://home.unicode.org/emoji/about-emoji/
[5] https://www.iemoji.com/
[6] https://emojidictionary.emojifoundation.com/
[7] https://babelnet.org/

3.2.2 Emoji-based Models

The growing availability of emoji-based resources has prompted researchers to develop a range of models and conduct extensive studies in the field of sentiment analysis that incorporate emoji. In the recent past, deep learning models such as convolutional neural network (CNN), recurrent neural network (RNN), long short-term memory (LSTM), bidirectional long short-term memory (Bi-LSTM), gated recurrent unit (GRU) and bidirectional gated recurrent unit (Bi-GRU) have gained popularity for sentiment analysis tasks based on emoji [131]. Later, advanced deep learning techniques, namely *embedding* [130] and *attention* [132] have been adopted. The two techniques are often used as a preprocessing step in NLP tasks. The **embedding** (e.g., word2vec [130], FastText [133] and Glove [134]) is an algorithm that involves representing tokens (i.e., characters, words, phrases, or sentences) as vectors in a continuous vector space, which can capture semantic and syntactic relationships between tokens. On the other hand, **attention** is a technique that allows neural networks to focus on different parts of the input data depending on the task at hand. It works by assigning a weight to each input element, which determines how much attention the network should pay to that element [132].

Yuan, Hu, Zhang, et al. [135] proposed a model (i.e., **EmoGraph2vec**) to capture the semantic information of emoji that affected the sentiment analysis of texts. From a large-scale corpus, they created an emoji co-occurrence graph network that was augmented with emoji semantic information using EmojiNet [128] to embed the emoji nodes. The embeddings were also provided with additional information about the emoji position in the sentence to make use of the order of the words and emoji. This forms the EmoGraph2vec model, which was used, in a later phase, to develop a neural network that integrated text and emoji information in sentiment analysis. To enhance the performance of their model, they also incorporated a "*hybrid-attention*" module in conjunction with a TextCNN-based [136] classifier. However, a significant constraint of this model is its dependency on EmojiNet,

which restricts its applicability to only English texts.

Recently, transfer learning has witnessed significant advances driven by transformer-based language models (LM) such as BERT [137] and XLM-R [138]. These models adapt the encoder representations to the specific source task, making them informative and task-oriented. In this learning approach, the learnt encoder representations can then be applied (i.e., transferred) to related target tasks. Sentiment analysis (SA) has benefited from transfer learning techniques, including approaches such as pre-trained sentiment embeddings [139] and context vectors based on machine translation [140]. The work of Boy, Ruiter, and Klakow [141] is aligned with the parameter transfer approach, where they take advantage of encoder representations learnt from emoji-based source tasks and transfer them to sentiment target tasks. Specifically, they examined the effectiveness of transferring knowledge from a single emoji or a supervised/unsupervised emoji cluster prediction source task (ST) to a sentiment detection target task (TT) under three conditions. First, they investigated the impact of the amount of emoji content present in the TT, comparing low and high amounts. Second, they considered the balance of the sentiment label distribution in the TT, comparing balanced and unbalanced scenarios. Finally, they explored the effectiveness of transferring knowledge from a single language (i.e., German) or multilingual (i.e., German, English, Spanish, Polish and Arabic) learnt ST, which is particularly relevant for low-resource languages where a TT could benefit from the use of the knowledge learnt in multiple languages. These conditions correspond to common characteristics found in sentiment corpora, where label distributions are often imbalanced, and the presence of emoji varies across different data sources. Despite its potential, this transfer learning model exhibited inadequate performance when applied to Arabic text. The limitations arise from the researchers' failure to address the specific considerations associated with working with Arabic. This involves employing a suitable dataset, implementing Arabic-focused preprocessing and normalisation techniques, and leveraging an appropriate multi-dialectical transformer-based language model tailored for Arabic.

Compared to other languages, even less research has been done on emoji for sentiment

in the Arabic language. However, the utilisation of emoji as crucial features in intelligent systems has recently gained significant attention in Arabic research. Consequently, several studies have incorporated emoji into their models, recognising their potential impact on sentiment analysis as follows.

In an early study by Refaee and Rieser [142] [143], a distant supervision approach was employed to investigate the subjective and sentiment of Arabic tweets. The study used emoticons to collect and annotate a dataset of Arabic tweets, which consisted of two manually and automatically annotated datasets. Various features, including bag-of-words (BOW), morphological, and semantical features, were used in the analysis. Although emoticons were considered semantic features, they were excluded during the evaluation of the automatically annotated dataset. The authors found that the emoticon-based distant approach to Arabic subjectivity and sentiment analysis outperformed fully supervised approaches and proved to be useful for annotating larger amounts of data.

One of the first works on analysing Arabic emoji usage for emotional content was by Hussien, Tashtoush, Al-Ayyoub, et al. [144]. The researcher claimed that training a classifier to detect emotions in automatically annotated tweets (based on emoji) is better than training it using manually annotated tweets. In their methodology, they collected 22,752 tweets with emoji, extracted the top frequently occurring emoji (that is, 58 emoji) and assigned a sentiment weight to each based on the AFINN sentiments lexicon [145]. Subsequently, each emoji was categorised into one of the four emotions categories: joy, sadness, anger, and disgust. As an automatic labelling approach, they label each tweet with an emotional label based on the sum of the weights of the emoji it contains. For manual labelling, they selected 2,025 tweets annotated by humans with the four adopted emotional labels. Then, they applied two machine learning classification models (i.e., SVM and multinomial naive Bayes) on both automatically and manually labelled training datasets. Finally, they evaluated each model's results on a testing dataset. Their results showed that the performance of the machine learning classifiers on the automatically labelled data (using

emoji) outperformed that of the machine learning classifiers on the manually labelled data. This study has been extended with an additional classification model (i.e., Random Forest (RF)) and more detailed analysis by Hussien, Al-Ayyoub, Tashtoush, et al. [146]. The results were almost the same. They restate that using automatically annotated training data with emoji (i.e., only one order of magnitude larger than the manually annotated one) gives better results in almost all settings they considered.

Other work aims to explore the impact of combining emoji-based features with various forms of textual features on the classification of sentiment of dialectical Arabic tweets [147]. Researchers used bag-of-words (BOW), latent semantic analysis (LSA), and word embedding as feature-extraction models. The dataset they used contained 1,101 tweets containing 120 emoji and emoticons. For sentiment classification, they applied a sequential minimal optimisation-based support vectors machine (SMO-SVM) classifier (with and without feature selection) to examine the effect of fusing emoji with texts as features. They concluded that merging emoji with word embedding and a selection of the most relevant subset of features as input to a simple sentiment classifier like SVM can produce good classification results.

A different work by the same researchers adopted the Euro-ESL [1] lexicon, mentioned above, to evaluate emoji as non-verbal features for sentiment analysis in Arabic texts [148]. Several machine learning algorithms were evaluated on the suggested features. The experimental results demonstrated that emoji-based features alone can be a very effective means of detecting sentiment polarity. The researchers explored a new approach for sentiment polarity detection in Arabic text using non-verbal emoji-based features while addressing the class imbalance problem. The proposed method was based on the Bootstrap Aggregating (Bagging) algorithm and Synthetic Minority Oversampling Technique (SMOTE) to build and combine multiple models from the training dataset. Three different classifiers were evaluated as single and ensemble classifiers: naive Bayes, k-NN, and decision trees. Their model performance was evaluated and compared on three datasets with a varying imbalance ratio

ranging from two to more than seven. This experiment showed that the proposed approach performs better than other approaches in most of the cases considered.

Al-Azani and El-Alfy [149] extended their previous work mentioned above by expanding the dataset with more instances of Twitter and YouTube comments to become 2,091 texts with 429 unique emoji. All instances were manually annotated as positive or negative, and each has at least one emoji. For feature extraction, they used two techniques: ReliefF and Correlation-Attribute Evaluator (CAE). For classification, they generated 429 emoji-based feature vectors and used them to construct and evaluate various machine learning classifiers, including naive Bayes (NB), multinomial naive Bayes (MNB), stochastic gradient descent (SGD), sequential minimal optimisation-based support vector machines (SMO-SVM), decision trees (C4.5 and REP trees), repeated incremental pruning to produce error reduction (RIPPER), and random forests (RF). By testing the performance of these eight machine learning classifiers, the experimental results demonstrated that emoji-based features alone can be a very effective means for detecting sentiment polarity with high performance.

Moreover, based on their extended dataset, Al-Azani and El-Alfy [150] empirically evaluated two state-of-the-art deep recurrent neural network models to detect the sentiment polarity of Arabic microblogs using emoji as features. They applied both unidirectional and bidirectional long-short-term memory (LSTM) and its simplified variant Gated Recurrent Unit (GRU). Then, they compared the performance to baseline traditional learning methods and deep neural networks. The experimental results revealed that the LSTM and GRU-based models significantly outperformed other classifiers with a slight difference between them, with the best results attained when using bidirectional GRU.

Building on their previous work, Al-Azani and El-Alfy [151] presented a comprehensive analysis of the effects of emoji on the sentiment of Arabic texts. This methodology includes several key steps to investigate the extent and effectiveness of emoji use in enhancing sentiment polarity detection. First, a dataset is prepared by collecting tweets containing

emoji and manually annotating them as positive or negative based on both text and emoji. Pre-processing is carried out at multiple levels for emoji-based features, structural features, and textual features. Feature extraction methods are then applied to represent the textual and emoji-based features, including TF-IDF, Latent Semantic Analysis (LSA), structural features, emoji2vec, and Word2Vec embedding models (CBOW and Skip-Gram). Unimodal opinion mining is carried out by applying feature engineering and training machine learning classifiers, followed by an evaluation using various measures. Fusion approaches, such as feature-level fusion, score-level fusion, and decision-level fusion, are explored to combine textual and emoji-based features. The findings reveal that negative emoji result in more disagreement, with readers perceiving sentiments as 26% worse than intended. For textual features, Word2Vec embedding models, particularly Skip-Gram, outperformed the traditional TF-IDF approach, achieving an accuracy of 0.82 when using the SVC classifier. Emoji-based features combined with Skip-Gram and analysed using the Logistic Regression (LR) classifier achieved the highest accuracy of 0.79. Furthermore, the study demonstrates that combining text and emoji representations at the score level using fusion rules such as sum, prod, or max significantly improves performance, with a maximum accuracy of 0.85 when using the max fusion rule (SE (Text Skip-Gram + Emoji Frequencies), S (Text Skip-Gram), E (Emoji Frequencies)). The authors conclude that emoji play a crucial role in sentiment analysis on social media platforms. One of the limitations of this study is the lack of research on the nuanced roles of emoji in sentiment analysis. Although the study focusses on the binary classification of sentiment polarity as positive or negative, emoji can convey a wide range of emotions and nuanced sentiments. Incorporating a wider range of sentiment categories could lead to a more comprehensive understanding of the impact of emoji on sentiment analysis and improve the accuracy and applicability of sentiment classification models in real-world scenarios.

On the other hand, Abdellaoui and Zrigui [104] used ten subjective Euro-ESL emoji [1] alongside the Ar-SeLn Arabic word sentiment lexicon [152] to construct and annotate a

large-scale Arabic dataset for sentiment analysis. Their process used a dataset that contains Arabic tweets with a vocabulary of 602,721 distinct entities. They named their dataset TEAD and released a subset of it for public use.

Recently, Al-Mutawa and Al-Aama [153] investigated the prediction of user opinions based on user ratings for Arabic hotel reviews. The study used an ensemble-based deep learning approach, using a soft voting mechanism, and incorporated Arabic resources, various generated features, and artificial intelligence techniques. Part of the Arabic resources they used were two of our released emoji lexicons. Arab-ESL [2] and CF-Arab-ESL [38]. The proposed approach involved the creation and use of the ArEmo lexicon[8]. ArEmo lexicon contains 301 emoji and emoticons, each with its associated sentiment score. It is worth noting that at the time of writing this thesis, the ArEmo lexicon was not available for public use. In addition, the study utilized the publicly available Arabic HARD[9] dataset [154]. Experimental evaluations were conducted on unbalanced and balanced variations of the dataset. The results showed that the proposed approach achieved an increase in prediction accuracy of 3.21% for the balanced dataset and 2.17% for the unbalanced dataset compared to previous studies using the HARD dataset. Overall, the ArEmo lexicon played a significant role in enriching the sentiment analysis process by incorporating emoji and emoticon information, ultimately enhancing the performance of the opinion prediction model in the context of Arabic hotel reviews.

From another research perspective, hate speech and offensive language have been analysed in Arabic texts using emoji by Husain [155]. The study approach was based on applying intensive pre-processing techniques to their dataset before it was further processed and fed into the classification model. One of these techniques was to convert emoji and emoticons into their Arabic descriptions (i.e., their official Unicode names translated to

[8] https://github.com/ralmutawa/files

[9] HARD is an Arabic dataset consisting of 409,562 hotel reviews from **Booking** website associated with ratings, starting from one to five.

Arabic) and use them as sentiment features to train their Linear SVM-based classifier for hate speech and offensive language detection. Their results reported better performance than the other model that did not consider emoji.

Similarly, Mubarak, Hassan, and Chowdhury [156] employ the paralinguistic information embedded in the emoji to collect many offensive texts that contain hate speech, vulgar and violent content. Then, they used their dataset as a benchmark for detecting offence and hate speech using different transformer architectures. For evaluation, they used different datasets that had been collected differently. They found that the data collected using emoji captures universal characteristics of offensive language. In addition, as a benefit of using emoji, their findings showed common words used in offensive communications, common targets for hate speech, and specific patterns in violent tweets. This study also highlighted common classification errors due to the need to understand the context, consider culture and background, and the presence of sarcasm, among others.

Using emoji, Althobaiti [157] presented an automatic method to detect offensive language and fine-grained hate speech in Arabic tweets. The study compared the performance of BERT, SVM, and LR models for three tasks: offensive language detection with '*offensive*' and "*not offensive*" labels; hate speech detection with "*hate speech*" and "*not hate speech*"; and fine-grained hate speech recognition with seven labels. In particular, the use of sentiment analysis and textual descriptions of emoji as additional features was explored. The experiments demonstrated that the BERT-based model outperformed other models in all three tasks, achieving F1 scores of 0.84 for offensive language detection, 0.81 for hate speech detection, and 0.45 for fine-grained hate speech recognition. The incorporation of sentiment analysis slightly improved the performance of the models in offensive language and hate speech detection tasks, but had limited impact on identifying the type of hate speech. However, the use of textual emoji descriptions showed mixed results, depending on the number of annotated examples per class and the distinctiveness of the emoji between classes.

On the other hand, Alshehri, Nagoudi, and Abdul-Mageed [158] presented an investigation into the detection of dangerous speech on Arabic social networks. The authors highlighted the importance of addressing dangerous speech, which refers to language or communication that involves explicit threats or incitation to physical harm, violence, or discrimination against individuals or groups. Although previous research has focused on offensive and hateful language, dangerous speech has not been extensively studied. To address this gap, the authors created a dataset of dangerous speech and developed effective models for its detection. The dataset consists of tweets that contain threatening phrases that indicate physical harm. Manual annotation of the dataset reveals patterns and characteristics of dangerous speech in Arabic Twitter. Deep learning models, including BERT and BERT-Emotion, are trained in the dataset and outperform the baseline, achieving F1 scores between 53.42% and 59.60%. The results demonstrate the effectiveness of the models in detecting dangerous speech. Emoji played a prominent role in the study, with around 40% of the annotated datasets including them. The researchers observed that participants used emoji to reduce the severity or clarify the intent of their threats. It was observed that the majority of the emoji used conveyed a threatening tone rather than a friendly tone. Moreover, the study found a higher incidence of expressions that involve body parts such as eyes, head, face, and nose in the 'dangerous' class of tweets. Threatening texts accompanied by positive emoji, like *Slightly Smiling Face* (🙂) or *Blue Heart* (💙) are considered non-threatening. On the contrary, when paired with negative emoji, such as *Knife* (🔪) or *Pistol* (🔫), threats become more alarming.

3.3 Literature Gaps and Limitations

As has been reviewed, the expansive domain of NLP has seen remarkable advancements over the years, with numerous studies delving into embodying emoji in sentiment analysis. Focussing on the Arabic language, while significant strides have been made, there remain

areas that were approached with limitations and inherent biases, outlined below.

3.3.1 Emoji-based Sentiment Resources Limitations

One of the pronounced challenges in emoji-based sentiment analysis emerges from the inherent language constraints present in the main sentiment resources. The Euro-ESL, for instance, is predominantly designed for European languages, leaving its effectiveness in non-European languages like Arabic largely uncharted. Similarly, LEED, rooted in Portuguese linguistic nuances, may not necessarily align with sentiments in other languages or cultural backgrounds. The MLEmoji and EmojiNet, while vast in their scope, are primarily English-centric, which potentially limits their universality across languages. The emoji2vec model, despite its potential, is tailored based on the English language, raising questions about its applicability in capturing subtleties in the Arabic language. Some lexicons, especially the one created by Fernández-Gavilanes, Juncal-Mart'inez, Garc'ia-M'endez, et al. [126], are tuned to specific cultural nuances in English and Spanish. Although beneficial within those cultural contexts, its extrapolation to broader cultural contexts remains debatable.

In addition, many emoji-based sentiment resources, like the Euro-ESL and LEED lexicons, in their quest for standardisation, allocate singular, fixed sentiment scores to emoji. This methodology often overlooks the fluid nature of emoji, which their sentiment interpretation can change based on context. For example, EmojiNet, despite its ambitious undertaking, might not always grasp the vast emotional depth associated with emoji, given its primary focus on linking emoji with static semantic definitions. likewise, models such as emoji2vec, while groundbreaking, are largely tethered to textual Unicode descriptions. This approach might narrow down the interpretation of emoji to pre-set descriptions, overshadowing broader, more dynamic contextual applications.

Additionally, most existing emoji-based sentiment resources suffer from coverage con-

cerns. A comprehensive representation of the wide range of emoji remains elusive. Resources like MLEmoji cover only 10% of emoji from Unicode version 15.0. Also, despite the commendable multidimensional approach of this lexicon, its omission of the neutral sentiment dimension hints at a potential incomplete representation of sentiment norms. In a similar vein, the lexicons of Kimura and Katsurai [124] and Ghaban [117] are noticeably limited compared to its more extensive counterparts. Furthermore, manually annotated emoji-sentiment resources, such as LEED and Ghaban's list [ibid.], base their sentiment scores or labels on subjective evaluations. Although this offers a ground-up perspective, it might not encompass the broader range of interpretations that an emoji might command in varied scenarios.

Lastly, the academic realm has expressed concerns about the limited accessibility of certain lexicons. Tools such as those produced by Kimura and Katsurai [124], Fernández-Gavilanes, Juncal-Mart'inez, Garc'ia-M'endez, et al. [126], and Al-Mutawa and Al-Aama [153] are relatively inaccessible and hinder the academic community from drawing on their insights for broader sentiment analysis endeavours.

3.3.2 Emoji-based Arabic Sentiment Models Limitations

The complexity of interpreting emoji in sentiment analysis, particularly in the Arabic language, adds another level of challenge for Arabic researchers. Therefore, different approaches have been employed to address this challenge. In some studies, researchers have chosen to completely ignore emoji, considering them as noise in the dataset, and discarding them during the data cleaning phase [159]–[162]. They assume that the presence of emoji introduces complexity into the analysis process, leading to textual ambiguity and potential misguidedness for the classification model [163]. However, other studies heavily rely on emoji as sentiment indicators for texts. Furthermore, they use non-Arabic resources or weakly labelled resources to associate specific emoji with sentiment categories [104], [164]–[166]. The rationale behind such an approach is that emoji are considered globally accessible and universally understood,

making them a direct resource for capturing and interpreting sentiment in texts. A third approach involves substituting emoji for their equivalent official Unicode names, translated from English to Arabic [157], [167]–[171]. This allows researchers to represent emoji as words or phrases in the Arabic language. By treating emoji as linguistic elements, researchers aim to align them with the linguistic and cultural context of the Arabic language and incorporate their potential influence on sentiment analysis.

Despite these attempts, none of the considered approaches appears to be fully adequate for the task of sentiment classification in Arabic texts. This is due to several reasons. Firstly, emoji play a significant role as non-verbal cues in communication, conveying meanings and emotions. It has been established that they contribute to the overall sentiment of a text [1], [28]. Therefore, if emoji exist in a given text, they should be taken into account as influential features for sentiment analysis. However, relying solely on emoji as the main sentiment indicators, without considering the surrounding context, and utilising non-cultural-specific emoji-based resources can lead to arbitrary sentiment classification. Emoji meanings and interpretation can vary greatly depending on context and cultural factors, and accurate analysis requires an understanding of the specific cultural and contextual nuances in which they are used [172]. Lastly, the translation of Unicode names may not capture the full range of meanings and nuances associated with emoji in the Arabic language. Interpretations of emoji can fluctuate significantly across different cultures, and the reliance on their translated names may not sufficiently encapsulate the culturally specific connotations and comprehensions linked to the *Visual Metaphor* [12] and the *Digital Semantic Shift* [173] of them in the context of Arabic communication. Take *Black Universal Recycling Symbol* emoji (i.e., ♻) as an example. Although the Unicode description links this emoji with the recycling concept, Arabic users often utilise it as a prompt to encourage content sharing through re-posting [141]. This new meaning has become widely understood and accepted in certain digital communication contexts, illustrating a type of crowd-sourced or community-driven semantic change [173]. In summary, while there have been strides in Arabic emoji-based

sentiment analysis, there is much ground to cover in addressing these challenges and refining the approach.

3.4 Chapter Conclusion

This chapter provided a comprehensive overview of the literature related to emoji-based sentiment analysis. It delved into the pragmatic use of emoji in the Arabic context, examined available emoji-based sentiment resources, and explored state-of-the-art models for text sentiment analysis using emoji, both in Arabic and other languages. As the culmination of this review, significant gaps and limitations within the existing literature were identified. In summary, while existing research offers valuable perspectives, there remains a pronounced need for deeper, culturally informed investigations of emoji-based sentiment analysis in Arabic contexts. The pressing need of the hour is to develop dedicated Arabic tools and resources for this field that honour the unique linguistic and cultural intricacies of the Arabic region. The forthcoming chapter will delineate the problem statement and an overview of the adopted analysis methodology, followed by the scope and constraints of this thesis.

Chapter 4

Methodology Overview

In this chapter, we provide an in-depth exploration of the methodology adopted for our study on emoji and their potential roles in sentiment analysis within Arabic texts. We begin by elucidating the problem statement, grounded in the current discourse on emoji as versatile communicative tools. Subsequently, we detail our analytical model, emphasising how various emoji can influence sentiment interpretation, particularly in the context of the Arabic language. The chapter also outlines the requirements and structure of our analytical framework and delineates the specific scope and constraints of our research. By the end of this chapter, the reader will have a comprehensive understanding of the methodological foundation upon which the subsequent analyses are based.

4.1 Problem Statement

As explored in earlier chapters, ever since their introduction, emoji have undeniably become a fundamental component of communication worldwide, facilitating individuals from various linguistic and cultural backgrounds to express and comprehend ideas and emotions more effectively. This has led to the hypothesis that emoji could potentially evolve into a universal language, given their adaptable communication features and their constantly expanding lexicon [12], [174], [175]. However, this idea remains controversial [10], [173], [176]–[178], as the use of emoji during communication is influenced by various factors. This includes socio-demographics (i.e., age [179]–[184], gender [185], [186], race/ethnicity [187]–[189], religion [190], and cultural background [65], [172], [191]–[193]), personal characteristics (i.e., identity [194], [195], personality [196], [197], mentality [198], [199], and physical ability [200]–[203]), relationships (spouses/close partners [59], [86], [204], [205], workmates [206]–[208], family and friends [27], [54], [209], [210]), technical and visual characteristics of emoji [211]–[214], platform functionalities (e.g., Facebook reactions [213], [215], Twitter bios [216]), and the context of the conversation (e.g., Covid-19 pandemic [217], Black Lives Matter movement [218]). Emoji as visual cues can amplify, mitigate, or modify the sentiment conveyed by the text. Extensive research has been dedicated to examine various affected factors and their influence on the interpretation of emoji sentiment [85], [219]–[222]. However, existing research, particularly in the context of the Arabic language, has yet to explore and identify the nuanced roles that emoji can play in sentiment analysis. This thesis aims to develop an approach to explore, identify, and analyse these roles.

4.2 Model of Analysis

Through the analysis of a text with and without emoji, we can evaluate the influence of emoji on altering the sentiment of that text and discern the overall intended sentiment articulated

through these non-verbal cues. Consider the sentence "أنا مشغولة الآن" (i.e., "*I'm busy right now*"). Without the emoji, it may not be clear how the speaker is feeling. However, with the addition of different types of emoji, the sentiment of being busy becomes clearer and more accurate, as is shown in the examples below:

- I'm busy right now 😩 (negative).
- I'm busy right now 🕛 (neutral).
- I'm busy right now 🤱 (positive).

While emoji in these examples act as sentiment triggers, there are other roles that they can play in different contexts. Also, the emoji in these examples occur individually, while they can come in groups (i.e., patterns), where each emoji has its own characteristics that affect the perceived sentiment differently. Therefore, in our analysis, we will focus on the accompanying words and the combinations of other emoji in the message that influence the various potential sentiment roles of an emoji in Arabic texts. In other words, the contextual interpretation of emoji and cultural sensitivity to Arabic are considered. Specifically, analysing Arabic text with and without emoji implies the impact of a specific emoji on a specific text. We refer to this as an emoji "*Sentiment State*". For example, if the text with and without emoji is annotated as positive, then the sentiment state will be ***Keep-positivity***. However, if the sentiment of the text changes after adding emoji from positive to negative, then the sentiment state will be ***Reverse-to-Negativity***. We assumed that there are **nine** possible emoji sentiment states that might occur in such a comparison. These states are: *Keep Positivity*, *Add Positivity*, *Reverse-to-Positivity*, *Release Negativity*, *Neutral-State*, *Keep Negativity*, *Add Negativity*, *Reverse-to-Negativity* or *Release Positivity*. These states are considered to be an intermediate phase in our model, which transfers the analysis to explore the emoji sentiment roles.

Knowing these intermediate sentiment states along with the sentiment of the included emoji pattern leads to the identification of **thirteen** possible "*Sentiment Roles*" that an emoji

can play within a text (see Figure 7.2). These roles are *Emphasis*, *Indication*, *Mitigation*, *Reversing* and *Triggering* under each of the positive and negative sentiment norms. Furthermore, emoji could have a *Neutral-Effect* role reflecting the neutrality sentiment norm. Figure 4.1 summarises all possible emoji sentiment roles based on all possible cases between each of the sentiment states, along with the emoji sentiments.

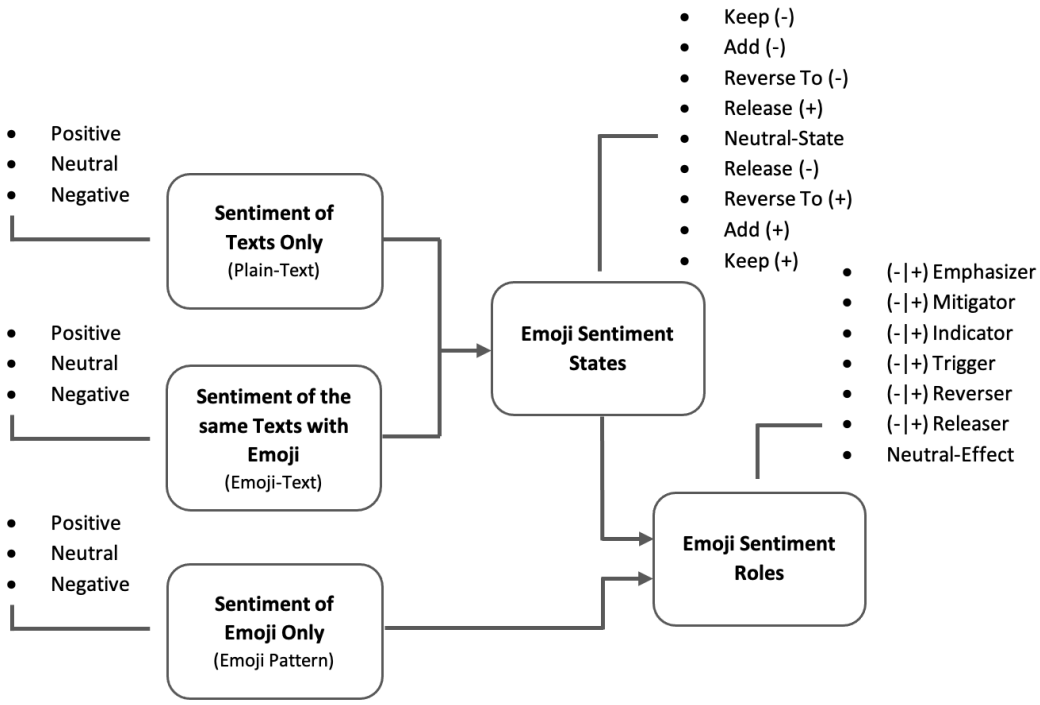


Figure 4.1: Emoji Sentiment States and Roles. (-) Means Negative and (+) Means Positive Sentiment.

After identifying the sentiment role of emoji in each text in our dataset, we will calculate the frequency distribution of all the sentiment roles for each emoji. This will result in a sentiment lexicon based on emoji roles that are tailored to the Arabic context. A detailed description of how we can obtain these states and roles and how we construct the sentiment model based on the emoji-role lexicon will be discussed in Chapter 7.

4.3 Analysis Requirements

To achieve the objectives of this thesis, it is imperative to develop reliable emoji-centric sentiment analysis resources tailored for Arabic. This involves gathering and processing an appropriate dataset, formulating Arabic emoji sentiment lexicons, establishing a comprehensive lexicon for Arabic dialectical words, building an emoji-sensitive Arabic sentiment classifier, and implementing measures for scaling, validation, and performance.

4.3.1 Lexicon-Based Sentiment Analysis Classification

Our sentiment analysis will depend on a lexicon-based approach. Despite its limitations, the lexicon-based method can be more transparent, interpretable, accessible, traceable, and replicable, offering a clearer understanding of sentiment derivation compared to complex models.

As was seen in the literature review, the conception and validation of an emoji sentiment lexicon have many benefits that are of great value to the field of NLP. Given the increasing complexity of the technological tools used in Arabic sentiment analysis, there is a need for resources that are easily accessible and do not require high levels of technical expertise. The first merit of an emoji sentiment lexicon lies in its universal accessibility, offering an inclusive tool that broadens the scope for researchers, without the need for programming proficiency.

Advanced sentiment analysis tools, although innovative, often produce results that are difficult to interpret. An emoji sentiment lexicon eliminates this interpretability issue, which brings more practical relevance to research outputs. The interpretability of lexicons offers more transparency than most machine learning methods, creating results that can be understood by researchers and a wider audience alike. This feature of an emoji sentiment

lexicon improves its usability for various stakeholders, including researchers, policymakers, marketers, and the general public.

Furthermore, the dynamism of an emoji sentiment lexicon is another significant advantage. Its adaptability to new emoji and changing interpretations across cultures and over time makes it a flexible research tool in an ever-evolving digital communication landscape. The use of a defined and validated emoji sentiment lexicon can increase the reproducibility of research findings, thus improving the reliability of studies conducted across various platforms, populations, and periods. This reproducibility is critical in the scientific community, enabling researchers to corroborate findings and contribute to the robustness of the collective knowledge base.

4.3.2 Scores-to-Labels Sentiment Scales

Mapping sentiment scores to a "*three-class*" sentiment label using the sign (+, 0, -) to identify sentiment classes (positive, neutral, negative) is simple but prone to inaccurate classification. Furthermore, there is no clear justification for the implicit claim that neutral is a single point (zero). Satthar, Evans, and Uchyigit [3] proposed a method to address these concerns by calibrating the mapping from a numerical score to sentiment polarity labels using precision vs. recall curves. We adopted their method to scale the resultant sentiment scores both in our lexicons and from our lexicon-based classifier, converting them into 3-class sentiment labels. To transform a numeric scale to an ordinal (categorical) scale, the boundaries (upper and lower) for each sentiment class needed to be identified from the given numeric scale. These boundary values are '*cut-off*' values for the sentiment classes and are the parameters for a multiclass sentiment classification system based on the numerical scores. To assign cut-off values for each class, we used a learning-based evaluation technique. This transformation allows us to both optimise and evaluate a system that gives numeric outputs against a gold standard dataset that contains fixed categorical outputs. In this calibration

method, the visualisation of the precision-recall (PR) curve is used only to set values for boundaries of sentiment classes. In addition, the validation technique used in this method is inspired by the cross-validation mechanism. Applying this method, we have established three sentiment scales for emoji, words, and sentences, converting sentiment scores to labels, as shown in Figure 4.2. Due to space constraints, the detailed process for creating these scales is elaborated in the appendices: **Appendix A** for the emoji scale, **Appendix B** for the word scale, and **Appendix C** for the sentence scale.



Figure 4.2: Scores-to-Labels Sentiment Scales for Emoji, Words and Sentences.

4.3.3 Measures of Analysis

Agreement Tests: Cohen's Kappa (κ) and Krippendorff's Alpha (α)

Cohen's Kappa (κ) [223] is a measure used to evaluate the agreement between two raters (or annotators) beyond what would be expected by chance. This metric takes nominal (categorical) variables. Therefore, we use the converted scores to sentiment labels, using the *scores-to-labels sentiment scales* in Figures 4.2, when applying this metric. The (κ) values range from -1 to 1, where: ($\kappa = 1$) implies perfect agreement; ($\kappa = 0$) suggests agreement equivalent to what would be expected by random chance; and ($\kappa < 0$) indicates disagreement or agreement less than what would be expected by chance. To provide a more nuanced perspective, Landis and Koch [224] provided the following interpretive scale for Cohen's Kappa, as shown in Table 4.1.

On the other hand, Krippendorff's Alpha (α) [225] is a statistical measure used to determine the agreement among more than two raters or coders working on a dataset. The interpretation of the results of this metric is based on the ranges given in Table 4.1.

Table 4.1: Interpretative Scales for Cohen's Kappa (κ) and Krippendorff's Alpha (α) Values.

#	**Kappa (κ)**	**Interpretation**
1	(-1.00) to (0)	Poor
2	(0) to (0.20)	Slight
3	(0.21) to (0.40)	Fair
4	(0.41) to (0.60)	Moderate
5	(0.61) to (0.80)	Substantial
6	(0.81) to (1.00)	Almost perfect

#	**Alpha (α)**	**Interpretation**
1	$\alpha \leq (0.2)$	Slight
2	$(0.2) < \alpha \leq (0.4)$	Fair
3	$(0.4) < \alpha \leq (0.6)$	Moderate
4	$(0.6) < \alpha \leq (0.8)$	Substantial
5	$\alpha > (0.8)$	Near-Perfect

Euclidean Distance (*L2*)

The Euclidean distance (*L2*) [226] is a measure of the distance between two points in Euclidean space. It is the length of the straight line that connects the two points. In a two-dimensional space, the (*L2*) distance between points $(x1, y1)$ and $(x2, y2)$ can be calculated using the formula:

$$L2 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{4.1}$$

In our case, we will use this measure to compare the annotation of the same emoji in two different lexicons: Lexicon-1 and Lexicon-2. Each point (x, y) represents the coordinates of the emoji in a lexicon, where the x coordinate is the sentiment score of the emoji in that lexicon, and the y coordinate is the total sentiment probability of that emoji in that lexicon (as is exemplified in Figure 4.3).

For the coordinate x, we used the sentiment scores in Lexicon-1 and the sentiment scores in Lexicon-2. To calculate the total sentiment probabilities as a coordinate y for the emoji in each lexicon, we used the following formula:

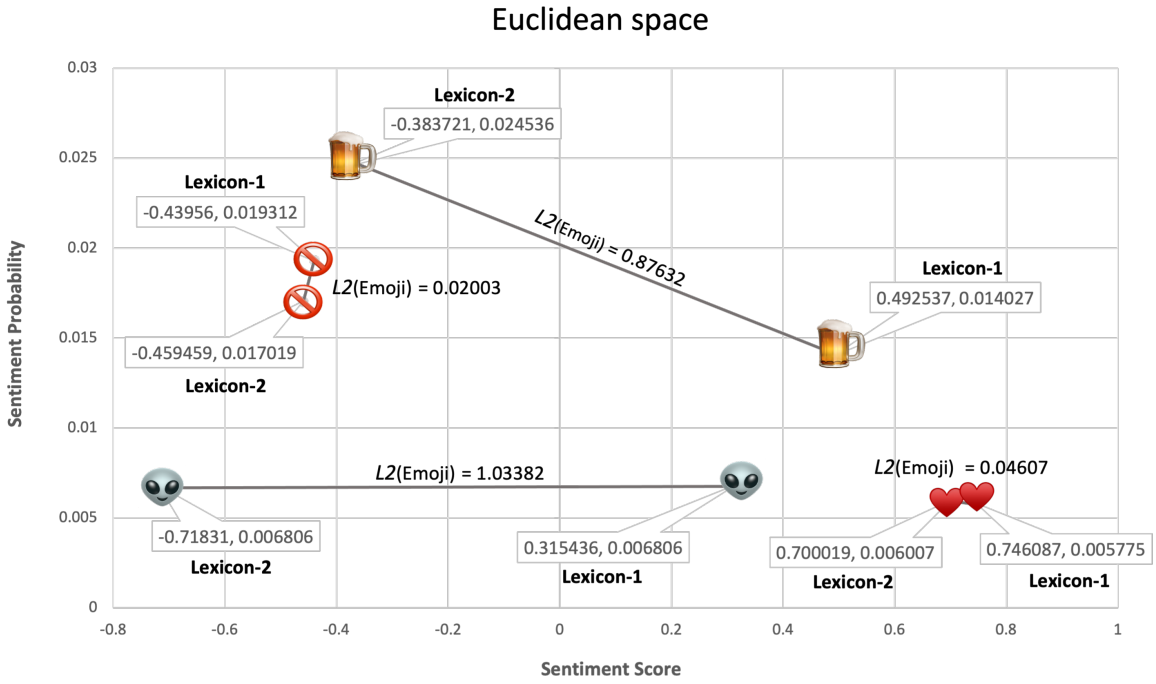


Figure 4.3: The Calculation of Euclidean Distance $L2_{(Emoji)}$ for Four Emoji from Lexicon-1 [1] and Lexicon-2 [2].

$$y = P_{(Emoji.Neg.)} \cdot P_{(Emoji.Neut.)} \cdot P_{(Emoji.Pos.)} \tag{4.2}$$

where $P_{(Emoji.Neg.)}$, $P_{(Emoji.Neut.)}$, and $P_{(Emoji.Pos.)}$ are the probabilities that the sentiment of the emoji in a lexicon is negative, neutral, and positive, respectively. Then we calculated the $L2_{(Emoji)}$ distance for each emoji in both lexicons based on the following formula:

$$L2_{(Emoji)} = \sqrt{(x_{(Lexicon-2)} - x_{(Lexicon-1)})^2 + (y_{(Lexicon-2)} - y_{(Lexicon-1)})^2} \tag{4.3}$$

where $x_{(Lexicon-2)}$ and $x_{(Lexicon-1)}$ are the emoji sentiment scores in Lexicon-1 and Lexicon-2, respectively; and $y_{(Lexicon-2)}$ and $y_{(Lexicon-1)}$ are the total sentiment probabilities of that emoji in Lexicon-2 and Lexicon-1, respectively. As an example, Figure 4.3 visualises the ($L2$)

distance between 4 emoji in Lexicon-1 (i.e., extracted from Arab-ESL [2]) and Lexicon-2 (i.e., Euro-ESL [1]) in a two-dimensional Euclidean space.

Root Mean Squared Error (RMSE)

The mean squared error (MSE) [227] gauges the average squared difference between the corresponding values in two datasets, capturing how the sentiment intensity of emoji aligns between two lexicons. A lower MSE suggests that the sentiment scores assigned by the two lexicons for the same emoji are in closer agreement. Given that the sentiment scores range from -1 to 1, an MSE of 0.2154055, for instance, indicates a relatively significant average difference in the sentiment scores assigned by the two lexicons.

The root mean squared error (RMSE) [ibid.], on the other hand, is the square root of the MSE. It conveys the magnitude of the average error in the original units of the variable, making it more interpretable than the squared units of the MSE. Although MSE gives an overall idea of model error, RMSE is particularly useful because it provides a clearer, more tangible sense of the average error magnitude. Being in the same units as sentiment scores, RMSE offers a more direct understanding of the differences. In simpler terms, if we are trying to gauge how 'off' predictions or measurements might be on average, RMSE provides a clearer picture. In our lexicons' comparisons, RMSE helps in determining the average magnitude of disagreement in sentiment score assignments between the two lexicons, offering a more intuitive grasp of the discrepancies.

Performance Metrics (Accuracy, Precision, Recall, F1)

The descriptive term that indicates the accuracy, precision, recall, and F1 score is "*evaluation metrics*" or "*performance metrics*". These metrics are commonly used to assess the performance of classification or prediction models in various machine learning and data analysis

tasks. They provide valuable insight into how well the model performs in terms of correctly identifying and classifying different classes or categories. Here is a brief explanation of each metric:

1. **Accuracy:** It measures the overall correctness of the model's predictions, i.e., the ratio of correctly classified instances to the total number of instances.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Instances}}$$

2. **Precision:** It measures the proportion of true positive predictions among the instances that the model classified as positive. Indicates the accuracy of the positive predictions made by the model.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

3. **Recall:** Also known as *sensitivity* or *true positive rate*, it measures the proportion of true positive predictions among all instances that actually belong to the positive class. The recall indicates the model's ability to correctly identify positive instances.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

4. **F1 Score:** The F1 score is the harmonic mean of precision and recall [228]. Provides a balance between precision and recall, giving a single metric to evaluate the model's performance when dealing with imbalanced datasets.

$$F1 = \frac{2 \text{ x Precision x Recall}}{\text{Precision} + \text{Recall}}$$

These evaluation metrics collectively provide a comprehensive view of the effectiveness of the model and help make informed decisions about the model's performance and potential improvements.

4.4 Analysis Framework

To execute the tasks aforementioned, we have laid out a framework segmented into four clear phases, as shown in Figure 4.4. The **first phase** emphasises data collection and preprocessing, during which the dataset is cleaned, normalised, and annotated for sentiment using both manual and automated techniques. This uses various Arabic sentiment analysis models to assign sentiment to texts, both with and without emoji. This phase resulted in two datasets: gold and silver. In the **second phase**, we create sentiment lexicons for emoji and words using the silver dataset. These preliminary lexicons are then refined and validated through the gold dataset for use in our lexicon-based sentiment classifier. In the **third phase**, as visualised in Figure 4.1, we explore the sentiment roles of different emoji patterns, culminating in a holistic lexicon that captures the various sentiment roles of emoji. The **final phase** involves evaluating, through a case study, how these identified emoji roles enhance sentiment classification within ironic and non-ironic Arabic textual contexts. This evaluation utilises the gold dataset as the basis for the analysis.

4.5 Research Scope and Constrains

This thesis focusses on specific constraints and factors related to the use of emoji in Arabic texts in the context of public, asynchronous, and informal communication on the Twitter platform. It is confined to the analysis of short, subcontextual, multi-aspect, and multi-dialect texts, strictly adhering to the predefined parameters of our research. We briefly tested the influence of culture, gender (female and male), contextual settings (text-sensitive vs. text-free), and irony (sarcasm vs. humour) on the sentiment of emoji. However, it is important to note that our study does not cover certain factors. For example, we do not consider the age of the interlocutors, the specific relationships between them, or the variations in Arabic dialects. Additionally, other NLP tasks such as hate-speech detection, disaster

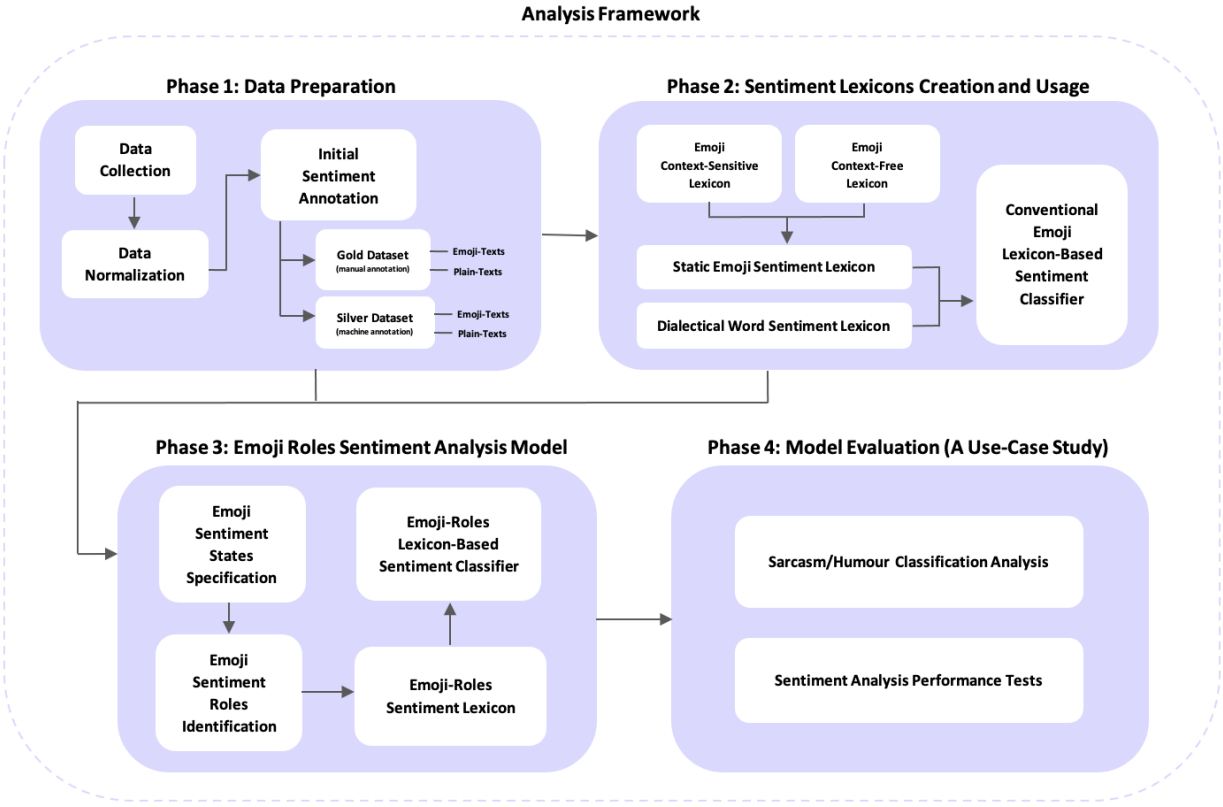


Figure 4.4: Analysis Framework Diagram.

detection, and political speech are beyond the scope of our thesis. Furthermore, we do not analyse the position and order of emoji in a text; different visualisations of emoji renderings; the integration of emoji with sounds, videos, or pictures; platform-specific features; conversational texts involving synchronous communication; or the distinction between formal and informal texts.

4.6 Chapter Conclusion

This chapter detailed the methodology used in this thesis, emphasising the role of emoji in the analysis of Arabic sentiments. An analysis model presented potential emoji sentiment roles within texts. Our structured approach covered stages from data collection to evaluating

emoji sentiment roles, focussing mainly on the sentiment of short Arabic texts containing emoji extracted from Twitter. Despite certain constraints, this research is precise in its analysis. The next chapter will explore the process of collecting and preparing the essential data for our research.

Chapter 5

Data Preparation

The initial step in our analysis is to obtain an appropriate dataset composed of text with emoji. In this chapter, we explore Arabic data sources, spotlighting datasets with a significant presence of emoji-infused texts (mainly tweets from Twitter). Given the unique nature of nonstandard Arabic tweets containing emoji, we outline a systematic preprocessing method tailored for these texts, ensuring that they are ready for our sentiment analysis task. Additionally, the chapter delves into utilising established Arabic sentiment classifiers to attain reliable sentiment annotations for our data. By its conclusion, the reader will be familiar with the essential processes needed to prepare Arabic texts enriched with emoji for sentiment analysis.

5.1 Data Collection

Before we collected our data, some criteria were defined. Our consideration was on data that were from a social media platform, written in the Arabic language, multi-dialect, multi-aspect and, more importantly, containing emoji. With such criteria, collecting, cleaning, and preparing a great deal of raw data for sentiment annotation in a short time is impossible. Therefore, we focused on **sixteen** different public datasets from Arabic social networks (all are tweets from the Twitter platform). Since these tweets are accessible to the public, there was no need for a review by an institutional ethics board. These contain **372,765** tweets that meet our criteria. The data collection procedure resulted in a dataset that is diverse in its Arabic dialects. They are from all the Arabic regions: Levant (Syria, Lebanon, Jordan and Palestine), Iraq, Gulf (Saudi Arabia, Kuwait, Qatar, Bahrain, UAE and Oman), Yemen, Egypt, Sudan and North Africa (Libya, Algeria, Tunisia and Morocco). The dialect classifier in CAMeL-Tools [106] was used to detect and classify these dialects in our dataset based on their Arabic regions, including modern standard Arabic (MSA), as illustrated in Figure 5.1.

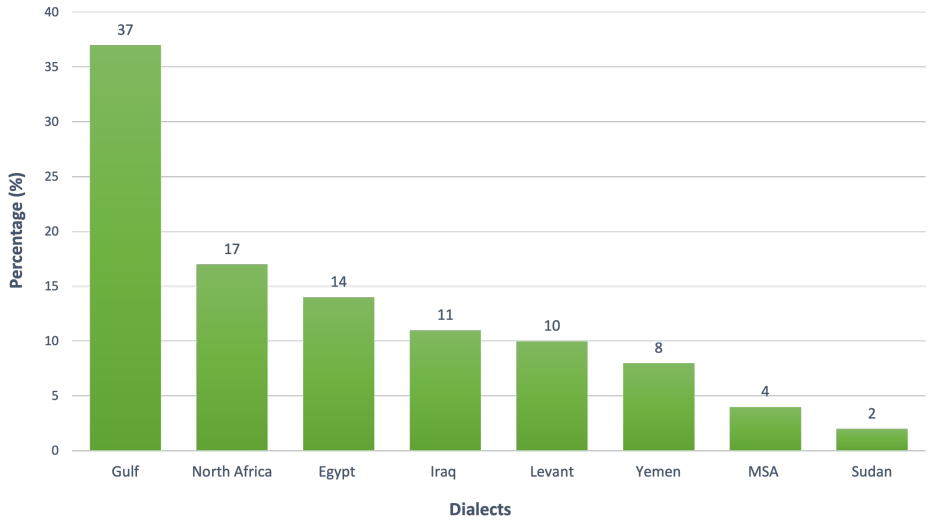


Figure 5.1: A Regional-Based Distribution of the Arabic Dialects in the Collected Dataset.

Some of the targeted datasets were constructed for sentiment classification tasks or other related tasks, such as hate-speech detection. Therefore, these datasets have been manually annotated with sentiment labels, emotional labels, or other related labels like *hate* and *offensive*. For some other datasets (i.e., TEAD [104] and AraSenCorpus [229]), they were available for public use with automatically predicted sentiment labels. This meant that we had to re-annotate these datasets with sentiment labels after testing their reliability. The details of these procedures are explained in the following subsection. Table 5.1 summarises all the details of the tweets considered from the targeted datasets.

5.2 Data Normalisation

5.2.1 Texts Normalisation

The procedure of cleaning and normalising texts should not compromise their contextual meaning. It is a necessary step for sentiment analysis, aiming to minimise irrelevant content, reduce bias, produce consistent results, and increase classification accuracy. This is achieved in two steps: noise elimination and text normalisation. To eliminate noise, we removed URLs, emoticons and symbols similar to emoji (i.e., dingbats)[1] like (❀, ✈, ✍, ☎, and ❤), as well as special characters such as (#, @, &, $, and £). We also removed all punctuation marks and non-Arabic words (except English words). Numbers (in Arabic and English) and English words were kept due to their contextual importance within an Arabic text. For the Arabic-specific text normalisation, we followed what most Arabic NLP researchers do [230]–[232]. So, we removed word elongation (i.e., kashida[2] and unnecessary letter repetition), diacritics, non-alphabetic characters (e.g., Quranic symbols) and unified letters that appear in different forms in their standard forms. For instance, the letter '*Alif*' comes in

[1] https://en.wikipedia.org/wiki/Zapf_Dingbats.
[2] https://en.wikipedia.org/wiki/Kashida.

Table 5.1: Datasets Details.

#	Dataset Name	Reference	Tweets' Time	Analysis Task	Annotation Process	Sentiment Labels	Original Size	Used Size
1	SyriaTweets	[233]	2014	Sentiments	Manual	positive, neutral, negative	2 K	64
3	SemEval-2017 (Task 4)	[234]	2016 - 2017	Sentiments	Manual	positive, neutral, negative	1.6 K	263
2	SemEval-2018 (Task 1 & 2)	[235] [236]	2017	Emotions	Manual	anger, fear, sadness, joy	1.4 K	668
5	ArSenTD-Lev	[159]	2017	Sentiments	Manual	very positive - very negative, neutral	4 K	389
4	TEAD	[104]	2017	Sentiments	Automatic	positive, neutral, negative	6 M	11,950
6	ArSAS	[110]	2017	Sentiments, Speech-Acts	Manual	positive, neutral, negative, mixed	21 K	6,070
8	DART	[237]	2018	Dialects	Manual	none	24.2 K	599
9	L-HSAB	[160]	2018 - 2019	Hate-Speech	Manual	abusive, hate, normal	5.8 K	65
7	SS2030	[238]	2018	Sentiments	Manual	1 (positive), 0 (negative)	4.2 K	1,061
10	ATSAD	[239]	2019	Sentiments	Manual	Pos, Neg	8 K	3,775
15	ArSarcasm	[240]	2013 - 2015	Sarcasm, Dialects, Sentiments	Manual	positive, neutral, negative, objective	10.5 K	1,093
12	ASAD	[241]	2012 - 2020	Sentiments	Manual	positive, neutral, negative	95 K	11,969
14	ArCovid-19	[242]	2020 - 2021	Propagation Networks	Automatic	none	2.7 M	45,440
13	AraSenCorpus	[229]	2007 - 2020	Sentiments	Automatic	positive, neutral, negative	4.5 M	280,739
11	Kawarith	[243]	2018 - 2020	Crisis	Manual	none	12 K	2,975
16	Sa'7r	[244]	2011-2021	Irony	Automatic	none	26.3 K	5,645
						Total	**13.4 M**	**372,765**

three different forms (أ), (إ), and (آ). We normalise them to their standard form (ا). We also applied this normalisation to the letters "*Alif Maqsurah*" (i.e., ى) and "*Taa Marbutah*" (i.e., ة), which were normalised into '*Ya*' (i.e., ي) and '*Ha*' (i.e., هـ), respectively. In addition, we identified letters such as (ﺤ), (ﻋ), and (ﻛ) that were written in Persian or Urdu languages and rewrote them in Arabic letters.

Furthermore, we manually replaced some well-known Arabic scripts with their corresponding written words, since these phrases had appeared within the texts as Unicode characters with assigned codepoints[3]. An example of these phrases is the respectful abbreviation for the Arabic phrase "صلى الله عليه وسلم" which translates to (may Allah bless him and grant him peace). This phrase is often used after the name of the Islamic prophet *Muhammad* as a sign of respect and honour. The codepoint of this script in Unicode is (U+FDFA). Likewise, the prophet's name 'محمد' meaning (Muhammad) has a specific Unicode character with codepoint (U+FDF4) and was found within our dataset. Table 5.2 illustrates some of these scripts and how we modified them.

5.2.2 Sentiment Labels Normalisation

As mentioned above, ten out of the sixteen datasets were originally manually annotated with inconsistent sentiment labels. Therefore, the unification of the annotation labels was necessary and was applied as follows. Syria Tweets [233], SemEval-2017 (Task 4) [234], ArSenTD-Lev [159], ArSAS [110], ArSarcasm [240] and ASAD [241] datasets already had one of the three sentiment labels: positive, neutral, and negative. In this case, we only lowercase the first letter for each label. Furthermore, the ArSenTD-Lev dataset [159] had two extra labels: *very-positive* and *very-negative*. Here, we replaced these extra labels with the words *positive* and *negative*, respectively. Also, the ArSAS dataset [110] had a group of tweets labelled as *Mixed* which we kept for later manual re-annotation with sentiments.

[3] https://www.compart.com/en/unicode/scripts/Arab.

Table 5.2: The Modifications of Some of the Unicode Arabic Scripts.

Arabic Script	Unicode code-point	Modification	Arabic Script	Unicode code-point	Modification
ﷺ Arabic Ligature Mohammad Isolated Form	U+FDF4	محمد	﷽ Arabic Ligature Bismillah Ar-Rahman Ar-Raheem	U+FDFD	بسم الله الرحمن الرحيم
ﷺ Arabic Ligature Salam Isolated Form	U+FDF4	صلى الله عليه وسلم	ﷺ Arabic Ligature Rasoul Isolated Form	U+FDF6	رسول
ﷺ Arabic Ligature Sallallahou Alayhe Wasallam	U+FDF4	صلى الله عليه وسلم	ﷻ Arabic Ligature Jallajalalouhou	U+FDFB	جل جلاله
﷼ Rial Sign	U+FDFC	ريال	ﷲ Arabic Ligature Allah Isolated Form	U+FDF2	الله

Similarly, ArSarcasm had some tweets labelled as *Objective* which we changed to *neutral*. In the ATSAD dataset [239], the sentiment labels were abbreviated into *Neg* and *Pos* for *negative* and *positive* sentiments, respectively. Therefore, we replaced the abbreviated labels with their corresponding full labels. Similarly, the sentiment labels in the SS2030 dataset [238] were digitised as 0 for *negative* and 1 for *positive*. We converted these digits into their corresponding words.

The labels in the L-HSAB [160] and SemEval-2018 (Task 1 & Task 2) [235], [236] datasets were not explicitly for sentiment. The L-HSAB dataset is intended for an offensive/hate-speech detection task. In this dataset, we replaced the labels *Abusive* and *Hate* with the label *negative*. However, we kept the tweets that were labelled as *Normal* for later manual re-annotation with the sentiment. In SemEval-2018, the labels were for emotions rather than sentiments. Therefore, the negative labels (i.e., *Anger*, *Fear* and *Sadness*) were replaced by the label *negative*; and the positive label (i.e., *Joy*) was replaced by the word *positive*. The TEAD [104] and AraSenCorpus [229] datasets were created for sentiment analysis tasks, but

their annotation relied mainly on machine learning techniques. The DART [237], ArCovid-19 [242], Kawarirth [243] and Sa'7r [244] datasets were created for natural language processing tasks other than sentiment analysis. The DART dataset was for an Arabic dialect identification task, while the Kawarirth and ArCovid-19 datasets were for crisis and propagation networks detection tasks, respectively. The Sa'7r dataset was created for irony detection.

To expand the number of manually annotated tweets with sentiment, we added Kawarirth and DART datasets to the tweets that were labelled as *Mixed* in the ArSAS dataset, *Objective* in the ArSarcasm dataset, and *Normal* in the L-HSAB dataset. This formed a collection of tweets for manual re-annotation of sentiment. The re-annotation was carried out independently by eight native Arabic-speaking annotators, comprising three males and five females. Further details on the re-annotation process will be provided in Section 5.3.1.

5.2.3 Emoji Normalisation

We conducted additional normalisation on our dataset by converting all emoji ZWJ sequences[4] to their base emoji. An emoji ZWJ sequence is a combination of multiple emoji that appear as a single emoji on supported platforms and is created by joining multiple emoji with a Zero Width Joiner (ZWJ) character, an invisible Unicode character that creates a new emoji sequence. As an example, the *Woman Facepalming: Light Skin Tone* emoji (i.e., 🤦🏻‍♀️) is a ZWJ sequence comprising *Person Facepalming* (🤦), *Light Skin Tone* (🏻), *Zero Width Joiner* (U+200D), and *Female Sign* (♀️). In such cases, we normalised the emoji into its base emoji, which is the *Person Facepalming* (🤦), by removing the codepoints of the ZWJ connector, the gender sign and the skin-tone indicator. Figure 5.2 shows all the possible variations of this emoji as ZWJ emoji sequences. This normalisation reduced the redundancy of an emoji by eliminating all possible visual occurrences that are not relevant

[4] https://emojipedia.org/emoji-zwj-sequence/.

to our analysis, such as skin tones, gender, and hair colour. By converting all emoji ZWJ sequences into their base emoji, we were able to standardise the emoji format, remove visual distractions, and ensure a focused analysis. This initial data preparation procedure aims to normalise the data into a coherent form so that it can be handled easily for sentiment analysis by both humans and machines. The outcome was a total of **780,300** emoji, consisting of **1,272** unique emoji, which formed **59,546** distinct emoji combinations (i.e., emoji patterns) within the collected dataset.

Emoji Decoding to Arabic Text

Applying a machine sentiment annotation on Arabic texts using already existing Arabic classifiers requires particular preprocessing steps. In our case, in addition to the preparation of the dataset mentioned above, the following steps were applied. First, all the emoji in the collected dataset were extracted, and all their official Unicode English names were found. We use the Python library *emoji*[5] for that. Then, the English Unicode names of the emoji were translated into Arabic in two steps: first using the *Google Translate* API for Python[6], then verifying the translation results by an Arabic linguist. Lastly, each emoji symbol within a text was replaced with its Arabic name. This is to ensure that the machine will not neglect any token (i.e., Arabic word) in the provided textual context, and it will classify its sentiment accordingly.

5.3 Data Annotation

At this initial stage, annotating the datasets with sentiment was essential to create sentiment lexicons for emoji and words, and to utilise these datasets for validation tests.

[5] https://pypi.org/project/emoji/
[6] https://pypi.org/project/googletrans/

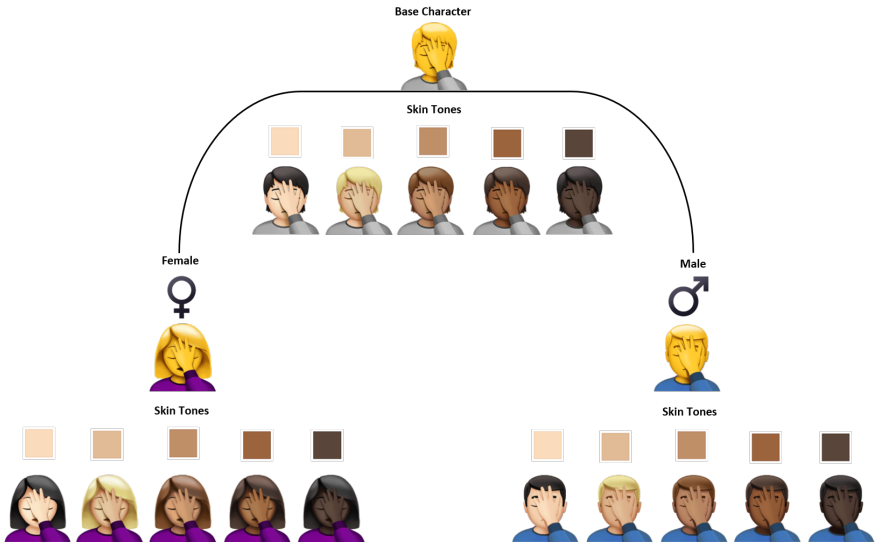


Figure 5.2: *Person Facepalming* Emoji As an Example of **ZWJ** Characters.

5.3.1 Gold-Standard Dataset: Manually Annotated

In the field of NLP, the term "*gold standard*" dataset is used to describe a dataset that has been manually annotated or labelled by humans and is widely considered a reliable and accurate representation of data [245], [246]. For this research, we aim to create a gold standard dataset by manually annotating two groups of texts. One has 10,179 tweets containing emoji (i.e., Emoji-Texts) and an equivalent set of 10,179 tweets without emoji (i.e., Plain-Texts). For this task, we recruited eight participants, five females, and three males. Some of the participants were directly asked to volunteer while others were hired via Khamsat[7]. The demographic details of the participants are shown in Table 5.3.

The Emoji-Texts dataset contains a substantial number of texts that have already been manually annotated in its resources. However, a portion of these texts required re-annotation, as explained in Section 5.2.2. Furthermore, a randomly selected subset of texts from the Kawarirth and DART datasets was added to be manually annotated as well. To ensure the accuracy and reliability of the sentiment annotation, a three-round annotation

[7]The largest Arabic marketplace for digital services (www.khamsat.com).

Table 5.3: The Demographic Details of the Participants for the Manual Texts Sentiment Annotation

#	Gender	Age	Nationality	Country of Residence	Religion	Educational Qualification	Employment Status	Sight Medical Issues
1	Male	20	Saudi	Saudi Arabia	Muslim	Undergrad	Unemployed	None
2	Female	24	Jordanian	Jordon	Muslim	Undergrad	Unemployed	None
3	Female	24	Palestinian	Palestine	Muslim	Undergrad	Unemployed	None
4	Male	25	Saudi	Saudi Arabia	Muslim	Undergrad	Unemployed	None
5	Female	28	Palestinian	Palestine	Muslim	Undergrad	Unemployed	None
6	Female	28	Sudanese	Sudan	Muslim	Postgrad	Employed	None
7	Female	32	Saudi	Saudi Arabia	Muslim	Postgrad	Employed	None
8	Male	34	Saudi	Saudi Arabia	Muslim	Postgrad	Employed	None

process was employed. In each round, at least two annotators were required to agree on the sentiment label of each text. In the first round of annotation, one male and one female annotator were assigned to label the texts as positive, neutral, or negative. The agreement between the two annotators' labels was then checked. Texts with labels that disagreed were passed on to the second round. In the second round, a third male annotator was added to the annotation team and the agreement between at least two annotations was tested again. Texts with labels that were still disagreed with were then moved to the third and final round. In the third round, a female annotator was added to label the transferred texts from the previous round with sentiment. At this point, it was found that all texts had been labelled with sentiment labels, to which at least two annotators agreed. After completion of the annotation process, a total of 10,179 texts with emoji were manually annotated.

The Emoji-Texts dataset was modified to create the **Plain-Texts** dataset, which is the same as the former but with the emoji removed. To make the dataset more manageable for the annotators, we split it into two smaller subsets: one subset of 5,204 texts assigned to four annotators (three males and one female) and another subset of 4,975 texts assigned to four annotators (all were female). To assign the final sentiment label to each text, we utilised the *Majority Voting* mechanism, which required that a minimum of two annotators

come to a consensus on a singular sentiment label.

5.3.2 Silver Standard Dataset: Automatically Annotated

A gold standard dataset is considered the most reliable and accurate representation of the data because it has been manually annotated or labelled by humans. However, manual annotation is often time-consuming, expensive, and difficult to scale, especially for large datasets. In many cases, it may be impractical or infeasible to obtain a fully annotated gold standard dataset for a given task. To address this issue, researchers can instead use a "*silver standard*" dataset. A silver standard dataset is typically generated using automated, semi-automated, or heuristic methods, such as lexicon-based or rule-based algorithms [247]–[249]. For example, in sentiment analysis, a silver standard dataset can be generated by using a sentiment lexicon of words to label tweets as positive, negative, or neutral [99]. Since a silver standard dataset is generated using automated or semi-automated methods, it may be less reliable and precise than a gold standard dataset. However, it is a useful resource for training and evaluating machine learning models, especially when the dataset is large or when there are not enough gold standard datasets available for a particular task (as is in our case). To enhance the labelling quality of our silver standard dataset, we aggregated the results from multiple automated sentiment classifiers, rather than depending on the output of a single machine. These classifiers were Mazajak [105], CAMeL-Tools (AraBERT and mBERT modules) [106], ASAD [109]. We utilised the *Majority Voting* by the four machine annotators to assign the final sentiment label to each text of a total of **362,586** texts as our silver dataset. This will be explained next.

Before we aggregated the classifier annotations, we tested their individual performance. This was done on the 10,179 manually annotated texts from the gold standard dataset. The texts were Emoji-Texts and their corresponding Plain-Texts. Cohen's Kappa (k) [223], accuracy, and weighted F score ($F1$) [228] were then used to compare the ground

truth annotations with those produced by Mazajak, CAMeL-Tools (AraBERT), CAMeL-Tools (mBERT) and ASAD. The results, presented in Table 5.4, indicated that Mazajak had the highest accuracy and $F1$, with scores of 0.68 and 0.67, respectively, and a moderate agreement score of 0.52, with the Plain-Texts dataset. On the other hand, CAMeL-Tools (AraBERT) had the highest accuracy and $F1$, with scores of 0.74 and 0.75, respectively, and a moderate agreement score of 0.60, with the Emoji-Texts Dataset.

Machine Fusion for Sentiment Annotation

As is demonstrated in Table 5.4, it is evident that each sentiment classifier exhibited varying levels of accuracy. In our pursuit of enhancing the precision of sentiment annotation generated independently by each classifier, we employed a *majority voting* approach. This methodology harnesses the distinctive capabilities of individual classifiers while mitigating their respective shortcomings, producing sentiment labelling that is more resilient, reliable and precise.

Majority Voting Approach

Here, we describe the algorithm used to assign a final sentiment label using a *majority voting* approach among four machine sentiment classifiers: CAMeL-AraBERT, CAMeL-mBERT, Mazajak, and ASAD. This is summarised in Algorithm 1.

The algorithm begins by collecting the sentiment labels assigned by each of the four classifiers and counting how many times each sentiment label has been assigned to the text. This information is stored in a Python dictionary with three items, where the keys represent the sentiment labels: negative, neutral, and positive, and the values indicate the number of times the respective label has been assigned by each classifier. The algorithm then calculates the maximum count for each sentiment label in the four classifiers. If the maximum count is

Algorithm 1: Majority Voting Algorithm for Sentiment Analysis

Data: Sentiment labels assigned by 4 classifiers: $labels_{1...4}$

Result: Final sentiment label

begin

  `// Count the number of votes for each sentiment label`

  $sentiment_counts = \text{negative} : 0, \text{neutral} : 0, \text{positive} : 0$; **for** $i \leftarrow 1$ **to** 4 **do**

    $sentiment_counts[labels_i] \leftarrow sentiment_counts[labels_i] + 1$;

  end

  `// Select final sentiment label`

  $max_count = \max(sentiment_counts[\text{negative}], sentiment_counts[\text{neutral}], sentiment_counts[\text{positive}])$;

  if $max_count \geq 3$ **then**

    if $sentiment_counts[positive] = max_count$ **then**

      $final_sentiment \leftarrow$ Positive

    end

    else if $sentiment_counts[negative] = max_count$ **then**

      $final_sentiment \leftarrow$ Negative

    end

    else

      $final_sentiment \leftarrow$ Neutral

    end

  else

    if $sentiment_counts[negative] = 2$ *and* $sentiment_counts[neutral] = 1$ *and* $sentiment_counts[positive] = 1$ **then**

      $final_sentiment \leftarrow$ Negative

    end

    else if $sentiment_counts[negative] = 1$ *and* $sentiment_counts[neutral] = 2$ *and* $sentiment_counts[positive] = 1$ **then**

      $final_sentiment \leftarrow$ Neutral

    end

    else if $sentiment_counts[negative] = 1$ *and* $sentiment_counts[neutral] = 1$ *and* $sentiment_counts[positive] = 2$ **then**

      $final_sentiment \leftarrow$ Positive

    end

    else

      `// Select a final label from a specific classifier and dataset`

      if $classifier = CAMeL\text{-}AraBERT$ **then**

        $final_sentiment \leftarrow$ Sentiment label for $text$ from Emoji-Texts dataset

      end

      else if $classifier = Mazajak$ **then**

        $final_sentiment \leftarrow$ Sentiment label for $text$ from Plain-Texts dataset

      end

    end

  end

  return $final_sentiment$

end

three or more and the key associated with this count corresponds to a specific sentiment label, then the final sentiment label is set to that sentiment. For example, if the maximum count is associated with the positive sentiment label, the final sentiment label is set to positive. Similarly, if the maximum count is associated with the negative sentiment label, the final sentiment label is set to negative, and if the maximum count is associated with the neutral sentiment label, the final sentiment label is set to neutral. However, if the maximum count is less than three, the algorithm follows a series of conditional statements to determine the final sentiment label. If the number of negative sentiment labels is two and the number of neutral and positive sentiment labels is one, the final sentiment label is negative. Similarly, if the count of neutral sentiment labels is two and the count of negative and positive sentiment labels is one, the final sentiment label is neutral. If the count of positive sentiment labels is two and the count of negative and neutral sentiment labels is one, the final sentiment label is positive. Finally, if none of the above conditions is satisfied, the final sentiment label is determined based on the classifier used. Specifically, if the text comes from the Emoji-Texts dataset, the final label is set to the sentiment label assigned by the CAMeL-AraBERT classifier. However, if the text comes from the Plain-Texts dataset, the final label is set to the sentiment label assigned by the Mazajak classifier.

As shown in Table 5.4, the validation test that was applied to the same aforementioned sample of texts confirmed that the fusion of the four classifiers outperformed the results of each, individually, with the Emoji-Texts dataset, while maintaining about the same performance as Mazajak with the Plain-Texts dataset. As a result, we relied on this annotation process for labelling our silver standard dataset.

Table 5.4: Evaluation Results of the Machine Fusion for Sentiment Annotation.

	(a) Plain-Texts			**(b) Emoji-Texts**		
Sentiment Classifiers	**Cohen's** k	*accuracy*	$F1$	**Cohen's** k	*accuracy*	$F1$
CAMeL-AraBERT	0.41	0.61	0.59	**0.60**	**0.74**	**0.75**
CAMeL-mBERT	0.38	0.59	0.57	0.51	0.72	0.73
Mazajak	**0.52**	**0.68**	**0.67**	0.50	0.70	0.71
ASAD	0.20	0.45	0.58	0.32	0.56	0.61
Machines Fusion Annotation	**0.50**	**0.66**	**0.65**	**0.61**	**0.78**	**0.79**

5.4 Chapter Conclusion

In summarising this chapter, the foundational importance of obtaining an appropriate dataset, especially tweets infused with emoji, has been emphasised. Given the distinct nuances of informal non-standard Arabic short texts, we elaborated on a specific preprocessing method, ensuring these texts are ready for subsequent stages of analysis. Furthermore, our method of using existing Arabic sentiment classifiers underlined an approach for applying, to some extent, a reliable machine-based sentiment annotation. In the upcoming chapter, we will delve into the creation of the first Arabic-specific emoji-centric sentiment resources, primarily lexicons, which we have made freely available for research purposes. It will seek an answer to the first research question: "*RQ1: To what extent is the sentiment interpretation of an individual emoji consistent within the Arabic language?*".

Chapter 6

Sentiment Lexicons Creation and Usage

In this chapter, we dive deeply into the intricate process of creating sentiment lexicons uniquely tailored to the linguistic and cultural intricacies of the Arabic language and its diverse dialects. In the first section, we will elucidate the formulation of Arabic emoji sentiment lexicons. Initially, we will create a context-sensitive emoji sentiment lexicon by extrapolating sentiments from the prevalent usage of emoji in previously annotated Arabic texts. Then, we will introduce a context-free emoji sentiment lexicon, constructed via the manual annotations of 53 participants, allocating sentiment values to emoji independent of any textual context. Afterwards, with a focus on our first research question, "**RQ1: To what extent is the sentiment interpretation of an individual emoji consistent within the Arabic language?**", we will critically examine the alignment between the two distinct lexicons. This exploration culminates in the production of the aggregated "*Static*" emoji sentiment lexicon, distinguished by its fixed assignment of a single sentiment score and its associated label to each emoji. Also, we will develop a sentiment lexicon for dialectical Arabic words. These sentiment lexicons (for emoji and words) provide a foundational basis for developing our lexicon-based sentiment analysis.

6.1 Emoji Sentiment Lexicons

6.1.1 Context-Sensitive Emoji Sentiment Lexicon

We applied the Emoji Sentiment Ranking (ESR) model, which was proposed for Euro-ESL by [1], to construct the first Arabic Emoji Sentiment Lexicon (Arab-ESL) using the Emoji-Texts dataset from our prepared gold and silver standard data. In this model, the sentiment of emoji is computed from the sentiment of texts labelled by human and machine annotators. Sentiment labels can take one of three values: negative, neutral, and positive. Each sentiment label, **c**, is formally a discrete variable with three values: $\mathbf{c} \in \{-1, 0, +1\}$. This variable represents the order of the sentiment values and the distances between them. An emoji can occur in several tweets, which we labelled with the sentiment. A discrete distribution:

$$N(c), \sum N(c) = N,\ c \in \{-1, 0, +1\} \tag{6.1}$$

captures the sentiment distribution for the set of relevant tweets. **N** denotes the number of all occurrences of the object in the tweets, and $\mathbf{N(c)}$ are the occurrences in the tweets with the sentiment label **c**. We considered the multiple occurrences of an emoji in a single tweet. From the above, we form a discrete probability distribution:

$$(p_-, p_0, p_+), \sum_c p_c = 1 \tag{6.2}$$

The components of the distribution, i.e., p_-, p_0, and p_+ denote the negativity, neutrality, and positivity of the emoji, respectively. Then, we estimated the probabilities from relative frequencies:

$$p_c = \frac{N(c)}{N} \tag{6.3}$$

This estimation gives a good approximation for large samples. However, with small samples,

e.g., $\mathbf{N} = 5$, it is better to use the Laplace estimate (also known as the rule of succession) to estimate the probability [250]:

$$p_c = \frac{N(c)+1}{N+k}, \; (for\, large\, N : p_c \approx \frac{N(c)}{N}) \tag{6.4}$$

We applied the Laplace estimate when **N** is less than or equal to 900. Then, the sentiment score $\overline{S}$ of the emoji is computed as the mean of the distribution:

$$\overline{S} = (-1 \,.\, p_-) \; + \; (0 \,.\, p_0) \; + \; (+1 \,.\, p_+) \tag{6.5}$$

Finally, we assign the sentiment labels to the emoji in our lexicon based on the emoji sentiment scores-to-labels scale (detailed in **Appendix A**) as follows. Emoji with a sentiment score between 1 and 0.0625 was classified as positive. If a sentiment score was between -1 and -0.0625, the emoji was classified as negative. Lastly, an emoji was classified as neutral when its sentiment score was in the range between -0.0625 and 0.0625.

Annotation Validity Test

Validating the annotation of this lexicon, we used the emoji list provided by Ghaban [117] as an annotated Arabic gold standard emoji set. This list consists of 43 emoji, each annotated with sentiment and semantic interpretations, with their corresponding class type that we added for clarity. The list includes 40% positive emoji, 11% neutral emoji, and 49% negative emoji. Table 6.1 displays some examples from the list.

The evaluation test of our lexicon yielded a moderate agreement score (i.e., Cohen's Kappa $\kappa = \mathbf{0.56}$), along with a high accuracy value and weighted $F1$ score (i.e.,**0.74** and **0.73**, respectively). Our context-sensitive emoji sentiment lexicon boasts a comprehensive collection

Table 6.1: Examples of the Gold Standard Emoji List.

Emoji	Class	Semantical Meaning	Sentiment
✌️	Body Language	[‘Good Job’, ‘Well Done’, ‘Hooray’]	positive
🤲	Body Language	[‘Pray’, ‘Duaa’]	positive
💪	Body Language	[‘Work Hard’, ‘Workout’]	positive
👋	Body Language	[‘Hello’, ‘Bye’]	neutral
✋	Body Language	[‘My Turn’]	positive
🚫	Symbol	[‘Not Allowed’]	negative
😂	Facial Expression	[‘Funny’, ‘Sad’]	positive
😕	Facial Expression	[‘I Am Sad’, ‘I Cannot Follow You’]	negative
😅	Facial Expression	[‘I Am Sorry’, ‘I Am Just Kidding’]	positive

of **1,272** unique emoji [1]. Table 6.2 displays examples from this lexicon.

6.1.2 Context-Free Emoji Sentiment Lexicon

Interpreting the sentiment conveyed by these pictographic symbols is highly subjective, and it differs based on how people preconceived them. Furthermore, as shown in the previous section, cultural background is considered to be one of the main factors that affect the interpretation of emoji sentiment. Thus, we focus here on targeting people of Arab culture. This is done by constructing a context-free Arabic emoji sentiment lexicon annotated by Arabic native speakers from seven different regions (i.e., Gulf, Egypt, Levant, Sudan, North Africa, Iraq, and Yemen) to see how Arabic users label the sentiment of these symbols out of textual contexts.

[1] A preliminary Arabic context-sensitive lexicon (Arab-ESL) with 1034 emoji has been published by Hakami, Hendley, and Smith [2] as one of the contributions of this thesis

Table 6.2: Sample of the Context-Sensitive Emoji Sentiment Lexicon. $\overline{S}$ Denotes Scores and **L** Denotes Labels.

#	Emoji	Unicode Name	Arabic Name	Class	$\overline{S}$	L
1	😂	Face With Tears Of Joy	وجه بدموع الفرح	Facial Expression	0.118108	pos
2	💔	Broken Heart	قلب مجروح	Heart	-0.944357	neg
3	❤️	Red Heart	قلب احمر	Heart	0.700019	pos
4	😭	Loudly Crying Face	وجه يبكي بصوت عالي	Facial Expression	-0.566093	neg
5	😍	Smiling Face With Heart-Eyes	وجه مبتسم بعيون قلب	Facial Expression	0.907333	pos
6	🌹	Rose	ورده	Nature	0.859694	pos
7	🙂	Slightly Smiling Face	وجه بابتسامه خفيفه	Facial Expression	0.116966	pos
8	💕	Two Hearts	قلبين	Heart	0.603725	pos
9	😅	Grinning Face With Sweat	وجه مبتسم متعرق	Facial Expression	0.437387	pos
10	💙	Blue Heart	قلب ازرق	Heart	0.718288	pos
11	😔	Pensive Face	وجه متأمل	Facial Expression	-0.317116	neg
12	😄	Beaming Face With Smiling Eyes	وجه مشع بعيون مبتسمه	Facial Expression	0.436152	pos
13	💚	Green Heart	قلب اخضر	Heart	0.706600	pos
14	👍	Thumbs Up	ابهام متجه لاعلي	Body Language	0.294279	pos
15	👌	Ok Hand	حركه اليد لقول حسنا	Body Language	0.432817	pos
16	💛	Yellow Heart	قلب اصفر	Heart	0.455849	pos
17	😒	Unamused Face	وجه غير راضي	Facial Expression	-0.686371	neg
18	😢	Crying Face	وجه يبكي	Facial Expression	-0.645479	neg
19	💪	Flexed Biceps	عضلات	Body Language	0.312692	pos
20	🌸	Cherry Blossom	زهره الكرز	Nature	0.806993	pos
21	😩	Weary Face	وجه مرهق	Facial Expression	-0.537590	neg
22	💜	Purple Heart	قلب بنفسجي	Heart	0.659729	pos
23	😊	Smiling Face With Smiling Eyes	وجه مبتسم بعيون مبتسمه	Facial Expression	0.727871	pos
24	❤️	Heart Suit	قلب	Heart	0.709672	pos
25	😘	Face Blowing A Kiss	وجه يرسل قبله بقلب	Facial Expression	0.784876	pos
26	✋	Raised Hand	يد مرفوعه	Body Language	0.320645	pos
27	🤔	Thinking Face	وجه مفكر	Facial Expression	-0.571053	neg
28	🤣	Rolling On The Floor Laughing	يتدحرج على الارض من الضحك	Facial Expression	-0.344764	neg
29	✨	Sparkles	بريق	Object	0.639206	pos
30	😡	Pouting Face	وجه يشتاط غضبا	Facial Expression	-0.862091	neg
31	😉	Winking Face	وجه يغمز	Facial Expression	-0.257618	neg
32	😑	Expressionless Face	وجه بلا تعبير	Facial Expression	-0.600071	neg
33	😎	Smiling Face With Sunglasses	وجه مبتسم بنظارة شمسيه	Facial Expression	0.536065	pos
34	😀	Grinning Face	وجه ضاحك	Facial Expression	-0.329591	neg
35	🙏	Folded Hands	ايدي متقابله	Body Language	0.617149	pos

Emoji Selection

This lexicon encompasses all the 1,034 emoji in Arab-ESL[2] [2], a publicly accessible Arabic emoji sentiment lexicon that we have created and published. We also incorporated an additional 35 emoji, shown in Figure 6.1, deemed essential for this lexicon. Consequently, the total count stands at **1,069** emoji.



Figure 6.1: The Thirty-Five Extra Emoji Added for the Arab-ESL.

Annotation Interface

To perform an easier and more efficient emoji sentiment annotation, it was important to set up a user-friendly annotation interface. This was applied using *Google Forms*, an online web-based survey administration service provided by *Google*. We created two sets (each with five forms): one with official emoji names and the other without. Each set contains all 1,034 emoji. We think that by adding official names (i.e., emoji descriptions), the uncertainty about an emoji meaning that an annotator might encounter will be decreased. In addition, to provide a consistent representation of emoji graphical appearances, the Apple platform emoji rendering was used throughout. We uploaded the emoji to the forms as images rather than using Unicode-rendered characters. This is done to unify the visual appearance and size of the emoji on any web browser and operating system used by the annotators. Consequently,

[2] https://github.com/ShathaHakami/Arabic-Emoji-Sentiment-Lexicon-Version-1.0

we converted each emoji's official name into its UTF encode and used it as an emoji identifier within the forms. This is to facilitate the identification and extraction of each emoji with all its corresponding annotations by all annotators after the entire annotation task has been completed. For the annotation options, we chose to use a seven-point fine-grained sentiment label scale, ranging from "Very Positive" to "Very Negative", including "Neutral". Also, two additional options were added, which are "Mixed Sentiment" and "I don't know". Figure 6.2 illustrates the details of this annotation interface.

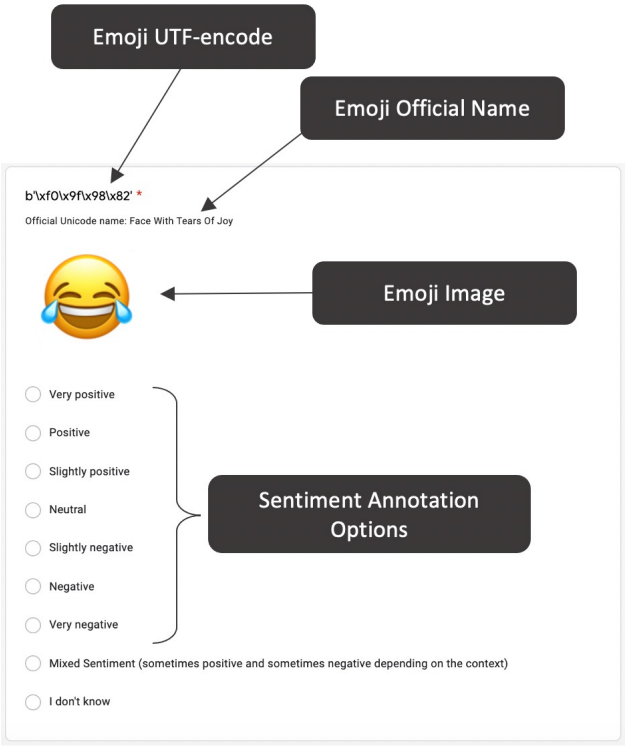


Figure 6.2: Emoji Sentiment Annotation Interface.

Participants Recruitment

We intend to recruit participants from all Arab regions. Some of the participants were directly asked to volunteer while others were hired via Khamsat[3], the largest Arabic market-

[3] www.khamsat.com

place for digital services. Initially, we recruited 83 native Arabic speakers, males and females, from the Gulf, Egypt, Levant, Sudan, North Africa, Iraq and Yemen. Each participant was provided with the URLs of five Google forms. In addition to the emoji annotation section, the first form collected demographic information and obtained informed consent. After analysing the forms as will be described later, we found that one participant disagreed with informed consent; 27 participants had not completed all five forms; one was dyslexic; and one failed the self-agreement annotation tests and was considered an unreliable annotator. Thus, the total of approved participants was 53 (28 women and 25 men). As a post-sentiment annotation procedure, in the last form (i.e., the fifth form), we asked the participants the following. First, we provide us with the five most frequently used emoji they use. Second, we answer a question regarding the impact of including emoji's official names along with their symbols on the emoji sentiment annotation process. The options of answer to this question were: "Partially important"; "Very important"; "Not important"; and "Causing confusion".

Demographic and Consent

Each participant was asked to provide the following information: gender, age, native country of residence, current country of residence, religion, educational qualifications, employment status, some health problems (i.e., dyslexia and colour blindness) and use of social media. We also asked about the device, operating system, and browser currently used, as part of the technical setup for the annotation task. After providing their demographic information, each participant was asked to agree or disagree with the use of that information for scientific research. As shown in Figure 6.3, the large variety of participants was from the Gulf region with 45%. The age of the majority of the participants (i.e., 86%) ranged between 18-34 years old; and almost all of them are Muslims (96%). Regarding health conditions, only one of the participants had dyslexia (and was excluded); and none of them had colour blindness. Also, most of the participants lived in their native countries (75%); and all were educated. For the annotation, as demonstrated in Table 6.3, 74% of the participants used a mobile phone

while 26% used a personal laptop. Furthermore, 53% performed the annotation using *iOS* operating system, and 47% used the *Chrome* web browser. Furthermore, the most frequently used social media platform was *WhatsApp* with 16%, and the least used was *SMS* with 7%. Lastly, Figure 6.4 showed that the most frequent emoji used by the participants is (😂); while the least commonly used emoji are (😊, 🤸, and 🙈).

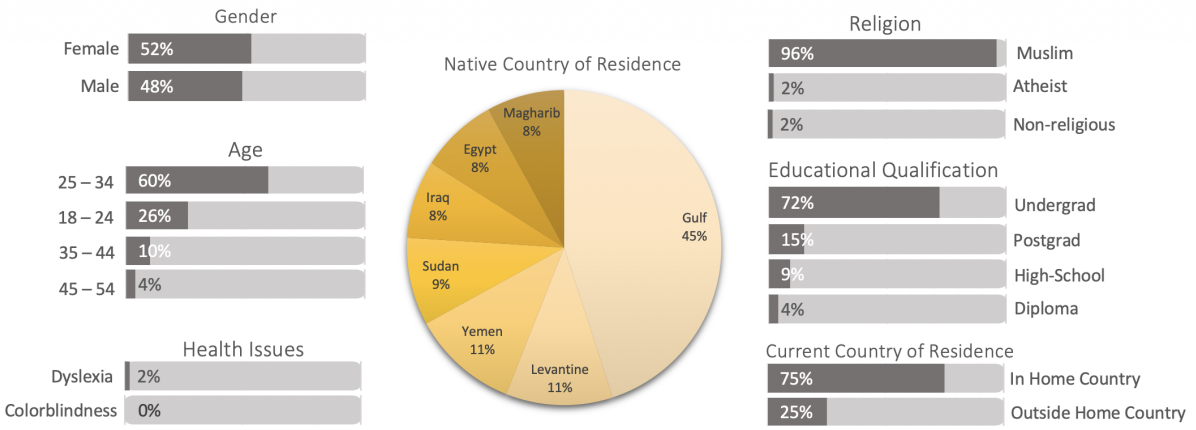


Figure 6.3: Participants' Demographic Information Summary.

Table 6.3: Technical Setup for the Annotation by the Participants.

Category	**Hardware / Software**	**Usage in (%)**
Device	Mobile Phone	74%
	Laptop	26%
Operating System	iOS	53%
	Android	28%
	Windows OS	19%
Web Browser	Google Chrome	47%
	Safari	42%
	Mozilla Firefox	9%
	Unmentioned Browser	2%

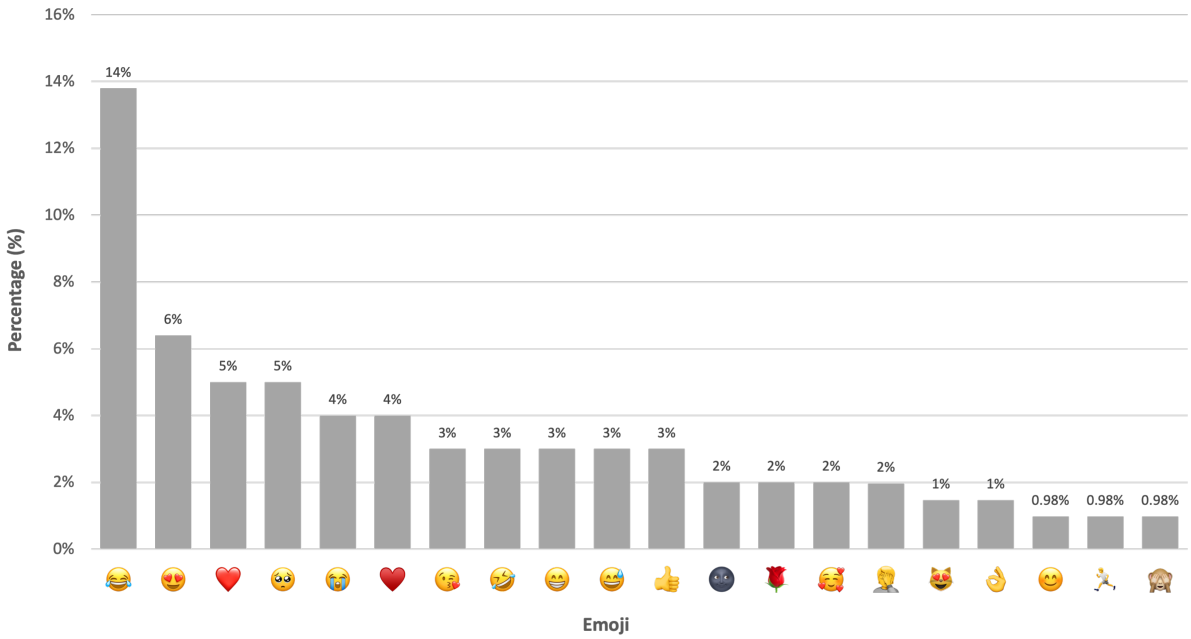


Figure 6.4: The Most Twenty Commonly Used Emoji by 53 Arabic Participants.

Annotation Process

Each of the five forms contained around 200 emoji, which were drawn from 1069 emoji in total. Each participant was asked independently to complete the five forms within seven days. They were asked to select an option, from a list, which represents their interpretation of the sentiment of each emoji. The list contains the following options: *Very Positive*, *Positive*, *Slightly Positive*, *Neutral*, *Slightly Negative*, *Negative*, *Very Negative*, *Mixed Sentiment*, and *I don't know*, presented as radio buttons. The annotation process was estimated to be approximately 15 seconds per emoji, which is about 50 minutes per form. All participants completed the entire data collection task over a period of six weeks.

Annotation Validity Test

To test an individual annotator's self-agreement, we used the Recall for sensitivity measure [251], and Krippendorff's Alpha (α) for consistency measure [225]. We applied these measurements, for each annotator, to the three norms of the sentiment label: negativity, neutrality, and positivity. We chose the following groups of emoji: (😔, 😒, 😞, 😕), (🕛, 🕒, 🕛, 🕘), and (❤️, ❤️, 💖, 💝), for negativity, neutrality, and positivity self-agreement tests, respectively. If the *recall* value or κ-Alpha value for an annotator, in any of the three sentiment norms, is less than 0.75, then we consider the annotator to be unreliable and their results of the annotation to be invalid. Thus, such an annotator will be excluded from the analysis. Table 6.4 displays a sample of the results of the two tests.

Table 6.4: A Sample of the Human Annotators' Self-agreement Tests. The Blue-Coded Annotations are the Outliers.

Negative Emoji	**Annotator ID**	😔	😒	😞	😕	**Alpha (α)**	**Recall**
	1002	negative	negative	negative	negative	1.00	1.00
	1003	negative	negative	negative	negative	1.00	1.00
	1004	negative	negative	negative	negative	1.00	1.00
	1005	negative	negative	negative	negative	1.00	1.00
	1007	negative	negative	negative	negative	1.00	1.00
Neutral Emoji	**Annotator ID**	🕛	🕒	🕛	🕘	**Alpha (α)**	**Recall**
	1002	neutral	neutral	neutral	neutral	1.00	1.00
	1003	neutral	neutral	neutral	neutral	1.00	1.00
	1004	neutral	neutral	neutral	neutral	1.00	1.00
	1005	**positive**	neutral	neutral	neutral	0.80	0.75
	1007	neutral	neutral	neutral	**disregard**	0.87	0.75
Positive Emoji	**Annotator ID**	❤️	❤️	💖	💝	**Alpha (α)**	**Recall**
	1002	positive	positive	positive	positive	1.00	1.00
	1003	positive	positive	positive	positive	1.00	1.00
	1004	positive	positive	positive	positive	1.00	1.00
	1005	positive	positive	positive	positive	1.00	1.00
	1007	positive	positive	positive	positive	1.00	1.00

Sentiment Scores Calculation

To associate each emoji with each sentiment label, we first unified the group of sentiment labels under one sentiment norm as one sentiment label. For example, we unified the labels "Very Positive", "Positive" and "Slightly Positive" under the *positive* label. The same was applied to labels under the negative sentiment norm, which were unified as *negative*. For the neutral sentiment norm, we unified the labels "Neutral" and "Mixed Sentiment" to be *neutral*. Lastly, any emoji label found to be "I don't know" was disregarded from the sentiment label count. For the calculation of the emoji sentiment score, we applied the procedure that has been done for the context-sensitive lexicon in Section 6.1.1. We started by identifying the frequency with which each emoji is associated with human sentiment annotation labels (negative, neutral, and positive). Then we formed a discrete probability distribution from relative frequencies of negativity, neutrality, and positivity for each emoji. Since we are dealing with small samples (i.e., the maximum **N** is 53, which is the maximum number of annotations agreed on a sentiment class), we used the Laplace estimate [250] to estimate the probability. Lastly, the sentiment score $\overline{S}$ of the emoji was calculated as the mean of the distribution. To convert sentiment scores into sentiment labels, we utilised the emoji *scores-to-labels* sentiment scale, illustrated in Figure 4.2. As a result, emoji with sentiment score i, where -1 $\leq i <$ -0.0625, was classified as negative. Emoji with sentiment score i, where $1 \geq i >$ 0.0625, was classified as positive. Lastly, an emoji was classified as neutral when its sentiment score i was in the range where -0.0625 $\leq i \leq$ 0.0625.

To evaluate the resulted lexicon, we used the emoji list provided by Ghaban [117] as a gold standard sentiment-annotated emoji list, as described earlier in Section 5.3.1. The resulting evaluation test showed a good agreement score (i.e., Cohen's Kappa $\kappa =$ **0.64**) and high accuracy and weighted $F1$ score values (i.e., **0.79** and **0.75**, respectively). Our context-

free emoji sentiment lexicon boasts a comprehensive collection of 1,069 unique emoji[4]. Table 6.5 displays examples from this lexicon.

6.1.3 Static Emoji Sentiment Lexicon

One of our primary aims is to develop an emoji sentiment lexicon, where each emoji is assigned thirteen sentiment scores. Each score indicates the likelihood of the emoji playing a particular sentiment role. According to this perspective, the annotations for the constructed sentiment lexicons, both context-sensitive and context-free, are termed "*Static*". This is because each emoji carries one sentiment score complemented by a singular, fixed sentiment label. Building upon the existence of both lexicons, we aim to address the initial research question of this thesis by assessing the consistency of sentiment annotations for emoji common to each lexicon.

Context-Sensitive vs. Context-Free Arabic Emoji Lexicons

In this exploration, we juxtaposed the Arabic context-free lexicon against the context-sensitive one. In addition to addressing **RQ(1)** of this thesis, this comparative analysis illuminated the disparities between the two, guiding our endeavours to avoid biases inherent to contextual subtleties when we formulate our static Arabic emoji sentiment lexicon[5]. To discern the variations in emoji sentiment annotations across the two lexicons, we employed three metrics. Cohen's Kappa (κ), RMSE, and the *L2* distance.

For that, we first identified emoji common to both lexicons with a minimum occurrence of 50 in our dataset, yielding a total of **459** emoji. By ranking the emoji in the

[4]This lexicon has been published by Hakami, Hendley, and Smith [38] as one of the contributions of this thesis.

[5]Preliminary findings were highlighted in [2], [38], [39].

Table 6.5: Sample of the Context-Free Emoji Sentiment Lexicon. $\overline{S}$ Denotes Scores and **L** Denotes Labels.

#	Emoji	Unicode Name	Arabic Name	Class	$\overline{S}$	L
1	😂	Face With Tears Of Joy	وجه بدموع الفرح	Facial Expression	0.839286	pos
2	💔	Broken Heart	قلب مجروح	Heart	-0.714286	neg
3	❤️	Red Heart	قلب احمر	Heart	0.910714	pos
4	😭	Loudly Crying Face	وجه يبكي بصوت عالي	Facial Expression	-0.446429	neg
5	😍	Smiling Face With Heart-Eyes	وجه مبتسم بعيون قلب	Facial Expression	0.946429	pos
6	🌹	Rose	ورده	Nature	0.857143	pos
7	🙂	Slightly Smiling Face	وجه بابتسامه خفيفه	Facial Expression	0.163636	pos
8	💕	Two Hearts	قلبين	Heart	0.910714	pos
9	😅	Grinning Face With Sweat	وجه مبتسم متعرق	Facial Expression	0.160714	pos
10	💙	Blue Heart	قلب ازرق	Heart	0.836364	pos
11	😔	Pensive Face	وجه متأمل	Facial Expression	-0.836364	neg
12	😄	Beaming Face With Smiling Eyes	وجه مشع بعيون مبتسمه	Facial Expression	0.839286	pos
13	💚	Green Heart	قلب اخضر	Heart	0.851852	pos
14	👍	Thumbs Up	ابهام متجه لاعلي	Body Language	0.767857	pos
15	👌	Ok Hand	حركه اليد لقول حسنا	Body Language	0.600000	pos
16	💛	Yellow Heart	قلب اصفر	Heart	0.745455	pos
17	😒	Unamused Face	وجه غير راضي	Facial Expression	-0.839286	neg
18	😢	Crying Face	وجه يبكي	Facial Expression	-0.803571	neg
19	💪	Flexed Biceps	عضلات	Body Language	0.781818	pos
20	🌸	Cherry Blossom	زهره الكرز	Nature	0.750000	pos
21	😩	Weary Face	وجه مرهق	Facial Expression	-0.800000	neg
22	💜	Purple Heart	قلب بنفسجي	Heart	0.851852	pos
23	😊	Smiling Face With Smiling Eyes	وجه مبتسم بعيون مبتسمه	Facial Expression	0.839286	pos
24	❤️	Heart Suit	قلب	Heart	0.946429	pos
25	😘	Face Blowing A Kiss	وجه يرسل قبله بقلب	Facial Expression	0.946429	pos
26	✋	Raised Hand	يد مرفوعه	Body Language	0.230769	pos
27	🤔	Thinking Face	وجه مفكر	Facial Expression	-0.092593	neg
28	🤣	Rolling On The Floor Laughing	يتدحرج على الارض من الضحك	Facial Expression	0.785714	pos
29	✨	Sparkles	بريق	Object	0.520000	pos
30	😡	Pouting Face	وجه يشتاط غضبا	Facial Expression	-0.857143	neg
31	😉	Winking Face	وجه يغمز	Facial Expression	0.709091	pos
32	😑	Expressionless Face	وجه بلا تعبير	Facial Expression	-0.600000	neg
33	😎	Smiling Face With Sunglasses	وجه مبتسم بنظارة شمسيه	Facial Expression	0.714286	pos
34	😀	Grinning Face	وجه ضاحك	Facial Expression	0.750000	pos
35	🙏	Folded Hands	ايدي متقابله	Body Language	0.692308	pos

context-sensitive lexicon based on their descending frequencies, we were able to organise the corresponding emoji in the context-free lexicon in the same order. This systematic alignment allowed us to evaluate the congruence and likeness of identical emoji across both lexicons.

For the RMSE tests, juxtaposing the sentiment annotations in both lexicons with a standard annotated emoji set (i.e., control data) helps quantify the disparities between both lexicons. As a result, we consolidated four lexicons: context-sensitive, context-free, female, and male. This consolidation helps mitigate potential biases related to gender and context in sentiment annotation. Next, we calculated the average probability distribution ($P(c)$) for each shared emoji in three sentiment norms (c): negative, neutral, and positive. Using the equations provided, we determine the standard emoji sentiment score ($\overline{S}_{Control}$) for every emoji as follows:

$$P(c)_{Control} = \frac{P(c)_{Sens} + P(c)_{Free} + P(c)_{Female} + P(c)_{Male}}{4},\ c \in \{neg,\ neut,\ pos\} \tag{6.6}$$

$$\overline{S}_{Control} = -P(neg)_{Control} + P(pos)_{Control} \tag{6.7}$$

Subsequently, we converted these scores into sentiment labels using the emoji scores-to-labels scale A.5. These labels were instrumental in segmenting ten independent emoji categories into three sentiment norms: negative, neutral, and positive. These categories are: *Facial Expression*, *Body Language*, *Human Activity*, *Hearts*, *Nature*, *Food*, *Object*, *Symbol*, *Place*, and *Flag*.

Applying Cohen's Kappa (κ) and RMSE on each category independently, the results are tabulated in Table D.1 and Table D.2 in **Appendix D**. For improved visual clarity, we represent the RMSE results in Figure D.1 in **Appendix D**. Finally, the L2 distance for all 459 emoji in both lexicons. Figure D.2 in **Appendix D** shows the 20 most similar and distinct emoji, highlighting the variance sentiment annotation of identical emoji with and without Arabic textual context.

As presented in the tables in **Appendix D**, there is a **moderate** general agreement

between the sentiment labels of the emoji in both lexicons, as indicated by Cohen's Kappa value (κ) of 0.5. A deeper examination reveals **Substantial** agreement for emoji under *Facial Expression* and *Heart* classes ($\kappa = 0.7$), while those under *Symbol* register **moderate** agreement ($\kappa = 0.5$). Emoji representing *Object*, *Flag*, *Food*, and *Body Language* exhibit **fair** agreement ($\kappa = 0.3$), and **slight** agreement is seen in the *Nature* ($\kappa = 0.2$) and *Human Activity* ($\kappa = 0.1$) classes. Emoji in the *Place* category demonstrate **poor** agreement with a κ value of 0.

The subtle discrepancies between these labels are evident when examining the intensities of emoji sentiment using their scores, determined by the RMSE and L2 metrics, as depicted in the figures in **Appendix D**. For example, specific emoji, such as (😡, 🔴, 🤦, 🐍, 🚨, and 🔕) were consistently labelled negative in both lexicons. Similarly, there was mutual agreement in both lexicons that emoji (🚩, ▫️, 🔁, and 🏳️‍🌈) conveyed a neutral sentiment, while emoji (🌹, 💖, 👑, ☔, 😇; and 🎂) were perceived as positive. The sentiment scores for these emoji were nearly identical across both lexicons, with minimal L2 distance values. However, the inclusion of textual context significantly affected the sentiment interpretations of certain emoji. This is especially pronounced for emoji symbolising animals (e.g., 🐏, 🐑, 🐶, 🐒, 🐐, 🦌, and 🐸), those denoting body language (e.g., 🙉, 🙈, 🐵 and ⛹️), and those illustrating facial expressions (e.g., 🤣, 🥳, 😋, 😆, 😀, 😉, 😜, 😝, 😛, and 🧓). These emoji, which predominantly displayed positive sentiments in a context-free lexicon, exhibited a shift toward negative sentiments in a context-sensitive setting. The L2 distance values for these emoji between the two lexicons were markedly high.

This can be attributed to several intertwined factors deeply rooted in the intricacies of the Arabic linguistic and cultural landscape. First, the Arabic language is rich in its contextual depth, with a single word or symbol often carrying multifaceted meanings, heavily influenced by the surrounding text. For example, animals like (🐏) or (🐏), while generally perceived neutrally or positively in isolation, might carry symbolic or allegorical connotations in certain Arabic stories or idioms, leading to a shift in sentiment when placed in specific

textual contexts. Second, Arabic culture, with its vast historical and regional variations, imparts unique emotional resonances to certain symbols. Emoji denoting body language or facial expressions, which are universally understood, can take on nuanced undertones within Arabic cultural narratives. Lastly, human annotators themselves bring their subjective experiences and biases to the annotation process. When not guided by a specific context, they might lean towards more general or universally accepted interpretations of emoji. However, when presented with a textual context, their annotations could be influenced by cultural, regional, or personal interpretations, leading to the significant L2 distance values of emoji observed between the two lexicons. Consequently, to address the pronounced discrepancies between the two lexicons, we converged the probabilities of emoji sentiment in our static emoji lexicon, ensuring a reduction in biases stemming from contextual nuances.

In sum, answering our first research question, the comparison between context-free and context-sensitive emoji lexicons, as annotated by Arabic annotators, underscores the pivotal role that context and cultural nuances play in sentiment analysis. Emoji, often seen as a universal language, can still be subjected to diverse interpretations, particularly in a language as layered and culturally rich as Arabic. This variability in sentiment highlights the importance of always considering cultural and contextual factors when applying emoji-based sentiment analysis in diverse linguistic landscapes. The vast differences in L2 distance values between the two lexicons further emphasise this.

Finalise Static Emoji Sentiment Lexicon

Constructing our static emoji sentiment lexicon, the final sentiment scores for the emoji were established by calculating the average probability distribution ($P(c)$) for each shared emoji in three sentiment norms (c): negative, neutral and positive. Using the following equations, we ascertained the emoji sentiment score ($\overline{S}_{Static}$) for every emoji:

$$P(c)_{Control} = \frac{P(c)_{Sens} + P(c)_{Free}}{2},\ c \in \{neg,\ neut,\ pos\} \tag{6.8}$$

$$\overline{S}_{Static} = -P(neg)_{Control} + P(pos)_{Control} \tag{6.9}$$

The $P(c)$ and $\overline{S}$ of emoji that were found to be exclusive in each lexicon were kept as they are. This resulted in a sentiment lexicon for **1,291** emoji, each has its score and converted label using the emoji sentiment score-to-label scale illustrated in Figure 4.2). Table 6.6 displays a sample of this lexicon.

6.2 Word Sentiment Lexicon

In this section, we dive into the process of creating a word lexicon, a pivotal step towards building our lexicon-based sentiment classifier. For that, we will rely on two resources for words: Ar-SeLn lexicon and the words from our dataset. The details of the applied procedure are as follows.

6.2.1 Ar-SeLn Lexicon

Ar-SeLn lexicon [152] is a publicly available, large-scale Arabic word sentiment lexicon, where each word is annotated with positive and negative sentiment scores and a part-of-speech (POS) tag. The lexicon originally contains 154,396 words that are all in the modern standard Arabic (MSA) dialect and are translated in the Buckwalter Scheme [252]. **Buckwalter Scheme** is an ASCII-only transliteration scheme for Arabic text, which represents Arabic orthography in a one-to-one manner [ibid.]. This means that each Arabic letter is transliterated into a corresponding ASCII character, without additional information about its morphology or pronunciation. The scheme is widely used in the fields of NLP and computational linguistics, as it provides a standardised way of representing Arabic text in ASCII format. Table 6.7 shows an example of how an Arabic sentence is translated in the Buckwalter scheme. To translate the words in the Ar-SeLn Lexicon from Buckwalter back to Arabic words, we used

Table 6.6: Sample of the Static Emoji Sentiment Lexicon. $\overline{S}$ Denotes Scores and **L** Denotes Labels.

#	Emoji	Unicode Name	Arabic Name	Class	$\overline{S}$	L
1	😂	Face With Tears Of Joy	وجه بدموع الفرح	Facial Expression	0.478697	pos
2	💔	Broken Heart	قلب مجروح	Heart	-0.829321	neg
3	❤️	Red Heart	قلب احمر	Heart	0.805367	pos
4	😭	Loudly Crying Face	وجه يبكي بصوت عالي	Facial Expression	-0.506261	neg
5	😍	Smiling Face With Heart-Eyes	وجه مبتسم بعيون قلب	Facial Expression	0.926881	pos
6	🌹	Rose	ورده	Nature	0.858418	pos
7	🙂	Slightly Smiling Face	وجه بابتسامه خفيفه	Facial Expression	0.140301	pos
8	💕	Two Hearts	قلبين	Heart	0.757220	pos
9	😅	Grinning Face With Sweat	وجه مبتسم متعرق	Facial Expression	0.299051	pos
10	💙	Blue Heart	قلب ازرق	Heart	0.777326	pos
11	😔	Pensive Face	وجه متأمل	Facial Expression	-0.576740	neg
12	😄	Beaming Face With Smiling Eyes	وجه مشع بعيون مبتسمه	Facial Expression	0.637719	pos
13	💚	Green Heart	قلب اخضر	Heart	0.779226	pos
14	👍	Thumbs Up	ابهام متجه لاعلي	Body Language	0.531068	pos
15	👌	Ok Hand	حركه اليد لقول حسنا	Body Language	0.516408	pos
16	💛	Yellow Heart	قلب اصفر	Heart	0.600652	pos
17	😒	Unamused Face	وجه غير راضي	Facial Expression	-0.762829	neg
18	😢	Crying Face	وجه يبكي	Facial Expression	-0.724525	neg
19	💪	Flexed Biceps	عضلات	Body Language	0.547255	pos
20	🌸	Cherry Blossom	زهره الكرز	Nature	0.778497	pos
21	😩	Weary Face	وجه مرهق	Facial Expression	-0.668795	neg
22	💜	Purple Heart	قلب بنفسجي	Heart	0.755790	pos
23	😊	Smiling Face With Smiling Eyes	وجه مبتسم بعيون مبتسمه	Facial Expression	0.783578	pos
24	❤️	Heart Suit	قلب	Heart	0.828050	pos
25	😘	Face Blowing A Kiss	وجه يرسل قبله بقلب	Facial Expression	0.865652	pos
26	✋	Raised Hand	يد مرفوعه	Body Language	0.275707	pos
27	🤔	Thinking Face	وجه مفكر	Facial Expression	-0.331823	neg
28	🤣	Rolling On The Floor Laughing	يتدحرج على الارض من الضحك	Facial Expression	0.220475	pos
29	✨	Sparkles	بريق	Object	0.579603	pos
30	😡	Pouting Face	وجه يشتاط غضبا	Facial Expression	-0.859617	neg
31	😉	Winking Face	وجه يغمز	Facial Expression	0.225736	pos
32	😑	Expressionless Face	وجه بلا تعبير	Facial Expression	-0.600035	neg
33	😎	Smiling Face With Sunglasses	وجه مبتسم بنظارة شمسيه	Facial Expression	0.625175	pos
34	😀	Grinning Face	وجه ضاحك	Facial Expression	0.210205	pos
35	🙏	Folded Hands	ايدي متقابله	Body Language	0.654728	pos

the *Buckwalter-to-Arabic untransliteration* function (i.e., `buckwalter.untransliterate()`) from the (`lang-trans`)[6] Python library.

Table 6.7: Example of the Buckwalter Translation Scheme.

Arabic Text	English Translation	Buckwalter Translation
الطَّقْسُ الْيَوْمَ مُشْمِسٌ وَلَكِنْ هُنَاكَ نَسْمَةٌ بَارِدَةٌ فِي الْهَوَاءِ. هَلْ تُودُّ أَنْ نَذْهَبَ لِنَتْنَاوَلَ الْغَدَاءَ فِي الْحَدِيقَةِ؟	The weather today is sunny, but there is a cool breeze in the air. Would you like to go have lunch in the garden?	AlTãqosu Aloyawoma mu$omisN walakino hunaAka nasomapN baAridapN fiy Alo-hawaAí. halo tuwdũ ano naohaba linatonaAwla Alo-gadaAá fiy AloHadiyqapi?

For the sentiment scores, we found that a word in the Ar-SeLn lexicon might be redundant with the same POS tag. Therefore, we first calculated the frequency of occurrence of each word and then computed the mean of the positive and negative scores of that word. As instructed by Badaro, Baly, Hajj, et al. [152], the final sentiment score S for each word was calculated as follows:

$$\mathbf{S} = (Positive_Score) - (Negative_Score) \tag{6.10}$$

Consequently, we got 15,376 unique (i.e., nonredundant) words, each annotated with a sentiment score and a POS tag.

6.2.2 Words from Our Dataset

Tokenization and Tokens Disambiguation

The crucial step in creating a word sentiment lexicon is to apply tokenization and disambiguation of words. For this task, we used the CAMeL-Tools disambiguation models [106].

[6] A transliteration library in Python programming language, primarily designed for non-Latin scripts, including Arabic and Japanese. www.pypi.org/project/lang-trans/

CAMeL-Tools has two built-in disambiguators: a simple low-cost disambiguator based on a maximum likelihood estimation (MLE) model [253] and a neural network disambiguator that provides improved disambiguation accuracy using multitask learning. Both models take as input the different possible morphological analyses of a word and a set of contextual features and then predict the most likely analysis based on these features. The contextual features used in the models include the surrounding words, their part-of-speech (POS) tags, and the semantic context of the word. These disambiguator models have been trained on a large corpus of Arabic text with MSA and Egyptian dialects and have achieved high accuracy in disambiguating Arabic words in these dialects. Additionally, they have been evaluated on various datasets and have been shown to outperform other state-of-the-art disambiguation models [106]. Using our Emoji-Texts dataset, these disambiguators treat emoji as punctuation marks in part-of-speech (POS) tagging. Because we cleaned out all the punctuation marks from the texts in the reprocessing step, it was obvious that the only punctuation marks tagged by the disambiguators in the texts were emoji. An example of sentence disambiguation results is shown in Figure 6.5.

As a result, we got 406,372 unique words (with 283,557 nouns, 92,576 verbs, and 30,239 adjectives) out of 3,553,345 words, in total. The sentiment score of each word was then calculated using the approach that we applied to calculate the emoji sentiment lexicons (as described in Section 6.1.1). The scores were then converted to labels using the word sentiment scores-to-labels scale, which is described in **Appendix-B**. According to Equation B.1, words with sentiment score i, where $-1 \leq i < -0.25$, were classified as negative. Words with a sentiment score i, where $1 \geq i > 0.25$, were classified as positive. Lastly, words were classified as neutral when their sentiment scores i were in the range where $-0.25 \leq i \leq 0.25$. Additionally, using CAMeL-Tools, we identified the dialect of each word according to the dialect of the texts. This resulted in 45,541 MSA words and 360,831 words in other dialects.

```
140280
افتتاح السينما قريبا اخرتها يجيك طعس يكتب قدام الكرسي ذكريات ابو طو وحمودتشي فلم مسدسات وعبيد 👨 🔫
('إفْتِتاحُ', 'noun', 'opening;inauguration')
('السِينَما', 'noun', 'cinema')
('قَرِيباً', 'adj', 'recent;soon')
('آخِرَتُها', 'noun', 'hereafter')
('يجيك', 'noun_prop', 'NO_ANALYSIS')
('طعس', 'noun_prop', 'NO_ANALYSIS')
('يَكْتُب', 'verb', 'write')
('قُدّامَ', 'noun', 'front')
('الكُرْسِيّ', 'noun', 'chair;seat')
('ذِكْرَياتُ', 'noun', 'memoirs;diary')
('أَبُو', 'noun_prop', 'Abu')
('طو', 'noun_prop', 'NO_ANALYSIS')
('وَحمودتشي', 'noun_prop', 'NO_ANALYSIS')
('فِلْمُ', 'noun', 'film;movie')
('مُسَدَّساتِ', 'noun', 'revolver;pistol;six-shooter')
('وَعُبَيْد', 'noun_prop', 'Obeid;Obaid;Ubeid;Ubaid')
('👨', 'punc', '👨')
('🔫', 'punc', '🔫')
```

Figure 6.5: Sentence Disambiguation Example.

6.2.3 Final Word Sentiment Lexicon

We augmented the resultant words in the Ar-SeLn lexicon with the extra set of words extracted from our dataset that was not in the Ar-SeLn lexicon. The concluded Arabic words lexicon contains 421,748 unique words with 290,957 nouns, 94,952 verbs, and 35,839 adjectives, annotated with sentiment scores, POS tags, and if they are dialectic or MSA, besides their semantics. Table 6.8 shows a sample of the resultant word lexicon.

6.3 Lexicon-Based Sentiment Classifier

Any lexicon-based approach involves calculating the sentiment polarity of a text from positively, neutrally, and negatively weighted tokens within the text. These tokens, in our case, are words and emoji. Thus, we employed two Arabic-language-based sentiment lexicons: one for words and one for emoji. For emoji, we used our static emoji lexicon described in Section 6.1.3. For words, we used the finalised word lexicon described in Section 6.2.3.

Table 6.8: Sample of the Words Sentiment Lexicon.

Word Source	Word	POS	Semantical Meaning	Sent. Score	Sent. Label	Dialect
ArSenL Lexicon	فَرِحَ	verb	rejoice; be_glad	0.500	positive	MSA
ArSenL Lexicon	أَرْبَك	verb	entangle	-0.125	neutral	MSA
ArSenL Lexicon	عُذُوبَة	noun	sweetness; pleasantness	0.375	positive	MSA
ArSenL Lexicon	أَزْمَة	noun	crisis	-0.391	negative	MSA
ArSenL Lexicon	أَثِير	adjective	favored; favourite	0.250	positive	MSA
ArSenL LexiconL	أَرْدَأ	adjective	worse; worst	-0.500	negative	MSA
Our-Data-MSA	رَحِمَهُ	verb	have_mercy_with	0.260	positive	MSA
Our-Data-MSA	يُؤْذِي	verb	injure; prejudice	-0.250	negative	MSA
Our-Data-MSA	نِعْمَة	noun	blessing	0.514	positive	MSA
Our-Data-MSA	فَيْرُوس	noun	virus	-0.667	negative	MSA
Our-Data-MSA	مُذْهِلٌ	adjective	amazing; startling	0.769	positive	MSA
Our-Data-MSA	مُحْزِنٌ	adjective	grievous; tragic	-0.500	negative	MSA
Our-Data-Dialectal	تَجْنُن	verb	go_crazy; become_insane	0.256	positive	Dialectal
Our-Data-Dialectal	فَشَّ	verb	cause_to_subside	-0.281	negative	Dialectal
Our-Data-Dialectal	لِعِيالكُم	noun	dependents	-0.333	negative	Dialectal
Our-Data-Dialectal	بِبلاش	noun	gratis	-0.379	negative	Dialectal
Our-Data-Dialectal	وَفَرْحانَيْنِ	adjective	cheerful; delighted	0.260	positive	Dialectal
Our-Data-Dialectal	مَنْفُوخَة	adjective	inflated; swollen; full_of_air; conceited	-0.571	negative	Dialectal

Sentence Sentiment Scoring and Labelling

To calculate the sentiment score of a sentence, we first tokenise it into tokens that comprise both words and emoji. These tokens were then disambiguated using the CAMeL-Tools disambiguator [106]. This disambiguation process involves determining the part-of-speech (POS) and the semantic meaning of each token, as illustrated in Figure 6.6. Moreover, the dialect identification of the tokens is determined based on the originating sentence's dialect. Subsequently, we looked up sentiment labels and scores for these tokens in their respective lexicons, categorising them into three sentiment groups: negative, neutral, and positive. If a token was a word, its sentiment score was taken from the word lexicon, taking into account its dialect, POS and meaning. The score was then assigned to one of the predefined lists: negative, neutral, or positive tokens. A similar approach was used for emoji tokens using the

Static emoji sentiment lexicon. Subsequently, we calculated the sentiment score, denoted as $\overline{S}_{Sentence}$, using Equation 6.11:

$$\overline{S}_{Sentence} = log(\sum Tokens_{(pos)} + 0.5) - log(\sum Tokens_{(neg)} + 0.5). \tag{6.11}$$

The formula calculates the logarithm of the sum of positive tokens (i.e., both words and emoji that have a positive sentiment) (i.e., $Tokens_{(pos)}$) and adds 0.5 to it. This value is then subtracted from the logarithm of the sum of negative tokens (i.e., both words and emoji that have a negative sentiment) (i.e., $Tokens_{(neg)}$) plus 0.5. The addition of **0.5** to both sums is a smoothing factor that helps to avoid divide-by-zero errors when there are no positive or negative tokens in the text. Taking the logarithm of the sums is a common technique for handling large or small values in text analysis, as it compresses the range of possible values and makes them more manageable. In addition, this formula tends to have the smoothest properties and is symmetric around zero [254]. The resulting sentiment score $\overline{S}_{Sentence}$ ranges from positive infinity ($+\infty$) to negative infinity ($-\infty$). Its values will be close to $+\infty$ if there are more positive tokens than negative tokens in the text and close to $-\infty$ if there are more negative tokens than positive tokens. Also, the values will be close to zero if there are roughly equal numbers of positive and negative tokens or if there are only neutral tokens in the text.

Finlay, the resulting scores were scaled to sentiment labels using the sentence's scores-to-labels scale, formulated in Equation C.1 in **Appendix-C**, as follows. Sentences with sentiment score i, where $-\infty \leq i <$ -0.5, were classified as negative. Sentences with sentiment score i, where $\infty \geq i >$ 0.5, were classified as positive. Lastly, sentences were classified as neutral when their sentiment scores i were in the range where -0.5 $\leq i \leq$ 0.5. The summary of this procedure is shown in Figure 6.6. Evaluation of this labelling mechanism will be discussed in detail in Chapter 8. Examples of the annotation of the Emoji-Texts from the gold standard datasets are presented in Figure 6.7.

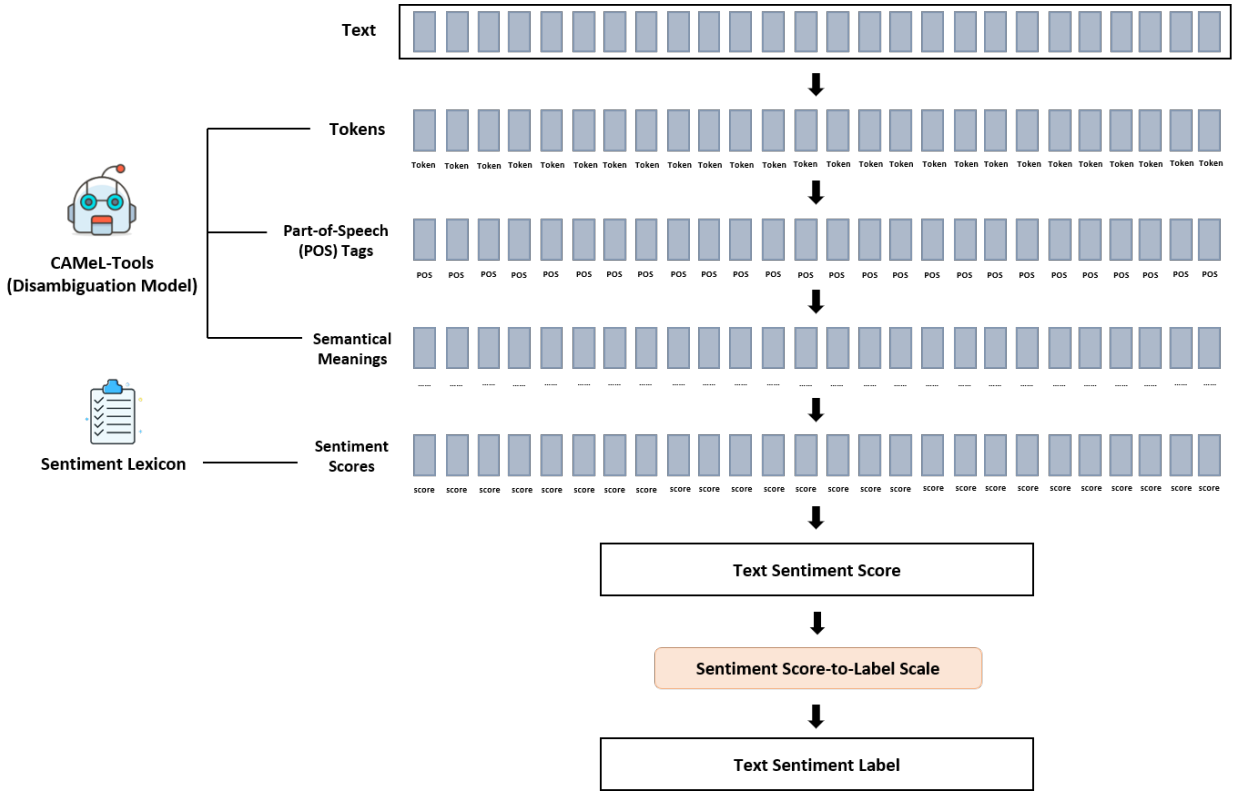


Figure 6.6: Sentence Sentiment Scoring and Labelling Approach.

Emoji Patterns Sentiment Scoring and Labelling

Emoji in texts can surpass singular formats and give rise to various patterns. We define an emoji pattern in a text as any grouping of emoji, regardless of their quantity, position, order, and sequence with words. For simplicity, we also regard a single emoji in a text as an emoji pattern. Such a pattern of emoji can be shown sequentially in a row, as in:

أنا جداً محبط لعدم حصولي على الترقية 😒🤭😩🙃 لقد بذلت لأجلها مجهوداً كبيراً.

I'm so disappointed that I didn't get the promotion 😒🤭😩🙃*I've been working so hard for it*

or separately between the words, as in:

أنا جداً محبط 😒 لم أحصل على الترقية 🤭 لقد بذلت لأجلها مجهوداً كبيراً 😩🙃 .

Example #	Emoji_Texts	True Label	Conventional Emoji Lexicon-Based			
			T_Score	T_Label	E_Score	E_Label
1	غرد بحبك لمحمد بن سلمان هو الحب كله 💚💚💚💚🇸🇦🇸🇦🇸🇦 Eexpressing love for Mohammed bin Salman, he is the whole love 💚💚💚💚🇸🇦🇸🇦🇸🇦	positive	1.66562	positive	1	positive
2	تحيه للمدرس المحترم 👇 👇 منتدي شباب العالم A salute to this respected teacher 👇 👇 from the World Youth Forum	positive	1.10265	positive	0	neutral
3	ابوي صاير حنين والله 💜 😢 صار يحضن يقلبوش 😢 My father has become tender, I swear to God 😢 💜. He has become so affectionate 😢	positive	0.157617	positive	-0.43958	negative
4	يعني شو بتتوقعو من واحد يومه حيخلص عال 😍 😍 😍 What do you expect from someone whose day will end on a high note? 😍 😍 😍	positive	1.188831	positive	1	positive
5	💪 ❤ ❤ ❤ ❤ ❤ ❤ WYF منتدي شباب العالم The World Youth Forum 💪 ❤️ ❤️ ❤️ ❤️ ❤️ ❤️ WYF	positive	1.515603	positive	1	positive
6	عمري في حياتي ماكلته ولا فكرت في الموضوع حتي بدافع الفضول مش فاهم ليه 😄 I've never eaten it in my life and never even thought about it out of curiosity. I don't understand why 😄	neutral	0.256646	positive	0.820731	positive
7	خليك محمد صلاح اتفرج علي الفيديو علي اليوتيوب من هنا 👇 Watch Mohamed Salah's video on YouTube from here 👇	neutral	0	neutral	0	neutral
8	لولا وقوف روسيا مع سوريا لكان الربيع دمر الوطن العربي من المحيط الي الخليج 😡 الف شكر لروسيا وصمود سوريا 👌 Had Russia not stood with Syria, the Arab homeland from the ocean to the Gulf would have been destroyed 😡. A thousand thanks to Russia and Syria's resilience 👌	neutral	0.586094	positive	-0.29093	negative
9	ابغي كوكيز 😔 I want cookies 😔	negative	-0.985997	negative	-0.986	negative
10	والله انت باهي اقسم بالله 😡 You are good. I swear by God, you are 😡	negative	-1.00035	negative	-1	negative
11	لا اريد التعلق باحد ثم يرحل 💔 🌿 🌸 فوجع الرحيل اشبه باستئصال عضو من دون مخدر 🌸 صباحكم جستن بيبر I don't want to get attached to someone and then they leave 🌸 🌿 💔. The pain of departure is like removing an organ without anesthesia 🌸. Your morning is like Justin Bieber	negative	-0.245287	negative	0.714049	positive
12	كلشي عفت لخاطرهِ وماجرحته بيوم 🧬 I gave up everything for his sake and never hurt him once 🧬	negative	-0.087969	negative	0	neutral
13	فيني برود ولا كانه عندي بكرهِ امتحان 👨‍⚕️ يا رب يعدي اليوم خير 😪 😳 I feel so chill as if I don't have an exam tomorrow 👨‍⚕️. Oh God, I hope this day goes well 😳 😪	negative	-0.681128	negative	-1	negative

Figure 6.7: Examples of the Conventional Emoji-Lexicon-Based Sentiment Classification. T_Score and T_label Denote the Sentiment Scores and Labels for Texts. E_Score and E_Label Denote the Sentiment Scores and Labels for Emoji patterns.

I'm so disappointed 😒 *I didn't get the promotion* 🤭 *I've been working so hard for it* 😩🙃.

Our observations have revealed that the emoji patterns have cumulative significance for the

overall sentiment of the text. Consequently, they are treated as a cohesive entity when labelling sentiment. To accurately assign a sentiment label to an emoji pattern within the context of the entire text, an additional step in our model becomes necessary. This step plays a crucial role in accurately categorising the sentiment impact of the emoji pattern based on its sentiment state within the text which will be explained later. The sentiment scores for each of these patterns were calculated using Equation 6.11, where $Tokens_{(pos)}$ indicates positive emoji and $Tokens_{(neg)}$ indicates negative emoji within a singular pattern. To assign the total sentiment scores of emoji within each pattern to a single label, we rescaled the scores to fit within the range [-1, 1]. We accomplished this using the `MinMaxScaler(feature_range=(-1, 1))` function from the Flair[7] Python library, which scales the scores to the desired range. We then used the emoji sentiment scale shown in Figure 4.2 to convert the rescaled scores into their corresponding sentiment labels. Examples of patterns with their sentiment scores and labels are provided in Table 6.9.

Table 6.9: Examples of Sentiment Scores and Labels for Emoji Patterns.

Emoji Pattern	Emoji Count	Emoji Load	Pattern Score	Pattern Label
[😃, 😀, 💏, 👏, 💏, 👏]	{'😃': 1, '😀': 1, '💏': 2, '👏': 2}	6	0.404585	positive
[👌, 💚, 🌿]	{'👌': 1, '💚': 1, '🌿': 1}	3	0.290282	positive
[😂, 😂, 😂, 😂, 😂]	{'😂': 5}	5	0.130429	positive
[😍, 😍, ▶, ▶, 💚]	{'😍': 2, '▶': 2, '💚': 1}	5	0.346373	positive
[🍃, 💕, 💕]	{'🍃': 1, '💕': 2}	3	0.284296	positive
[👇, 👇, 👇, 👇]	{'👇': 4}	4	-0.034827	neutral
[😎, 👉, 😩]	{'😎': 1, '👉': 1, '😩': 1}	3	-0.035139	neutral
[🖐, 👉, 👎, 👌]	{'🖐': 1, '👉': 1, '👎': 1, '👌': 1}	4	-0.037922	neutral
[🔴, ⚪, ⚫]	{'🔴': 1, '⚪': 1, '⚫': 1}	3	-0.047614	neutral
[🥒, 🥒, 🥒, 🥒]	{'🥒': 4}	4	-0.034827	neutral
[🙂, 🔪, 💔, 💔, 💔, 💔]	{'🙂': 1, '🔪': 1, '💔': 4}	6	-0.466283	negative
[😭, 😂, 😪, 🤐, 😒, 😓]	{'😭': 1, '😂': 1, '😪': 1, '🤐': 1, '😒': 1, '😓': 1}	6	-0.417135	negative
[😡, 😡, 😡]	{'😡': 3}	3	-0.420539	negative
[🌹, 💔, 🥀, 😔]	{'🌹': 1, '💔': 1, '🥀': 1, '😔': 1}	4	-0.142641	negative
[🤥, 🤥, 😉]	{'🤥': 2, '😉': 1}	3	-0.174148	negative

[7] https://pypi.org/project/flair/

6.4 Chapter Conclusion

In this chapter, we explored the creation of sentiment lexicons tailored for the Arabic language and its dialects. We developed two emoji sentiment lexicons: one based on context and the other based on individual interpretations from 53 participants. By comparing these, we addressed our first key research question, "RQ1" and introduced the "*Static*" emoji lexicon with fixed sentiment scores for each emoji. We also developed a sentiment lexicon for Arabic dialects. These tools paved the way for developing our lexicon-based sentiment classifier. In the upcoming chapter, we will proceed to answer the second research question: "**RQ2: What are the potential emoji roles in altering the sentiment of Arabic written messages?**".

Chapter 7

Emoji-Roles Sentiment Analysis Model

In this chapter, we are getting to the core of our thesis. We have gathered all the necessary tools for our sentiment analysis model: a dataset with annotations, lexicons of emoji and words, and a sentiment classifier based on these lexicons. With such resources, we are now ready to figure out how emoji affect sentiment in Arabic texts. We are also going to build a more detailed emoji sentiment lexicon, showing the probability that each emoji plays thirteen different sentiment roles. Understanding these emoji roles and their probabilities allows us to refine the conventional emoji-based sentiment classification of Arabic texts. In this chapter, we will tackle our second research question: "**RQ2: What are the potential roles of emoji in altering the sentiment of Arabic written messages?**".

7.1 Identifying Emoji Sentiment States and Roles

Our main focus is to determine the emoji sentiment roles in a detailed, quantifiable, and feasible mechanism. To specify the sentiment roles of emoji within the textual content, it is crucial to explore their typical behaviours in the context of emoji-sentiment co-existence. As a starting point, we examine potential sentiment states that may arise when comparing texts with and without emoji. For this purpose, we utilised the silver sentiment annotations from the Emoji-Texts dataset for texts containing emoji and referred to the silver sentiment annotations of the Plain-Texts dataset for emoji-free texts. Recognising these intermediary sentiment states, combined with the sentiment of the included emoji, allows us to pinpoint the various potential roles that an emoji might play within a text. The details of identifying these emoji sentiment states and roles are as follows.

7.1.1 Emoji Sentiment States

In our model, comparing the sentiment of a text with and without emoji leads to nine states within the negative, neutral and positive norms, as follows. Figure 7.1 summarises them all. The details of each state are described below.

1. **Keep Negativity:** is when the inclusion of an emoji does not change the negative sentiment that is already present in the text. The negative sentiment of the text remains unchanged, even if the emoji pattern used is positive or neutral in nature. This can happen when the text contains strong negative language or negative connotations that override the impact of the emoji. Consider the following example:

أنا جداً محبط لعدم حصولي على الترقية 😩 لقد بذلت لأجلها مجهوداً كبيراً

I'm so disappointed that I didn't get the promotion 😩

I've been working so hard for it

Example (1)

In this example, the negative sentiment of disappointment is already present in the

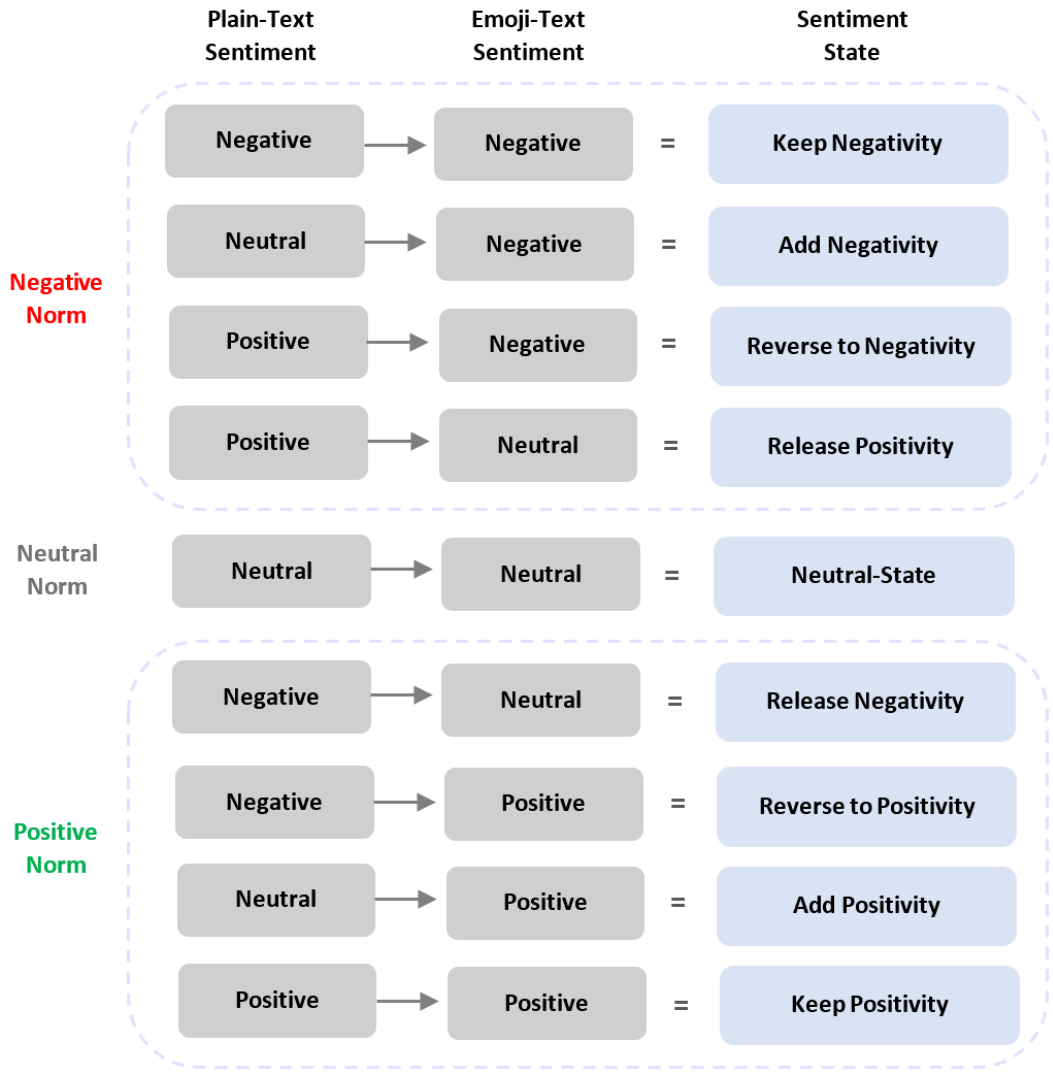


Figure 7.1: Summary of the Emoji Sentiment States Based on the Comparison of Plain-Texts and Emoji-Texts.

text without the emoji, and the addition of a negative emoji (i.e., *Weary Face* 😩) does not change the overall negative sentiment of the text. The negative language and tone of the text still convey disappointment and frustration, regardless of the presence of the emoji.

2. **Add Negativity:** is when the inclusion of an emoji changes a neutral to a negative sentiment. This can occur when the text contains a mixture of positive and negative

sentiments or when the tone of the words is objective. The emoji pattern acts as an emotional cue that influences the overall sentiment of the text, adding a negative tone. The following text is an example:

حُدِّد الاجتماع ليكون في الساعة الثانية ظهراً 😒 Example (2)

The meeting is scheduled for 2 PM 😒

Here, the text without an emoji is neutral and conveys only objective information about the meeting time. However, with the addition of a negative emoji (i.e., *Unamused Face* 😒), the text takes on a negative tone, indicating that the sender/writer is unhappy or dissatisfied with the meeting time. The negative emoji changes the overall sentiment of the text from neutral to negative.

3. **Reverse to Negativity:** is when the inclusion of an emoji changes a positive sentiment into a negative one. This can occur when the text without an emoji conveys a positive sentiment, but the addition of a negative emoji changes the overall sentiment of the text. Here is an example of a positive text that becomes negative with the inclusion of an emoji:

حصلت على العلامة الكاملة في الاختبار 😒 Example (3)

I got an A on my exam 😒

In this example, the text without an emoji conveys a positive sentiment, since the sender/writer is expressing happiness in getting an "*A*" on an exam. However, with the addition of a negative emoji (i.e., *Unamused Face* 😒), the text takes on a negative tone, indicating that the sender/writer may not actually be as happy as initially appeared. The negative emoji changes the overall sentiment of the text from positive to negative.

4. **Release Positivity:** is when the inclusion of an emoji changes a positive sentiment to a neutral one. This sentiment state indicates negativity in a more indirect and subtle way. The act of releasing positivity can be perceived as negative because it reduces

the level of the positive tone expressed by the words, making the overall sentiment less expressive. An example of this is as follows:

إنها إجازة نهاية الأسبوع يا شباب! 🧐 Example (4)

Here is the weekend guys! 🧐

In this example, the text without an emoji conveys a positive sentiment, since the sender is expressing excitement about the weekend. However, with the addition of a neutral emoji (i.e., *Face with Monocle* 🧐), the positivity of the text becomes less expressive and takes on a more neutral tone. The act of releasing positivity to neutral by adding a neutral or negative emoji pattern may be perceived as a negative action as it signals that the sender/writer is less confident or less committed to the positive sentiment. In this way, the "*Release Positivity*" state can be seen as an expression of negativity, even though the general sentiment has not changed to negative.

5. **Neutral-State:** is when the sentiment of the text remains neutral, regardless of the inclusion of an emoji. This can occur when the text without an emoji is already neutral (i.e., the sentiment of the words is mixed in with sentiments or is objective). The addition of an emoji may make the text more expressive, but it does not affect the overall sentiment of the text. For example:

الساعة الآن السادسة تماماً 🕕 Example (5)

It is 6 o'clock. 🕕

In this example, the text without an emoji is neutral and objective, since it states the time. The addition of a wall clock emoji (i.e., 🕕) serves as a figurative illustration of what is being written rather than a sentiment-indicating feature. Thus, the text remains neutral even with the inclusion of the emoji.

6. **Release Negativity:** is when the inclusion of an emoji changes a negative text sentiment to a neutral one, and the act of releasing negativity represents positivity. The indication of a positive sentiment can be felt when reading the text, as follows:

لقد فاتني الدرس 🙃 Example (6)

I missed the class 🙃

Here, the original sentiment of the text without the emoji is negative, as the sender is expressing disappointment about missing a class. However, with the addition of the *Upside Down Face* emoji (i.e., 🙃), the text's negativity becomes less expressive and takes on a more neutral tone. The act of releasing negativity by adding a neutral or a positive emoji can be perceived as a positive action, as it signals that the sender/writer is trying to find a light-hearted way to deal with the situation and is not dwelling on the negative outcome. In this way, the "*Release Negativity*" state can be seen as an expression of positivity, even though the overall sentiment has changed to neutral.

7. **Reverse to Positivity:** is when the insertion of an emoji transforms a negative sentiment into a positive one. This can occur when a text message, without an emoji, expresses a negative sentiment, but the addition of a positive emoji alters the overall sentiment of the text, creating a more optimistic tone. For example:

لم أحصل على الوظيفة التي أردت 😁 Example (7)

I did not get the job I wanted 😁

The original sentiment of "I did not get the job I wanted" is negative, but the addition of *Beaming Face With Smiling Eyes* emoji (i.e., 😁) changes the overall sentiment to a positive one, indicating that the sender/writer is trying to maintain a positive attitude and is finding a way to look at the bright side of the situation, despite the disappointment of not getting the job they wanted.

8. **Add Positivity:** is a situation in which the inclusion of an emoji arouses a positive sentiment within a text. This can occur in neutral texts where the tone of the words is either a mixture of negativity and positivity or is objective. The addition of a positive emoji can then shift the overall sentiment of the text toward a more positive one. For example:

لقد شربت قهوتي هذا الصباح 🤭 Example (8)

I had my coffee this morning 🤭

The original sentiment of "I had my coffee this morning" is neutral, but the addition of *Smiling Face with Smiling Eyes and Hand Covering Mouth* emoji (i.e., 🤭) changes the overall sentiment to positive, indicating that the sender/writer is happy or satisfied with having their coffee in the morning. This emoji adds positivity to the otherwise neutral statement.

9. **Keep Positivity:** is the situation where the addition of an emoji does not alter the already present positive sentiment in the text. The positive sentiment of the text remains unchanged, even if the emoji used has a negative or neutral sentiment. This can occur when the text contains strong positive language or positive connotations that overpower the influence of the emoji. For example:

كان يوماً رائعاً اليوم! 🌞 Example (9)

Today was a fantastic day! 🌞

In this example, the text "Today was a fantastic day!" conveys a positive sentiment on its own. The addition of *Sun with Face* emoji 🌞 does not change this positive sentiment but reinforces it instead.

7.1.2 Emoji Sentiment Roles

As previously shown, the sentiment impact of adding an emoji pattern to plain texts has been categorized into nine sentiment states. However, the sentiment of the emoji patterns within each state can be further classified into one of three sentiment norms: negative, neutral, and positive. Consequently, these emoji patterns can play a total of thirteen different sentiment roles, illustrated in Figure 7.2, as listed below:

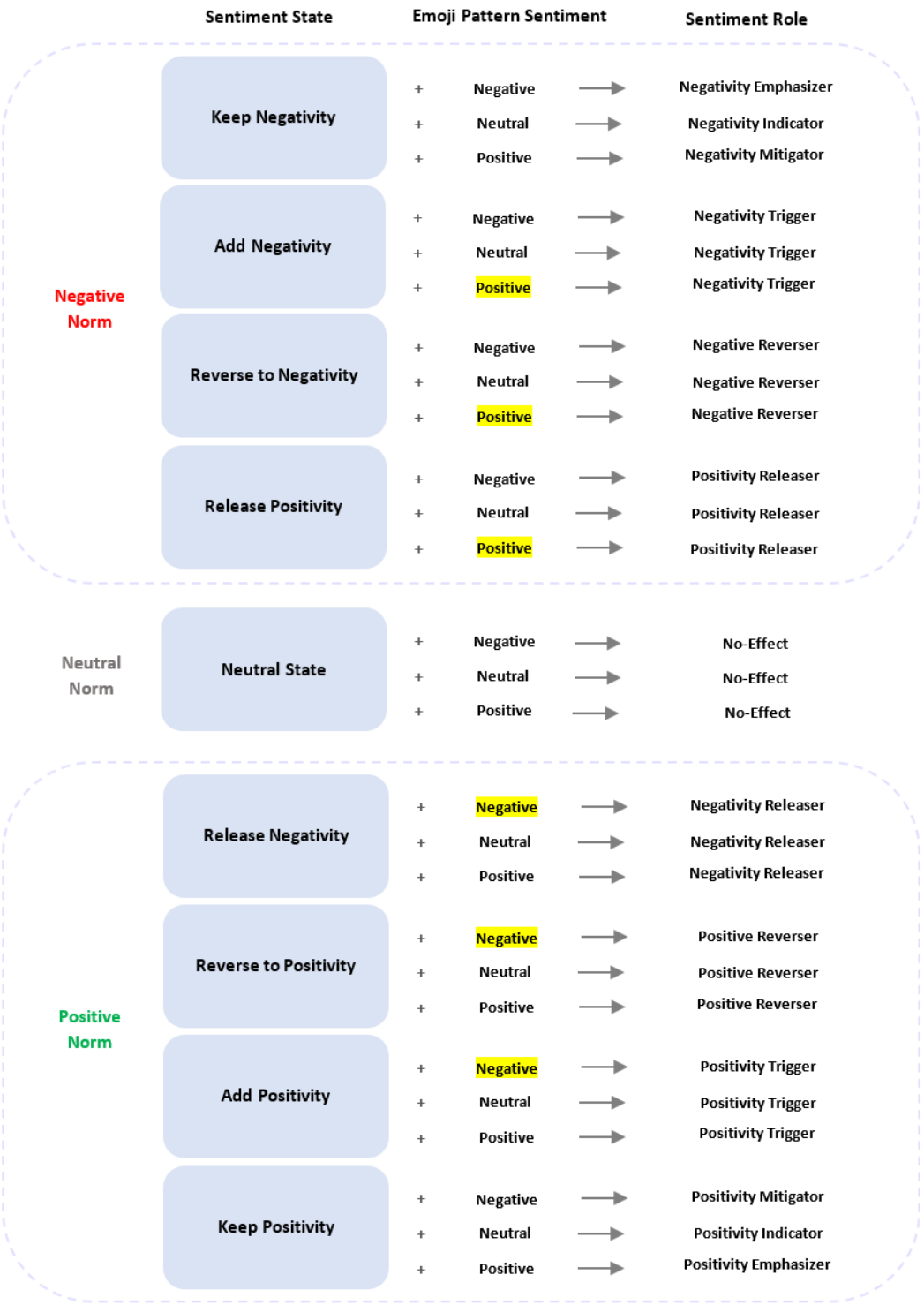


Figure 7.2: Summary of the Emoji Sentiment Roles. The highlighted Cases in Yellow Denote the Unusual Cases.

1. **Negativity Emphasizer:** This occurs when the overall sentiment state of a text with emoji is *Keep Negativity* and the sentiment of the emoji pattern within the text is also negative. For example:

   لا أصدق أنني رسبت في الامتحان 💔 Example (10)

   I can't believe I failed the exam 💔

   The text "I can't believe I failed the exam" expresses disappointment or frustration, and the *Broken Heart* (i.e., 💔) emoji reinforces the negativity of the text, indicating that the speaker is unhappy or displeased with the situation. In other words, the use of such a negative emoji pattern in a negative context serves to **emphasize** the negativity of the text and further communicate the negativity the writer/sender is feeling.

2. **Negativity Indicator:** is when the sentiment state of a text with emoji is *Keep Negativity* and the sentiment of the emoji pattern that occurs within the text is neutral. This is because the neutrality of the emoji can be changed based on the context in which it is used. In a negative context, a neutral emoji can have a negative connotation and indicate negativity. The choice of emoji used can greatly impact the overall tone and sentiment conveyed in a text, and the use of a neutral emoji in a negative context can serve as a pointer to the negativity expressed in the text. For example:

   لا أصدق أنني رسبت في الامتحان 🙏😭 Example (11)

   I can't believe I failed the exam 😭🙏.

   In this example, the pattern of using both a negative emoji (i.e., *Loudly Crying Face* 😭) and a positive emoji (i.e., *Person with Folded Hands* 🙏) could be considered neutral, as it represents a mix of emotions. In this context, the negative sentiment expressed in the text is reinforced by the use of the *Loudly Crying Face* emoji, but the positive sentiment expressed by the *Person with Folded Hands* emoji helps to balance out the tone of the negative emoji. However, this does not affect the overall negative tone of

the text. In such a case, the emoji pattern is considered an indicator of the negative sentiment expressed in the text.

3. **Negativity Mitigator:** is when the sentiment state of a text with emoji is *Keep Negativity* and the sentiment of the emoji pattern within that text is positive. The positive emoji would serve to mitigate the negativity of the text, indicating that the writers/senders may still have negative feelings, but they are trying to express them in either an optimistic way or a sarcastic way.

   لقد رسبت في الامتحان 👏 Example (12)

   I failed the exam 👏

   In this case, the text "I failed the exam" conveys disappointment or frustration. However, the *Clapping Hands* emoji (i.e., 👏), which is usually employed to express applause or encouragement, is used sarcastically. This maintains the overall negative sentiment of the text.

4. **Negativity Trigger:** is when the sentiment state of a text with emoji is *Add Negativity* and the sentiment of the emoji pattern within that text is either negative, neutral, or positive. This sounds normal when the sentiment of the emoji pattern is neutral (i.e., mixed in sentiments) or negative. For example:

   😤 اليوم هو يوم الاثنين Example (13)

   Today is Monday 😤

   In this example, the text itself is neutral, simply stating a fact ("Today is Monday"). However, the use of *Face with Steam From Nose* emoji (i.e., 😤), which is often used to represent frustration or anger, gives the text a negative connotation. The negative sentiment conveyed by the emoji serves to trigger a negative sentiment in the reader/receiver, indicating that the writer/sender is unhappy or frustrated about the fact that it is Monday. On the other hand, a writer/sender might use a positive pattern

of emoji with neutral text in a sarcastic manner, giving the text a negative connotation. For example:

بينما أنت مسترخية، أنا متعبة وعلي الانتهاء من كتابة واجبي المنزلي 🎉🎉 Example (14)

While you are relaxing, I am tired and have to do my homework 🎉🎉

In this case, the text could be considered neutral with mixed emotions, as it expresses both frustration or disappointment ("I am tired and have to do my homework") and a hint of sarcasm or irony ("While relaxing"). The use of *Party Popper* (i.e., 🎉) emoji, which is often used to represent celebration or excitement, serves to reinforce the negativity of the text sarcastically. In similar cases, our model considers positive emoji patterns as triggers for negativeness in the text and annotates the overall sentiment as negative.

5. **Negative Reverser:** This occurs when the overall sentiment state of the text, combined with the emoji, is *Reverse to Negativity* and the sentiment of the emoji pattern within the text can be negative, neutral or positive. Using neutral or negative emoji patterns in this context is common, as demonstrated in Example (15).

أخيراً حصلت على إجازة من العمل 💩 Example (15)

Finally, I got a day off work 💩

The text in this example expresses a positive sentiment ("Finally, I got a day off work!"), but the use of *Pile of Poop* emoji (i.e., 💩), which is often used to represent negative or unpleasant things, serves to change the sentiment of the text to a negative one. The negative sentiment conveyed by the emoji serves to trigger a negative sentiment in the reader/receiver, indicating that the writer/sender is unhappy or frustrated about the situation, even though the text itself expresses a positive sentiment.

However, with positive emoji patterns, as in:

ما شاء الله! يالذكائك 🙂 Example (16)

Oh! How smart you are 🙂

The use of *Slightly Smiling Face* emoji (i.e., 🙂) serves to reverse the sentiment of the text to a negative one in a sarcastic manner. The text expresses a positive sentiment ("Oh! How smart you are"), but the use of this emoji, which is often used to represent a neutral or polite sentiment, serves to indicate that the writer/sender does not actually mean what they are saying. The positive sentiment conveyed by the text is undermined by the positive sentiment conveyed by the emoji, indicating that the writer/sender is being sarcastic or making fun of the situation. The emoji in this context serves to emphasise the negativity of the (writer/sender)'s mood.

6. **Positivity Releaser:** This occurs when the combination of the general sentiment of a text with emoji results in a *Release Positivity* state, even though the sentiment of the emoji pattern within the text may be negative, neutral, or positive. The use of seemingly neutral or negative emoji patterns in this scenario is not uncommon, as evidenced by the following example.

لقد ربحت اليانصيب 😒😒 Example (17)

I just won the lottery 😒😒

In this example, the positive sentiment expressed by the text "I just won the lottery!" is changed to a neutral sentiment by using the *Unamused Face* emoji (i.e., 😒) emoji. The negative sentiment conveyed by the emoji effectively undermines the positive sentiment expressed by the text, resulting in a neutral overall sentiment for the text. Positive emoji patterns, likewise, can serve to release positivity in a text in certain contexts, as demonstrated in the following sentence:

حصلت على ترقية في العمل 😒🌹🌹🌹🌹 Example (18)

I got a promotion at work 🌹🌹🌹🌹😒

The text expresses a positive sentiment ("I got a promotion at work"). However, the use of the *Rose* emoji (i.e., 🌹) with the *Unamused Face* emoji (i.e., 😒) serves to change the sentiment of the text to a neutral one. The positive sentiment conveyed by the text is undermined by the sentiment conveyed by the emoji pattern, indicating that the writer/sender is not fully committed to their positive statement or that they are trying to play down their excitement. The use of this combination of emoji in this context serves to emphasise the neutral tone of the (writer/sender)'s state of mind.

7. **Neutral-Effect:** This occurs when the combination of a text with emoji results in a *Neutral-Effect* sentiment state, regardless of whether the sentiment of the emoji pattern within that text is negative, neutral, or positive. Neutral emoji, when they occur in neutral texts, are auxiliary visual characters for the words in the texts. For example:

👇 انظر إلى هذه الصورة 👇 Example (19)

Look at this picture

The use of *Backhand Index Finger Pointing Down* emoji (i.e., 👇) serves as a visual aid to direct the (reader/receiver)'s attention to the picture mentioned in the text. The overall sentiment of the text and the emoji are neutral and the emoji does not change the sentiment of the text. An example of a negative emoji pattern is as follows:

🔴 هذا ما قالته الصحف عن كوفيد ١٩ Example (20)

Here is what the news says about Covid-19 🔴

The neutral sentiment expressed by the text "Here is what the news says about Covid-19" remains unchanged by the use of the negative *Large Red Circle* emoji (i.e., 🔴). The warning symbol represented by the negative emoji does not shift the neutral stance of the text, but instead emphasises the caution associated with the information being conveyed. This emoji serves to capture the (reader/recipient)'s attention to the text. Another example with a positive emoji pattern is:

اكتشف الطريقة لتنظيم وقتك ✅ Example (21)

Discover the way to manage your time ✅

In this example, the neutral sentiment expressed by the text "Discover the way to manage your time" remains unchanged by using the *White Heavy Check Mark* emoji (i.e., ✅). The positive impact of the emoji does not alter the neutral sentiment of the text, but instead serves to visually clarify the information being stated.

8. **Negativity Releaser:** This occurs when the combination of a text with emoji results *Release Negativity* sentiment state, regardless of the negativity, neutrality or positivity of the emoji pattern. Positive and neutral emoji patterns can be seen as negative releasers, as shown in Example (**??**) previously. The negative emoji pattern, likewise, can play the same role in texts such as:

لا أصدق بأني علي الذهاب للطبيب مرة أخرى 😂😁😁 Example (22)

I can't believe I have to go to the doctor again 😁😁😂

The negative emoji pattern of the *Face with Medical Mask* (i.e., 😷) and *Face with Tears of Joy* (i.e., 😂) emoji released the negativeness of the text and made it neutral. Such a mixed-sentiment emoji pattern can balance the overall sentiment of the text and result in a neutral sentiment. However, the exact impact of the emoji pattern on the sentiment of the text would depend on the specific context, the choice of emoji and the content of the text.

9. **Positive Reverser:** This occurs when the overall sentiment state of a text with emoji is *Reverse to Positivity* and the sentiment of the emoji pattern within the text is either negative, neutral or positive. Using neutral or positive emoji patterns in this context is common, as demonstrated in Example **??**, previously. Negative emoji like *Black Heart* (i.e., 🖤), as it is negatively annotated in our lexicon, can be used in a context that makes it act positively, as in this sentence:

أنا لست سعيداً، أريد جهاز آيفون 🖤 Example (23)

I am not happy, I need an iPhone 🖤

In this example, the general sentiment of the text is only negative ("Not Happy, need an iPhone") but the use of the black heart emoji adds positivity to the text, regardless of its negative black colour (i.e., as it is seen by Arabic users). This reverses the negativity in the text and makes the overall sentiment of it positive. It is worth mentioning that such a text might have a sense of humour that can be detected by employing such emoji-role sentiment analysis.

10. **Positivity Trigger:** This refers to a situation where the general sentiment state of a text, when combined with an emoji, is *Add Positivity*. In other words, this emoji role occurs when the presence of an emoji pattern, regardless of its sentiment, induces positivity to a neutral text. This can be intuitive with neutral and positive emoji patterns, as shown in Example **??**. Negative emoji patterns can also play this role as in the following sentence:

إنها ووهان 🤦😂 Example (24)

It is Wuhan 🤦😂

In this example, our model perceives the use of the negative emoji pattern of the *Person Facepalming* emoji (i.e., 🤦) alongside the *Face with Tears of Joy* emoji (i.e., 😂) within a neutral text as a humorous indicator, adding a layer of positivity to the general sentiment of the text.

11. **Positivity Mitigator:** This refers to a situation where the sentiment of a text with emoji is in the *Keep Positivity* sentiment state, and the emoji pattern is negative. In such cases, the overall positivity of the text remains, with a hint of negativity implied by the emoji. For example:

لقد قُبلت في الجامعة التي حلمت بها 😭 Example (25)

I just got accepted into my dream school 😭

The sentiment of the text is positive as the person has achieved their dream of getting accepted into their desired school. However, the addition of the negative emoji *Loudly Crying Face* (i.e., 😭) adds a hint of sadness or negativity, mitigating the general positivity of the text. This shows that the use of emoji patterns may have a small impact on the sentiment of the text but may not totally change it.

12. **Positivity Indicator:** This occurs when the overall sentiment state of the text with emoji is *Keep Positivity* and the sentiment of the emoji pattern within the text is neutral. For example:

لقد قُبلت في الجامعة التي حلمت بها 💃😚😭💔 Example (26)

I just got accepted into my dream school 💔😭😚💃

The general sentiment of the text in this example is positive. However, the sentiment of the emoji pattern within the text, which includes a mix of negative emoji (i.e., the *Broken Heart* 💔 and the *Loudly Crying Face* 😭) and positive emoji (i.e., the *Face with Party Horn and Party Hat* 🥳 and the *Dancer* 💃), is neutral. This mixed-sentiment emoji pattern plays as **indicator** for the positive text.

13. **Positivity Emphasizer:** This occurs when the overall sentiment state of a text with the emoji is *Keep Positivity* and the sentiment of the emoji pattern within the text is also positive. For example:

لقد قُبلت في الجامعة التي حلمت بها 🎓🎊🎉 Example (27)

I just got accepted into my dream school 🎉🎊🎓

The positive emoji pattern consisting of *Party Popper*, *Confetti Ball*, and *Graduation Cap* emoji (i.e., 🎉, 🎊, and 🎓, respectively) serves as an **emphasizer**, reinforcing and highlighting the positive sentiment of the text.

7.2 Emoji Sentiment-Roles Lexicon

After determining the sentiment role of emoji in our Emoji-Texts dataset, we can compute the frequency distribution of these roles for every emoji. Using the Emoji Sentiment Ranking approach [1] as a guide, which we modified for our context-sensitive emoji sentiment lexicon, we created an emoji-roles sentiment lexicon. This lexicon is based on the probability distribution of each emoji in the thirteen sentiment roles.

To begin, we measure how often each emoji aligns with a specific sentiment role, using this equation: $N(c), \sum N(c) = N$. Where **N** denotes the number of times an emoji has been annotated with one of these labels: *negative*, *neutral*, or *positive*. **N(c)** are the occurrences of an emoji with the sentiment label **c**, where **c** is either *Negativity Emphasizer*, *Negativity Indicator*, *Negativity Mitigator*, *Negativity Reverser*, *Negativity Trigger*, *Positivity Releaser*, *Neutral-Effect*, *Negativity Releaser*, *Positivity Trigger*, *Positivity Reverser*, *Positivity Mitigator*, *Positivity Indicator*, or *Positivity Emphasizer*.

From the above, we form a discrete probability distribution: $\sum p_c = 1$; where $\mathbf{p_c}$ are the probabilities for each sentiment role that are estimated from relative frequencies as follows: $p_c = \frac{N(c)}{N}$. We used the Laplace estimate [250] as it is recommended to estimate the probability for small samples: $p_c = \frac{N(c)+1}{N+k}$, where **k** is the cardinality of the sentiment roles ($k = 13$ sentiment roles in our case). Figure 7.3 shows examples of the probability distribution $\mathbf{p_c}$ of the sentiment roles for some emoji that conduct the Arabic emoji-roles sentiment lexicon.

	Emojis	NegEmph	NegIndic	NegMitg	NegRev	NegTrig	NegRel	NoEffect	PosRel	PosTrig	PosRev	PosMitg	PosIndc	PosEmph
1	😂	0.077400	0.005112	0.012320	0.009430	0.021454	0.061663	0.014240	0.003889	0.055833	0.192998	0.341160	0.002081	0.202420
2	❤	0.003033	0.000637	0.004849	0.006965	0.004344	0.009530	0.014978	0.006179	0.031136	0.055963	0.041135	0.002696	0.818555
3	💔	0.596629	0.003936	0.082922	0.180935	0.093480	0.004017	0.003176	0.007654	0.001547	0.004994	0.010531	0.002171	0.008007
4	😭	0.467904	0.002488	0.143173	0.066266	0.075698	0.044534	0.036381	0.029160	0.015824	0.034826	0.011989	0.006150	0.065609
5	😍	0.001067	0.000978	0.001911	0.001778	0.001556	0.013289	0.011156	0.002889	0.069867	0.096444	0.018489	0.001556	0.779022
6	🌹	0.000229	0.000366	0.000870	0.003801	0.002381	0.010166	0.015844	0.005495	0.011723	0.015386	0.027017	0.000687	0.906035
7	💙	0.002318	0.001082	0.004120	0.020549	0.011330	0.004429	0.010094	0.003914	0.030077	0.047381	0.058866	0.001854	0.803986
8	🖤	0.002052	0.001758	0.004162	0.011020	0.009437	0.006624	0.010258	0.007327	0.024736	0.046307	0.050000	0.003986	0.822333
9	🤣	0.010113	0.003494	0.000552	0.037418	0.081180	0.111704	0.036499	0.012044	0.024088	0.050014	0.532776	0.000092	0.100028
10	💕	0.002305	0.002121	0.005440	0.019270	0.012263	0.009865	0.024986	0.009773	0.032454	0.033008	0.056426	0.008482	0.783607
11	😅	0.033184	0.004469	0.003803	0.005230	0.011981	0.124465	0.034420	0.007131	0.092707	0.217457	0.228012	0.001616	0.235523
12	👍	0.009600	0.001469	0.005780	0.015772	0.021062	0.028213	0.074255	0.038401	0.032817	0.031250	0.151744	0.000784	0.588852
13	💛	0.004781	0.000916	0.013327	0.013937	0.008342	0.008342	0.019939	0.012208	0.028891	0.038352	0.049542	0.002543	0.798881
14	👌	0.022342	0.001897	0.007693	0.008220	0.008958	0.086837	0.060596	0.019918	0.055222	0.085678	0.155759	0.001686	0.485193
15	🙂	0.139488	0.003612	0.010411	0.024222	0.035164	0.067141	0.045682	0.007968	0.069478	0.104961	0.314246	0.000850	0.176777
16	🙏	0.013404	0.004763	0.006536	0.028692	0.011189	0.010081	0.018168	0.009416	0.014069	0.017835	0.082087	0.003988	0.779772
17	💚	0.002237	0.000447	0.001790	0.003915	0.003915	0.008054	0.021365	0.006600	0.056711	0.063199	0.039374	0.002013	0.790380
18	😄	0.018178	0.002710	0.005081	0.002032	0.008468	0.119792	0.036694	0.007678	0.114373	0.224681	0.175793	0.001016	0.283505
19	😔	0.464366	0.003770	0.180469	0.058311	0.059607	0.035693	0.042643	0.039345	0.013194	0.017788	0.017434	0.003063	0.064319
20	💜	0.002898	0.001186	0.007904	0.011329	0.009353	0.011197	0.016862	0.015018	0.025820	0.051772	0.050191	0.004084	0.792386

Figure 7.3: A Sample of the Arabic Emoji Sentiment-Roles Lexicon.

7.3 Chapter Conclusion

In this chapter, we delved into the heart of our research, equipping ourselves with all the prerequisite instruments for an improved sentiment analysis model tailored to Arabic texts. Our extensive preparation, which involved annotated datasets, comprehensive lexicons of emoji and words, and a sentiment classifier, set the stage for a deeper exploration of the impact of emoji on the sentiment of Arabic messages. Consequently, we have made considerable progress in addressing our second research question, identifying the thirteen instrumental nature of emoji in modulating the sentiment of Arabic written communications. Furthermore, our endeavour to construct a detailed emoji sentiment lexicon, containing the probabilities of each emoji in the thirteen distinct sentiment roles explored, marked a significant advancement. This not only enhances our understanding of the various roles that emoji play, but also paves the way for a more nuanced approach to emoji-based sentiment analysis in Arabic. Thus, we were able to refine the conventional sentiment classifier based on the emoji lexicon that we built earlier. A further discussion of the evaluation of such classification will be presented in the next chapter.

Chapter 8

Emoji-Sentiment-Roles Model Evaluation

In this chapter, we confront the complexities of Arabic sentiment analysis, particularly when tackling texts enriched with irony, a nuanced linguistic element that intensifies the interpretative challenge. Using ironic features in Arabic texts as a case study, we critically evaluate our sentiment analyser based on the emoji-role lexicon. Taking into account the prevalent use of emoji in Arabic digital communications, the chapter provides a rigorous assessment of our model. Employing a blend of quantitative metrics (i.e., accuracy, precision, recall, F1, Cohen's Kappa) and qualitative analysis, we aim to highlight the model's strengths and pinpoint areas for refinement. This chapter also endeavours to address the third research question of this thesis: "**RQ3: How do alterations in emoji sentiment roles aid in discerning embedded sarcasm and humour in Arabic texts; and how does this enhance the accuracy of sentiment classification within these texts?**". By benchmarking our model against five renowned Arabic sentiment analysers and grounding our comparisons in a meticulously annotated dataset, readers will gain a comprehensive perspective on the model's performance in the intricate field of Arabic sentiment interpretation.

8.1 Emoji-Roles Lexicon-Based Sentiment Classifier

By leveraging the insights gained from the emoji-roles sentiment lexicon and combining them with our established knowledge of the sentiment roles associated with specific emoji patterns, we have made a significant improvement in the conventional sentiment classifier based on the emoji lexicon, as illustrated in Table 8.1 below. Traditional methods often assign a static sentiment score to an emoji, failing to consider its varying roles in different textual contexts. Our refined approach rectifies this oversight. Instead of considering a singular, unchanging sentiment score for each emoji, the classifier dynamically retrieves sentiment scores based on the specific role the emoji plays within a given sentence. To offer a clearer picture of this improvement, Figure 8.1 shows texts annotated both by our enhanced emoji-roles-lexicon-based classifier and the conventional emoji-lexicon-based method, juxtaposed against the manual true annotations from our gold standard dataset. A more thorough evaluation of these classifiers will be discussed in the following sections.

Table 8.1: Performance Evaluation of Annotating the Gold Standard Dataset by Seven Arabic Sentiment Classification Models.

	Emoji-Texts		
Sentiment Classifiers	**Cohen's** k	*accuracy*	$F1$
CAMeL-AraBERT	0.60	0.74	0.75
CAMeL-mBERT	0.51	0.72	0.73
Mazajak	0.50	0.70	0.71
ASAD	0.32	0.56	0.61
Machines Fusion Annotation	**0.61**	**0.78**	**0.79**
Emoji-Lexicon-Based Model	**0.45**	**0.69**	**0.68**
Emoji-Roles-Lexicon-Based Model	**0.71**	**0.84**	**0.84**

Example #	Emoji_Texts	True Label	Conventional Emoji Lexicon-Based				Emoji-Roles Lexicon-Based				Emoji Role
			T_Score	T_Label	E_Score	E_Label	T_Score	T_Label	E_Score	E_Label	
1	غرد يحبك لمحمد بن سلمان هو الحب كله 💚💚💚💚🇸🇦🇸🇦🇸🇦 Eexpressing love for Mohammed bin Salman, he is the whole love 💚💚💚💚🇸🇦🇸🇦🇸🇦	positive	1.66562	positive	1	positive	2.012436	positive	1	positive	Positivity Emphasizer
2	تحيه للمدرس المحترم 👇👇 منتدي شباب العالم A salute to this respected teacher 👇👇 from the World Youth Forum	positive	1.10265	positive	0	neutral	1.333555	positive	0.235403	positive	Positivity Indicator
3	ابوي صاير حنين والله 💜 😢 صار يحضن يقلبوش 🥺 My father has become tender, I swear to God 😢 💜. He has become so affectionate 🥺	positive	0.157617	positive	-0.43958	negative	0.675397	positive	-0.15282	negative	Positivity Mitigator
4	يعني شو بتتوقعو من واحد يومه حيخلص عال 😍 😍 😍 What do you expect from someone whose day will end on a high note? 😍 😍 😍	positive	1.188831	positive	1	positive	0.741302	positive	0.456581	positive	Positivity Reverser
5	💪 ❤ ❤ ❤ ❤ ❤ ❤ WYF منتدي شباب العالم The World Youth Forum 💪 ❤️ ❤️ ❤️ ❤️ ❤️ ❤️ WYF	positive	1.515603	positive	1	positive	0.695081	positive	0.394654	positive	Positivity Trigger
6	😁 عمري في حياتي ماكلته ولا فكرت في الموضوع حتي بدافع الفضول مش فاهم ليه I've never eaten it in my life and never even thought about it out of curiosity. I don't understand why 😁	neutral	0.256646	positive	0.820731	positive	-0.038958	neutral	0.301303	positive	Negativity Releaser
7	👇 خليك محمد صلاح اتفرج علي الفيديو علي اليوتيوب من هنا Watch Mohamed Salah's video on YouTube from here 👇	neutral	0	neutral	0	neutral	0	neutral	0	neutral	Neutral Effect
8	لولا وقوف روسيا مع سوريا لكان الربيع دمر الوطن العربي من المحيط الي الخليج 😡 الف شكر لروسيا وصمود سوريا 👌 Had Russia not stood with Syria, the Arab homeland from the ocean to the Gulf would have been destroyed 😡. A thousand thanks to Russia and Syria's resilience 👌	neutral	0.586094	positive	-0.29093	negative	-0.058408	neutral	-0.28323	negative	Positivity Releaser
9	ابغي كوكيز 😔 I want cookies 😔	negative	-0.985997	negative	-0.986	negative	-0.664604	negative	-0.1852	negative	Negativity Trigger
10	والله انت باهي اقسم بالله 😡 You are good. I swear by God, you are 😡	negative	-1.00035	negative	-1	negative	-0.661509	negative	-0.13031	negative	Negativity Reverser
11	لا اريد التعلق باحد ثم يرحل 💔 🌿 🌸 فوجع الرحيل اشبه باستئصال عضو من دون مخدر 🌸 صباحكم جستن بيبر I don't want to get attached to someone and then they leave 🌸 🌿 💔. The pain of departure is like removing an organ without anesthesia 🌸. Your morning is like Justin Bieber	negative	-0.245287	negative	0.714049	positive	-1.477475	negative	0.161073	positive	Negativity Mitigator
12	كلشي عفت لخاطرهِ وماجرحته بيوم 🚿 I gave up everything for his sake and never hurt him once 🚿	negative	-0.087969	negative	0	neutral	-0.707194	negative	0.005755	neutral	Negativity Indicator
13	🙄 فيني برود ولا كانه عندي بكرهِ امتحان 🤦 يا رب يعدي اليوم خير 😪 I feel so chill as if I don't have an exam tomorrow 🤦. Oh God, I hope this day goes well 🙄 😪	negative	-0.681128	negative	-1	negative	-2.035649	negative	-1	negative	Negativity Emphasizer

Figure 8.1: Examples of Texts Representing the Thirteen Emoji Roles Annotated by the Emoji-Role-Lexicon-Based Classifier and the Conventional Emoji-Lexicon-Based Classifier.

8.2 Ironic Text Use-Case Study

8.2.1 Sarcasm vs. Humour

Irony, sarcasm, and humour serve as playful or hilarious mediums of expression. Each, while sometimes intersecting, carries its unique definition and application. Irony generally denotes situations or expressions contrary to what is expected, manifesting verbally or situationally [255]. Sarcasm, a subset of irony, employs a sharp language tone to mock or critique, often exaggerating its stance [256]. In Arabic contexts, sarcasm frequently emerges as a tool for societal or political critique, challenging prevailing norms or authority figures [257], [258]. Humour, another facet of irony, captures the essence of amusement [259]. It spans a variety of topics, from jokes to witty remarks, often lightening a mood or entertaining an audience. Within Arabic traditions, humour is considered a key to successfully presenting intricate emotions in a delightful manner [260], [261].

Lately, emoji are gaining prominence in textual analysis. Their roles in conveying sentiments aid in detecting diverse linguistic phenomena, from bullying and hate speech to humour and sarcasm. Although written irony is deliberate, its paired emoji amplifies the intent. Therefore, the integration of emoji into sarcasm and humour studies is an evolving focus of research [262]–[265]. In our analysis, we explore this claim through a case study centred on humour and sarcasm classification. For our study, a text is deemed ironic, either sarcastic or humorous, only if it incorporates specific predefined emoji patterns with designated sentiment roles. Our applied model hinges on two primary features: the specific emoji patterns present within a text, termed the *ironic pattern*', and the sentiment role these patterns play in the contexts. The details of this model are as follows.

8.2.2 Irony Classification Model

Ironic Emoji Patterns Identification

To identify ironic emoji patterns, we first selected a specific group of emoji as 'seed' emoji. The selection of these seeds was based on their visually ironic nature. For example, emoji, such as *Face with Stuck-Out Tongue* (😛), *Face with Stuck-Out Tongue and Tightly-Closed Eyes* (😝), *Face with Stuck-Out Tongue and Winking Eye* (😜) and *Grinning Face With One Large and One Small Eye* (🤪) can indicate irony due to the 'tongue out' non-verbal cue [266]. Furthermore, studies have shown that emoji such as *Winking Face* (😉), *Slightly Smiling Face* (🙂), *Face with Rolling Eyes* (🙄), *Smirking Face* (😒) and *Face With Tears Of Joy* (😂) are a strong indicator of irony [56], [68], [266]. Consequently, if a pattern of emoji contains one or more of these seed emoji, along with other emoji from our static lexicon, we consider that pattern to be ironic.

Consequently, we manually selected a total of **23** seed emoji, under the assumption that users often intentionally chose them in some contexts to indicate irony. These emoji are shown in Table 8.2. Combining these emoji with some of the other 1,272 emoji in our lexicon (excluding all *Flags*, some *Natures*, and most of the *Hearts* emoji), we obtained **12,385** unique emoji patterns (with **15,101** variations in total) extracted from our dataset. This collection of ironic patterns consists of **8,990** positive patterns, **543** neutral patterns, and **5,568** negative patterns that can play different sentiment roles in sarcastic or humorous manners.

Table 8.2: Emoji Seeds for Sarcastic/Humorous Patterns Extraction.

Sentiment	**Emoji**													
Positive	😂	🙂	😅	😄	🤣	😉	😎	😁	😜	😹	😆	😝	😛	🤪
Negative	😒	🤔	😑	😏	🤦	🙄	😧	😐	🙃					

For better visualisation, we plotted the co-occurrences of the most 100 emoji in our lexicon with twelve of the ironic emoji patterns as shown in Table 8.3. This shows how emoji with different sentiments commonly cooccur in Arabic ironic contexts.

Sarcasm and Humour Classification

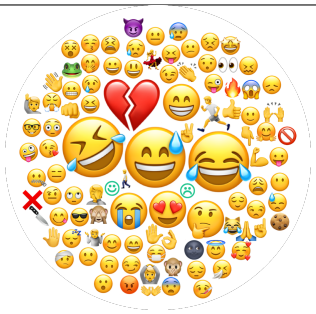
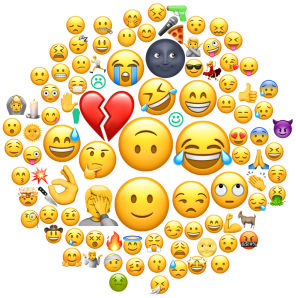
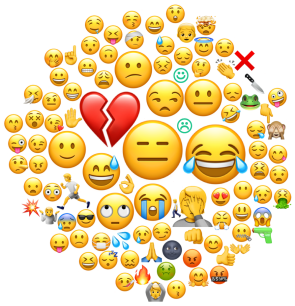
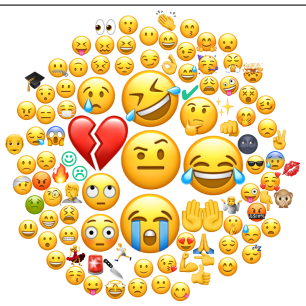
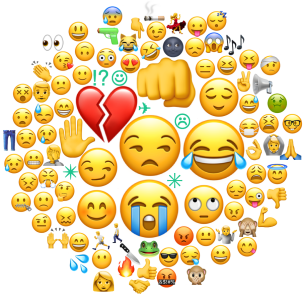
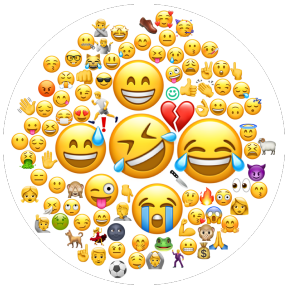
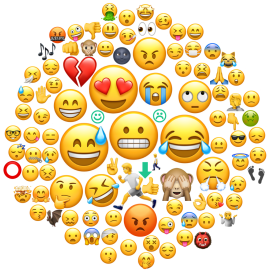
Using the emoji-role-lexicon-based sentiment model, we classified texts containing ironic statements (i.e., ironic emoji) with a negative connotation as sarcasm. In other words, the classification of sarcastic texts was based on the presence of predefined ironic emoji patterns that play negative sentiment roles. This was formulated as follows:

Plain Text + { Negativity **Emphasizer** Ironic Emoji Pattern | Negativity **Indicator** Ironic Emoji Pattern | Negativity **Mitigator** Ironic Emoji Pattern | Negativity **Trigger** Ironic Emoji Pattern | Negative **Reverser** Ironic Emoji Pattern | Positivity **Releaser** Ironic Emoji Pattern | **Neutral-Effect** (Negative | Neutral Ironic Emoji Pattern) } = **Sarcastic Text**

On the other hand, we classified texts containing ironic statements with a positive connotation as humour. This classification was based on the presence of predefined ironic emoji patterns that play positive sentiment roles, and was formulated as follows:

Plain Text + { Positivity **Emphasizer** Ironic Emoji Pattern | Positivity **Indicator** Ironic Emoji Pattern | Positivity **Mitigator** Ironic Emoji Pattern | Positivity **Trigger** Ironic Emoji Pattern | Positive **Reverser** Ironic Emoji Pattern | Negativity **Releaser** Ironic Emoji Pattern | **Neutral-Effect** (Positive Ironic Emoji Pattern) } = **Humorous Text**

Table 8.3: The Most 100 Correlated Emoji to Twelve of the Ironic Seed Emoji.

		
seed: (😅)	seed: (😎)	seed: (🤪)
		
seed: (🙂)	seed: (🙃)	seed: (😑)
		
seed: (😉)	seed: (🤦)	seed: (😒)
		
seed: (🤪)	seed: (🤣)	seed: (😬)

Irony Model Evaluation

To evaluate this model, we utilised two publicly available Arabic ironic datasets: Sa'7r [244] and ArSarcasm [240]. From the merged datasets, we retained only those texts containing emoji, which are **6,738** texts. Of these, **2,727** were labelled as ironic/sarcastic, while **4,011** were not. To establish a balanced sample, we arbitrarily chose **1,000** texts from both ironic and non-ironic categories, resulting in a total of **2,000** evaluation texts. Using the predefined ironic emoji patterns, we categorised this sample into ironic and non-ironic groups. We then gauged the efficacy of this classification by comparing its resulting labels with the benchmark labels. Impressively, our analysis reported **accuracy** of **0.91** when juxtaposed with the set of benchmarks. Cohen's (κ) agreement between our classifications and the benchmark annotations was also substantial, scoring a **0.83**.

Although the predefined emoji patterns clearly indicated irony in the texts, the difference between sarcasm and humour was not clear. To address this ambiguity, we first identified the sentiment roles of these emoji patterns, using the machine's fusion sentiment annotation technique for both texts with and without emoji (described in Section 5.3.2). Based on the sentimental roles provided by these emoji, we labelled the texts as either *sarcastic* or *humorous*. To validate these labels, we hand-annotated the sentiment of 600 representative texts, split equally between the humorous and sarcastic categories. The analysis of this subset yielded impressive consistency: a Cohen κ agreement of **0.97** for humorous (positive) texts and **0.95** for sarcastic (negative) texts. These results underscore our model's capability to discern between humorous and sarcastic undertones in ironic Arabic texts.

8.2.3 Sentiment Analysis Model Evaluation

Within this specific use case, our primary objective is to thoroughly assess the performance of our emoji-role-based sentiment classification model. To achieve this aim, we rigorously

tested the model using a manually annotated benchmark dataset and juxtaposed its results with five Arabic sentiment analysers. Our evaluation is rooted in a meticulously assembled collection of texts that have been manually annotated for sentiment, spanning the range from ironic to non-ironic content. Further details are as follows.

Benchmark Dataset

We used our gold standard data as the benchmark dataset, comprising **10,179** manually annotated texts, both with and without emoji. By identifying the sentiment emoji roles for each pattern within the texts, the application of the irony classification model to the dataset was simplified. The dataset contained **2,529** ironic texts (1,688 sarcastic and 841 humorous) and **7,650** non-ironic texts. Figure 8.2 illustrates the distribution of the sentimental roles played by the emoji patterns, paired with their associated ironic effects.

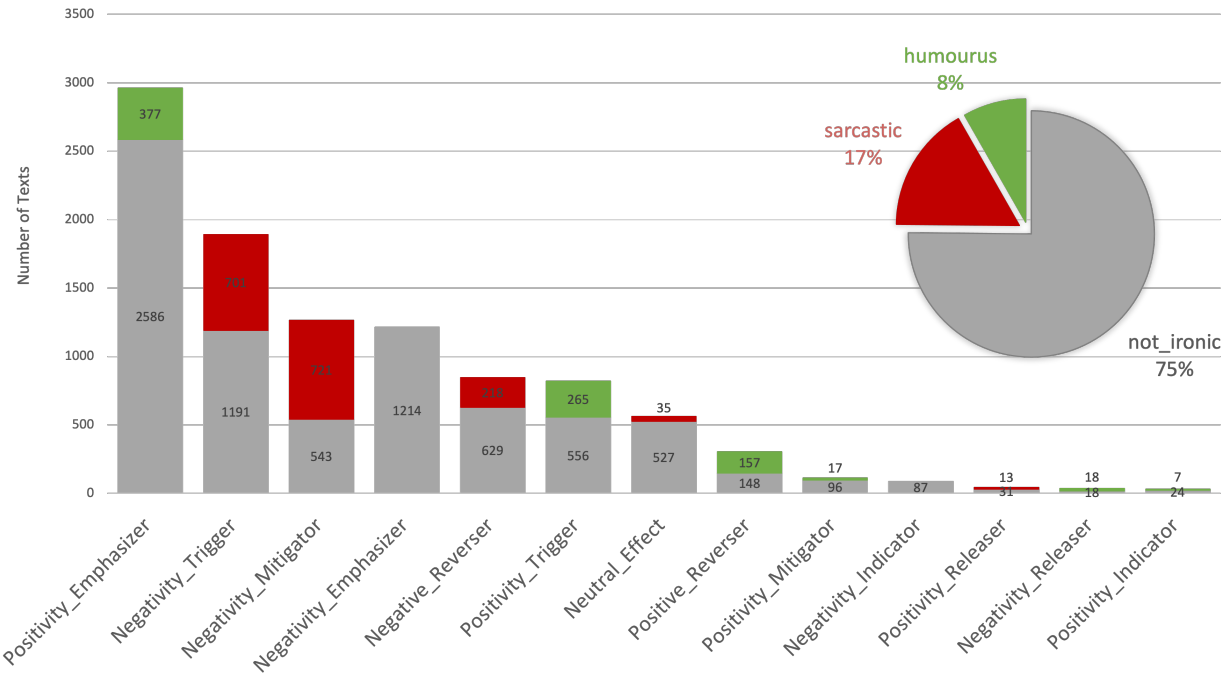


Figure 8.2: Graphical Representation of Emoji Sentiment Roles and Their Corresponding Ironic Effects in the Benchmark Dataset.

Quantitative Analysis

From a quantitative perspective, we conducted a thorough assessment of our emoji-role-lexicon-based sentiment analysis model using the benchmark dataset and juxtaposed its results with those of five Arabic sentiment analysers: CAMeL-AraBERT, CAMeL-mBERT, Mazajak, ASAD and the conventional emoji-lexicon-based sentiment classifier based on our static emoji sentiment lexicon. This evaluation employed a robust set of metrics, including Cohen's Kappa, accuracy, F1 score, precision, and recall. The results of this analysis are presented in Table 8.4 for ironic texts and Table 8.5 for non-ironic texts.

As shown in Table 8.4, our lexicon-based method that leverages emoji sentiment roles outperforms other Arabic sentiment classifiers. The model showed the highest accuracy **0.84** with remarkable precision, recall, and F1 scores when interpreting the sentiment of an ironic message, even when it contradicted the overt textual or emoji sentiment. Impressively, it aligns **substantially** with human annotation, indicated by $\kappa = \mathbf{0.7}$. In the context of non-ironic texts, its accuracy peaks at **0.85**, and its alignment with human judgment remains consistent at $\kappa = \mathbf{0.7}$. Considering the model's **sensitivity**, which represents the proportion of true positive cases accurately identified (i.e., the **recall** score values), we gleaned the following observations.

In Table 8.4, our model demonstrated impressive recall scores for various ironic text categories. For neutral ironic texts, it beats CAMeL-AraBERT by **66%**, CAMeL-mBERT by **77%**, Mazajak by **8%**, ASAD by **63%**, and the conventional emoji-lexicon-based method by **84%**, as underscored in Examples (1) and (2) from Table 8.6. Meanwhile, in the classification of positive ironic texts, the emoji-role-based sentiment model outperformed CAMeL-AraBERT by **7%**, CAMeL-mBERT by **34%**, Mazajak by **15%**, ASAD by **46%**, and the same conventional approach by **6%**, with this exemplary performance vividly depicted in humorous examples (3), (4), and (5) of Table 8.6. Furthermore, when classifying negative ironic texts, our model eclipsed its counterparts, most notably outdoing CAMeL-AraBERT

by **24%** and the conventional lexicon-based technique by **4%**, a prowess highlighted in sarcastic examples (6), (7), and (8) in Table 8.6.

Turning our attention to non-ironic texts as illustrated in Table 8.5, our model showcased commendable recall scores for both positive and negative sentiments, but fell short with neutral ones. For these neutral non-ironic texts, CAMeL-AraBERT outperformed our model by **33%**, followed by CAMeL-mBERT at **26%**, Mazajak at **26%**, and ASAD by **36%**. Interestingly, only the conventional lexicon-based approach that uses the static Arabic emoji lexicon lagged behind our model, underperforming by **43%**. These nuances in neutral sentiments are encapsulated in Examples (1), (2), and (3) in Table 8.7. On the other hand, when addressing positive non-ironic texts, our emoji-roles sentiment model triumphed over CAMeL-AraBERT and CAMeL-mBERT both by **19%**, Mazajak by **12%**, ASAD by **46%**, and the conventional emoji-lexicon-based method by **10%**, as captured in examples (4) to (11) in Table 8.7. Furthermore, in negative non-ironic classifications, our model surpassed CAMeL-AraBERT by **2%**, CAMeL-mBERT by **8%**, Mazajak by **22%**, ASAD by **18%**, and the conventional emoji-lexicon-based approach by **13%**. This distinction is highlighted in examples (12) to (19) presented in Table 8.7.

Table 8.4: Performance Comparison of Emoji-Roles-Lexicon-Based Model vs. Other Sentiment Classifiers on Ironic Texts.

Ironic Texts				
CAMeL-AraBERT				
Cohen's Kappa	0.3375140693232621			
Accuracy	0.64			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.06	0.20	0.09	66
positive	0.54	0.70	0.61	823
negative	0.83	0.63	0.72	1640
Weighted Avg	0.72	0.64	0.67	2529

CAMeL-mBERT				
Cohen's Kappa	0.26014453867997867			
Accuracy	0.66			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.05	0.09	0.06	66
positive	0.57	0.43	0.49	823
negative	0.73	0.80	0.76	1640
Weighted Avg	0.66	0.66	0.66	2529

Mazajak				
Cohen's Kappa	0.32822133797313224			
Accuracy	0.67			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.04	0.06	0.05	66
positive	0.54	0.62	0.58	823
negative	0.79	0.71	0.75	1640
Weighted Avg	0.69	0.67	0.67	2529

ASAD				
Cohen's Kappa	0.14566419090814464			
Accuracy	0.51			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.02	0.23	0.04	66
positive	0.62	0.31	0.42	823
negative	0.71	0.63	0.67	1640
Weighted Avg	0.66	0.51	0.57	2529

Emoji-Lexicon-Based Model				
Cohen's Kappa	0.18668961663638628			
Accuracy	0.53			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.01	0.02	0.01	66
positive	0.41	0.71	0.52	823
negative	0.82	0.47	0.59	1640
Weighted Avg	0.66	0.53	0.55	2529

Emoji-Roles-Lexicon-Based Model				
Cohen's Kappa	**0.6630244322713221**			
Accuracy	**0.84**			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.51	**0.86**	0.64	66
positive	0.78	**0.77**	0.78	823
negative	0.89	**0.87**	0.88	1640
Weighted Avg	0.84	0.84	0.84	2529

Table 8.5: Performance Comparison of Emoji-Roles-Lexicon-Based Model vs. Other Sentiment Classifiers on Non-ironic Texts.

Non-Ironic Texts				
CAMeL-AraBERT				
Cohen's Kappa	0.6228286964568549			
Accuracy	0.78			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.41	0.78	0.54	576
positive	0.83	0.76	0.79	3410
negative	0.85	0.79	0.82	3664
Weighted Avg	0.81	0.78	0.79	7650

CAMeL-mBERT				
Cohen's Kappa	0.5572209060836198			
Accuracy	0.74			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.46	0.71	0.56	576
positive	0.76	0.76	0.76	3410
negative	0.80	0.73	0.77	3664
Weighted Avg	0.76	0.74	0.75	7650

Mazajak				
Cohen's Kappa	0.5235200059539435			
Accuracy	0.71			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.37	0.78	0.50	576
positive	0.71	0.83	0.77	3410
negative	0.88	0.59	0.71	3664
Weighted Avg	0.77	0.71	0.72	7650

ASAD				
Cohen's Kappa	0.36424653731210965			
Accuracy	0.58			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.19	0.81	0.31	576
positive	0.78	0.49	0.60	3410
negative	0.75	0.63	0.69	3664
Weighted Avg	0.72	0.58	0.62	7650

Emoji-Lexicon-Based Model				
Cohen's Kappa	0.5368343948475618			
Accuracy	0.74			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.08	0.02	0.04	576
positive	0.67	0.94	0.78	3410
negative	0.92	0.68	0.78	3664
Weighted Avg	0.75	0.74	0.73	7650

Emoji-Roles-Lexicon-Based Model				
Cohen's Kappa	**0.7241588225687374**			
Accuracy	**0.85**			
	Precision	**Recall**	**F1-score**	**Support**
neutral	0.68	**0.45**	0.54	576
positive	0.80	**0.95**	0.87	3410
negative	0.92	**0.81**	0.86	3664
Weighted Avg	0.85	0.85	0.84	7650

Qualitative Analysis

Irony in language inherently creates a paradox in expressed sentiments. When emoji are added as non-verbal cues, a message might overtly appear positive but carry subtle negative hints or vice versa. This nuanced communication is difficult for humans to discern and even more challenging for machines to detect. Here, from a qualitative perspective, we are investigating the reasons that make our emoji-roles sentiment analyser outperform the other Arabic sentiment analysers on ironic and non-ironic short informal messages, as follows.

8.2.4 Ironic Texts Analysis

Neutral Ironic Texts

Our irony classification model determines a neutral ironic text as *humorous* if its emoji pattern exhibits positive sentiment roles and *sarcastic* if the emoji pattern manifests negative sentiment roles. Examples (1) and (2) from Table 8.6 further clarify this distinction.

Consider example (1) in Table 8.6 with the text: "*We crushed the enemies* 😌. *Shame on them* 😈😎". The introduction of the positive emoji sequence (😌 😈 😎) releases the negativeness of the plain text, rendering it neutral while infusing humour. Here, CAMeL-AraBERT, ASAD and the conventional emoji-lexicon-based approach were influenced by the static positivity of the emoji pattern. In contrast, CAMeL-mBERT and Mazajak assigned greater importance to the negative elements (both words and emoji) in the entire message. In tandem with identifying its neutral sentiment by our emoji roles-based sentiment model, the irony classifier adeptly assessed the overall humorous undertone of this message.

In Example (2) in Table 8.6, featuring the phrase, "*The Arab Spring seems like it's going to be a mess, my friend* 😂", our model skilfully identified the underlying neutrality through its assessment of the emoji sentiment roles. Here, the term 'معلم' is colloquially

understood in some Arabic dialects to mean 'teacher'. However, in casual settings, it often translates to "my friend" or 'buddy'. Similarly, 'معجنة' is employed colloquially to depict a chaotic or convoluted situation. The neutrality of the text, which features positive terms like 'Spring' and 'friend', and the negative 'mess', remains unswayed by the accompanying positive emoji (😂). This arises from how our emoji-roles sentiment classification system works: when this specific emoji has a neutral impact, it receives a sentiment score of **0.014240**. Using the emoji scores-to-labels scale, this translates to a *neutral* label. In this case, the neutral nature of the emoji maintains the sentiment of the text, which our irony classification system then reads as sarcasm.

Navigating this intricate example, CAMeL-mBERT labelled the text as negative, while the other Arabic machine classifiers leaned towards a positive annotation. Possible explanations include the following. First, the conventional emoji-lexicon-based approach consistently interprets the *Face with Tears of Joy* (😂) emoji as intrinsically positive. This biases the text towards a positive classification. Second, Arabic machine classifiers process this emoji as a collection of words (i.e., its formal description translated from English to Arabic). Moreover, these classifiers, mainly pre-trained in modern standard Arabic (MSA), might struggle with the dialectal variations found on social media. Their narrow dialectal understanding, coupled with the predominantly positive meaning of the emoji, leads them to categorise the text as positive.

Positive Ironic Texts

Positive ironic texts, according to our irony classification model, are perceived as humorously exaggerated if the accompanying emoji accentuate positive sentiment roles. Examples (3), (4), and (5) from Table 8.6 shed light on this intricate interpretation.

Example (3) in Table 8.6 presents the nuances of the Moroccan dialect, Darija. The statement presented in this example reads: "*Even if, we're just teasing you for fun* 😂".

In Darija, 'واخا' is equivalent to "even if", and 'نريقو' colloquially translates to 'joking' or 'teasing'. The word 'ساط', commonly used, resonates as 'buddy', often amplifying the statement's positive sentiment. Paired with the expressive emoji (😂), the message exudes a light-hearted jest. This positive playful undertone was perceptible in our emoji-roles sentiment model, Mazajak, and the conventional emoji lexicon-based method. However, the misinterpretation by CAMeL and ASAD as negative possibly arises from their restricted exposure to the intricacies of Moroccan Darija.

Consider example (4) in Table 8.6: "*May God help you* 😅*. Today, I felt your struggle; it seemed like with every game you were cursing*". This example showcases the humorous exaggeration characteristics of Iraqi colloquial expressions. The Iraqi colloquial is presented in the words 'وي' that means 'with'; the word 'جنت' that means "you were", and the word 'تكفر' that means 'to curse'. The humour arises from the amplified portrayal of an individual's reactions during gameplay. The inclusion of the *Grinning Face with Sweat* (😅) emoji adds a light-hearted touch, signalling jest or playful teasing. Such statements highlight the intricacies in dialectal exchanges and the significant influence emoji have on shaping sentiment. Our emoji-roles sentiment model aptly identified this text as positive, recognising the emoji's role as an emphasizer of its positivity. Although CAMeL-AraBERT, Mazajak, and the conventional emoji lexicon-based model concurred on its positive nature, CAMeL-mBERT interpreted it negatively and ASAD deemed it neutral.

In example (5) from Table 8.6, the conveyed message is: "*Thank God I'm not there* 😜". This expresses light-hearted relief or gratitude for not being in a specific situation. Although the plain text seems negative on the basis of human interpretation, the addition of the emoji injects humour and reverses it to a positive. CAMeL-AraBERT annotated the text as neutral, but all other classifiers aligned with human judgment, recognising its positive tone.

Negative Ironic Texts

Negative ironic texts, as defined by our irony classification model, are interpreted to have a sarcastic exaggeration when the associated emoji underscore negative sentiment roles. Examples (6), (7), and (8) from 8.6 provide clarity on this sophisticated understanding.

In Example (6) in Table 8.6, the text reads: "*Bro, your team is experienced in flopping; don't stand up and lecture us* 😂". In particular, while other Arabic dialects may use different terms for 'bro', the Gulf dialect utilises 'خوي'. The text here underscores the team's inconsistent reputation, suggesting that they lack the authority to give guidance. Although human reviewers labelled the message as neutral, the addition of the non-verbal sarcastic sign (😂), which suggests laughter, gives it a hint of negativity. Our emoji-role-based sentiment model, in alignment with most of the other classifiers, interpreted this text as negative. On the contrary, only the conventional emoji-lexicon-based model assigned it a positive sentiment. This could be due to the "one-size-fits-all" sentiment interpretation of the emoji on which this model is based.

Examine example (7) from Table 8.6: "*Now, honestly, does this look like someone who has money for a hall, dinner, and a Taha Suliman concert?* 😂💔". This statement highlights the sarcastic overtones typical of Sudanese colloquial expressions. The Sudanese vernacular is evident in words like 'هسي' (meaning 'now'), 'زول' (referring to a person or 'buddy'), and 'قروش' (indicating 'money'). Moreover, "طه سليمان" or "Taha Suliman" is a renowned Sudanese singer. The message sarcastically questions the affordability of such lavish events. Although human annotators initially perceived textual sentiment as neutral, incorporation of the emoji pattern (😂💔) changed its tone towards negativity. Given this context, the irony classifier labels the text as sarcastic. Similarly to Example (6), while most sentiment classifiers agreed on the negative tone in this example, the conventional emoji lexicon-based model was an exception with a positive label.

Finally, we looked at Example (8) in Table 8.6: "*Aren't these youth conferences, Oh you educated ones, Oh you from the schools?* 🙄 *#World_Youth_Forum*". This sentence, expressed in a colloquial and playful tone, questions the legitimacy or quality of the mentioned conferences. The embedded emoji, *Face with Rolling Eyes* (🙄), imparts a sense of irony and scepticism. Although humans generally annotated the plain text without the emoji as neutral, the addition of this emoji injected a sarcastic and negative nuance. Notably, all classifiers detected this negative undertone, except CAMeL-mBERT.

Table 8.6: Examples of Ironic (Sarcastic and Humorous) Texts. CAMeL(1) is CAMeL-AraBERT, CAMeL(2) is CAMeL-mBERT, Lex(1) is the Conventional Emoji Lexicon-Based Model and Lex(2) is the Emoji Roles-Based Model.

Examples (#)	Text	True Label	Dialect	Irony Label	CAMeL(1)	CAMeL(2)	Mazajak	ASAD	Lex(1)	Lex(2)	Ironic Cue	Emoji Role
1	لقد سحقنا الاعداء 😌 تبا لهم 😎 😈 We crushed the enemies 😌 Shame on them 😎 😈	neutral	MSA	humourus	positive	negative	negative	positive	positive	**neutral**	😎	Negativity Releaser
2	الربيع العربي شكله هيبقي معجنه يا معلم 😂 The Arab Spring seems like it's going to be a mess, my friend 😂		Egyptian	sarcastic	positive	negative	positive	positive	positive	**neutral**	😂	Neutral Effect
3	واخا غير نريقو معاك ساط 😂 Ok, we just mess with you for fun, bro 😂	positive	Moroccan	humourus	negative	negative	positive	negative	positive	**positive**	😂	Positivity Emphasizer
4	هـ الله يساعدك 😅 اليوم حسيت بمعاناتك احسك وي كل لعبة جنت تكفر May God help you 😅. Today, I felt your struggle; it seemed like with every game you were cursing		Iraqi	humourus	positive	negative	positive	neutral	positive	**positive**	😅	Positivity Emphasizer
5	الحمد لله ماني موجود 😜 Thank God I'm not there 😜		Gulf	humourus	neutral	positive	positive	positive	positive	**positive**	😜	Positive Reverser
6	يا خوي فريقك خبرهـ في التبطح لا تقوم تشيخ علينا 😂 Bro, your team is experienced in flopping; don't stand up and lecture us 😂	negative	Gulf	sarcastic	negative	negative	negative	negative	positive	**negative**	😂	Negativity Trigger
7	هسي في ذمتك دي خلقه زول عندو قروش لصاله وعشاء وحفله طه سليمان 💔 😂 Now, honestly, does this look like someone who has money for a hall, dinner and a Taha Suliman concert? 😂 💔		Sudanese	sarcastic	negative	negative	negative	negative	positive	**negative**	😂	Negativity Trigger
8	مؤتمرات شباب دي ولا مش مؤتمرات يامتعلمين يابتوع المدارس 🙄 منتدي شباب العالم Aren't these youth conferences, Oh you educated ones, Oh you school folks? 🙄 #World_Youth_Forum		Egyptian	sarcastic	negative	positive	negative	negative	negative	**negative**	🙄	Negativity Trigger

8.2.5 Non-ironic Texts Analysis

In the field of sentiment analysis, the assessment of non-ironic textual content illuminates a unique investigative pathway, particularly when juxtaposed with the intricate nuances of ironic expressions. Shifting our attention to non-ironic Arabic tweets enriched with emoji, our objective is to unravel the clear-cut relationship between textual content and the sentiment conveyed by emoji. The conspicuous sentiment in non-ironic contexts has led to a notable enhancement in the performance of all the Arabic sentiment classifiers under evaluation. This enhancement becomes evident when contrasting the results presented in Table 8.4 with those in Table 8.5. For qualitative insight, we will investigate the examples outlined in Table 8.7, showcasing non-ironic short texts categorised into the primary sentiment norms: neutral, positive, and negative.

Neutral Non-ironic Texts

Determining text neutrality might seem straightforward, however, it is a task fraught with nuances and subjectivity. While human judgment, shaped over years of linguistic encounters and socio-cultural experiences, deftly navigates these subtleties, algorithmic classifiers, bound by pre-defined datasets and coding, may not always resonate with this human discernment. This divergence in interpretation becomes evident when reviewing examples (1), (2) and (3) in Table 8.7. Although both human annotators and five machine classifiers agreed on the neutral sentiment of the texts, our emoji-roles sentiment classifier assigned a different sentiment.

Consider example (1) in Table 8.7, "*Harry Potter* 🎩👓". Our model interprets this as a neutral factual statement referencing "Harry Potter", using the emoji pattern (🎩👓) to symbolise his iconic glasses and wizard attire. For example (2) in Table 8.7, "*The World Cup qualifiers are still ongoing* 🏆", our emoji-role-based sentiment classifier perceives a

positive undertone, suggesting that there is still an opportunity to catch the "World Cup qualifiers". The presence of *Trophy* emoji (🏆) amplifies this positive sentiment in the model's perspective. In example (3) in Table 8.7, "🔛 *Mohamed Salah out, James Milner in*", the departure of *Mohamed Salah* (i.e., a famous Egyptian footballer) from a football match was deemed negative. In our classifier schema, this sentiment is underscored by the Arabic term 'خروج' (out) and the inherent neutrality of the emoji (🔛), which tends to mirror the sentiment of the accompanying text.

This challenge of our emoji-role sentiment classifier misclassifying neutral texts, especially when juxtaposed against human interpretation, can be attributed to a variety of factors. **First**, texts that are neutral might encompass a broad spectrum, ranging from a lack of sentiment to a mix of positive and negative sentiments. Hence, the model might struggle to differentiate between genuinely neutral texts and those that present a balanced sentiment. **Second**, the training data provided to the classifier was predominantly polar (i.e., mainly positive or negative) and limited in a representative sample of neutral or mixed-sentiment texts. **Third**, the model lacks the broader context that humans inherently consider. For example, cultural nuances, idiomatic expressions, or current events could influence the neutrality of a text, making humans better equipped to identify neutrality. **Fourth**, neutrality is, by nature, more subjective than clear positive or negative sentiments. While one person might view a statement as neutral, another might see it as slightly positive or negative based on their personal experiences and biases. Our model, which works on predefined algorithms, cannot capture this human-like subjectivity, making it challenging to consistently align with human judgments on neutrality. **Fifth**, in the text classification process, the features selected to represent the text play an essential role. If the selected features (words and emoji) do not capture the intricacies of neutrality (e.g., if the classifier heavily relies on high-polarity words or emoji), the classifier may err in its judgment. **Lastly**, neutral texts often possess inherent ambiguity. A statement could be interpreted in multiple ways depending on the reader's perspective. Our model, which is deterministic by nature, might struggle with such

ambiguity.

Positive Non-ironic Texts

In analysing positive non-ironic texts, it becomes evident how emoji work in tandem with words to create a holistic sentiment narrative. In the subsequent examination of examples (4) to (11) in Table 8.7, several attributes regarding this synergistic relationship between text and emoji sentiment become apparent.

In the positive examples provided, emoji such as *Red Heart* (❤️), *Smiling Face with Heart-Eyes* (😍), and *Thumbs Up* (👍) are globally recognised to have positive sentiments. Take, for example, Example (4) from Table 8.7: "*You're indeed right* 👍"; the thumbs-up emoji here functions to bolster the affirmation and concurrence of the statement. This synergy between text and emoji is maintained consistently, with emoji complementing, not contrasting, the textual sentiment. In Table 8.7, examples (6): "*Very beautiful* 👌"; (9): "*Good Morning* 🌸❤️"; (11): "*Amen* 😘" and (10): "*Congratulations on the win* 💙" exemplify this harmonious interaction, with the emoji reinforcing the positivity of the words 'beautiful', 'good', 'Amen', 'congratulations' and 'win'. Even seemingly neutral statements can be infused with depth through emoji. Consider example (9): "*Okay, thank you* 🙏", where simple gratitude is enriched with sincerity via the emoji.

In certain instances, emoji extend beyond just complementing the text and act as replacements for textual expressions. Consider the sentiment in example (7) from Table 8.7: "Mohamed Salah 🇪🇬😍💪". This sentiment is multifaceted in its positivity. The Egyptian flag emoji (🇪🇬) represents Salah's nationality, while the *Smiling Face with Heart-Eyes* (😍) and the *Flexed Biceps* (💪) emoji convey admiration and strength, respectively. This obviates the need for additional textual exposition. Similarly, emoji can graphically represent a text's sentiment. This is evident in example (5): "You deserve a heart ❤️", where the heart emoji both reinforces and emphasises the sentiment articulated in the text.

Negative Non-ironic Texts

Focussing on negative non-ironic texts, it becomes evident how emoji have evolved to serve as pivotal adjuncts to textual content, especially in encapsulating and accentuating sentiments in brief messages. In the examples (12) to (19) provided in Table 8.7, each message succinctly conveys an emotion, be it exhaustion, surprise, or anger. These emotions are then distinctly amplified by the accompanying emoji, acting as a visual emphasis to the sentiment expressed in words.

Emoji, such as 💔, 😡, 😥, 😞, 😳, 😖 and 😷, serve not merely as decorations, but as integral elements that help communicate the depth or intensity of the feeling more explicitly. This interplay between text and emoji offers a richer layer of understanding, especially in short messages, where brevity might limit expressive depth. In each instance, whether it is weariness accentuated by 😥 or the stern warning echoed by 😡, emoji work in tandem with the text to ensure that the sentiment is conveyed and accentuated, making the emotion palpable and clear to the reader.

A particularly nuanced example from Table 8.7 is sentence (18): "*Eventually, he will be fucked up* 😷". Here, the *Face with Medical Mask* (😷) emoji usually denotes illness or a concern about spreading or catching a disease. However, its broader interpretation can symbolise something being 'contaminated' or 'toxic'. Within this context, the emoji does not merely emphasise negativity, but suggests a harmful, possibly toxic future trajectory for the individual. This layering adds depth to the statement, hinting that the outcome might not just be unfavourable but also detrimental to one's health or wellbeing.

Table 8.7: Examples of Non-ironic Texts. CAMeL(1) is CAMeL-AraBERT, CAMeL(2) is CAMeL-mBERT, Lex(1) is the Conventional Emoji Lexicon-Based Model and Lex(2) is the Emoji Roles-Based Model.

Examples (#)	Text	True Label	Dialect	Irony Label	CAMeL(1)	CAMeL(2)	Mazajak	ASAD	Lex(1)	Lex(2)	Nonverbal Cue	Emoji Role
1	هاري بوتر 👓🎩 Harry Potter 👓🎩	neutral	MSA	not ironic	neutral	neutral	neutral	neutral	positive	**neutral**	👓🎩	Neutral Effect
2	تصفيات كاس العالم ماڑالت متواصله 🏆 The World Cup qualifiers are still ongoing 🏆		MSA	not ironic	neutral	neutral	neutral	neutral	positive	positive	🏆	Neutral Effect
3	خروج محمد صلاح دخول جميس ميلنر 🔛 .🔛 Mohamed Salah out, James Milner in		MAS	not ironic	neutral	neutral	neutral	neutral	neutral	negative	🔛	Neutral Effect
4	بالفعل صدقتي 👍 You're indeed right 👍	positive	MSA	not ironic	positive	positive	positive	positive	positive	positive	👍	Positivity Emphasizer
5	خذ قلب ❤ You deserve a heart ❤		Gulf	not ironic	positive	positive	positive	positive	positive	positive	❤️	Positivity Emphasizer
6	جميل جدا 👌 Very beautiful 👌		MSA	not ironic	positive	positive	positive	positive	positive	positive	👌	Positivity Emphasizer
7	محمد صلاح 🇪🇬😍💪 Mohamed Salah 🇪🇬😍💪		MSA	not ironic	positive	positive	positive	positive	positive	positive	🇪🇬😍💪	Positivity Trigger
8	صباح الخير 🌸❤️ Good morning 🌸❤		MSA	not ironic	positive	positive	positive	positive	positive	positive	🌸❤️	Positivity Emphasizer
9	اوك شكرا 🙏 Okay, thank you 🙏		Gulf	not ironic	positive	positive	positive	positive	positive	positive	🙏	Positivity Trigger
10	مبروك الفوز 💙 Congratulations on the win 💙		Gulf	not ironic	positive	positive	positive	positive	positive	positive	💙	Positivity Trigger
11	امين يارب 😘 Amen 😘		Gulf	not ironic	positive	positive	positive	positive	positive	positive	😘	Positivity Emphasizer
12	والله تعبت 😔 I swear, I'm exhausted 😔	negative	Gulf	not ironic	negative	negative	negative	negative	negative	negative	😔	Negativity Trigger
13	من سنوات 😓 For years 😓		MSA	not ironic	negative	negative	negative	negative	negative	negative	😓	Negativity Trigger
14	شايف كيف 😠 You see? 😠		Gulf	not ironic	negative	negative	negative	negative	negative	negative	😠	Negativity Trigger
15	يبما وشصاير 😳 Oh my, what's happening? 😳		Gulf	not ironic	negative	negative	negative	negative	negative	negative	😳	Negativity Trigger
16	النشله ذبحتني 💔 The cold killed me 💔		Gulf	not ironic	negative	negative	negative	negative	negative	negative	💔	Negativity Trigger
17	انا خوفت 😟 I got scared 😟		Egyptian	not ironic	negative	negative	negative	negative	negative	negative	😟	Negativity Emphasizer
18	بالاخير يلقم 😁 Eventually, he will be fucked up 😁		Gulf	not ironic	negative	negative	negative	negative	negative	negative	😁	Negativity Trigger
19	لاتغلط هاه 😡 Don't be offensive huh 😡		Gulf	not ironic	negative	negative	negative	negative	negative	negative	😡	Negativity Emphasizer

8.3 Reflection and Discussion

Based on the data analysis performed, our sentiment classifier based on the emoji-roles lexicon performs better than models such as Mazajak [105], CAMeL-Tools [106] and ASAD [109] in the analysis of Arabic texts with emoji. We found that although these advanced models are good at identifying patterns in large datasets, they might have difficulty understanding subtle sentiments in ironic contexts, especially when emoji are used.

The existing Arabic sentiment analysis models do not adapt to the use of emoji. Our classifier stands out because it comprehensively analyses emoji, giving them up to thirteen different sentiment scores based on their role in a text. This method recognises the various sentiments that emoji can convey, providing a more in-depth analysis than other models. Especially in Arabic texts where irony might have subtle hints or cultural nuances expressed through emoji. Furthermore, in straightforward texts, emoji usually emphasise and enhance the main sentiment of the text. However, in ironic texts, emoji can confuse rather than clarify the message. The adaptability of the emoji sentiment scores based on the contexts makes our approach perform better.

In addition, existing Arabic sentiment analysis models sometimes overlook linguistic subtleties, such as irony, due to their insufficient training methods. One challenge is that many training datasets focus more on straightforward sentiments and less on irony. Another challenge is that these models are mainly trained on MSA data and disregard other dialects. Therefore, classifiers based on such limited data may struggle in ironic contexts. This highlights the complexity of irony and the need for detailed large-scale Arabic training data. Current Arabic sentiment classifiers that are not designed for this depth may not perform well. The independence of our enhanced lexicon-based sentiment classification model from fixed training data allows it to adaptively capture the sentiment relationship between emoji and text in both ironic and straightforward contexts.

8.4 Chapter Conclusion

In summary, evaluating sentiment classifiers in ironic versus non-ironic Arabic short texts (i.e., tweets), especially those with emoji, reveals a set of unique challenges and possibilities. Simple texts that express sentiments clearly make it easier for classifiers to interpret. Ironic texts, with their multiple layers and possible double meanings, are more challenging. For a complete sentiment analysis, we need more than just well-designed training data. A deep understanding of the Arabic language and its subtle details in various contexts is vital. We will dive deeper into these insights, their limitations, and potential research areas in the next and final chapter of this thesis.

Chapter 9

Conclusion

In this final chapter, we summarise our research journey, looking back at our main goals and key discoveries. We will explain how our results address the main research questions and compare our findings with those of the current literature. We will outline the practical, theoretical, and conceptual impacts of our study and discuss its limitations. We will also suggest directions for future research and offer advice to relevant parties.

9.1 Research Summary

As we wrap up our study on the sentiment roles of emoji in Arabic texts, it is clear that digital communication combines a mix of verbal and non-verbal cues. This research emphasises the vital role of emoji, especially within the intricate nuances of the Arabic language.

In this research, we started by exploring the history and significance of emoji in communication, observing their development and ability to convey non-verbal signals. After reviewing current studies and understanding the previous methods, we identified areas where our work could fill in the gaps. We focussed on collecting a large Arabic dataset to design emoji-centric sentiment resources (i.e., lexicons) that are tailored to capture the essence of Arabic nuances. Our aim was to explore how emoji impact sentiment in Arabic and to what extent they are consistently interpreted in relation to sentiment. Finally, in a case study, we concluded by testing our emoji-role-based sentiment analysis approach on Arabic texts, especially those with irony, and comparing our findings with other existing Arabic sentiment models to determine strengths and areas to improve.

In considering the results of this research, it was clear that in the digital age today, the role of emoji in communication is significant. Emoji are not just digital symbols; they play an important role in conveying sentiment, especially in languages with many dialects like Arabic. Through thorough analysis, we addressed the core question of this thesis: "**How can sentiment analysis be refined to interpret emoji more effectively within the Arabic-specific cultural and linguistic context?**". Our findings suggest that emoji can represent various sentiments in short Arabic texts, depending on the context. Current Arabic sentiment analysis models may seem restrictive, in contrast to our adaptable approach. As the language landscape changes online, emoji adjust to cultural and dialectal variations, and our model responds effectively to these changes.

Our sentiment analysis model based on emoji roles offers a different approach com-

pared to other existing Arabic models. While these models assign a fixed sentiment to emoji regardless of context, our model considers the text's intricacies. Focussing on deeper sentiments rather than just surface-level interpretations, the model recognises the nuanced sentiment that emoji can express depending on the context. This approach aligns with the current understanding of emoji in Arabic literature and challenges traditional sentiment analysis methods in Arabic digital communication. The study highlights the importance of understanding the complex roles emoji play in Arabic tweets and the evolving nature of language online. Traditional Arabic sentiment models, with their fixed perspectives, may not always grasp these new digital sentiments effectively.

Looking ahead, the intersection of linguistics, technology, and cultural/social details is an exciting area to explore. This research provides a foundation for further studies in this field.

9.2 Primary Research Outcomes

Providing brief insights and conclusive findings that capture the essence of our scholarly investigation, the responses to the three key research questions are as follows.

RQ1: To what extent is the sentiment interpretation of an individual emoji consistent within the Arabic language? Comparing our context-sensitive emoji sentiment lexicon with the context-free one reveals that there is a moderate general agreement between the sentiment labels of the emoji in both lexicons. However, subtle discrepancies between these labels are evident when examining the intensities of emoji sentiment using their scores, determined by the RMSE, as shown in Figure D.1. Differences in emoji interpretations in Arabic can be attributed to the rich contextual depth of the language, the unique emotional meanings assigned within Arabic cultural narratives, and the influence of subjective experiences and biases of human annotators, which vary based on context and cultural factors.

RQ2: What are the potential emoji roles in altering the sentiment of Arabic written messages? We found that each emoji can play thirteen different sentiment roles within Arabic texts depending on the context. This leads us to be able to construct our role-based emoji sentiment lexicon, which is illustrated in Figure 7.3.

RQ3: How do alterations in emoji sentiment roles aid in discerning embedded sarcasm and humour in Arabic texts; and how does this enhance the accuracy of sentiment classification within these texts? Based on the sentiment model that uses the role-based emoji sentiment lexicon, ironic emoji patterns that play negative sentiment roles led to the classification of texts as sarcasm, while those that play positive sentiment roles resulted in the classification of texts as humorous. With ironic texts, our model showcased the highest accuracy scores (0.84) and agreement scores (0.66) with recall scores: 0.77, 0.86, and 0.87 for positive, neutral, and negative texts, respectively; compared to other Arabic sentiment classifiers. On the other hand, with non-ironic texts, our model demonstrated high recall scores for the negative (0.81) and positive (0.95) ones, but a low recall score (0.45) with the neutral ones. This arises due to the limited supply of neutral texts in the data used to build lexicons, leading to the difficulty of distinguishing genuinely neutral texts from those that present a balanced sentiment. In addition, the model struggles with low recall scores in neutral texts, heavily relying on high-polarity words or emoji. This is attributed to the influence of cultural nuances, idiomatic expressions, or current events on text neutrality, which is inherently subjective and it is challenging for a deterministic algorithm to consistently align with human judgments.

9.3 Pitfalls and Limitations

Our model addresses the nuances of digital sentiment analysis, particularly for Arabic texts that contain emoji. It aims at greater accuracy and sensitivity than the earlier models.

However, given the expansive nature of digital analysis, no model is without limitations. Thus, our sentiment classification journey has its own set of pitfalls.

An apparent limitation is that the emoji-role-based sentiment model is primarily built on emoji lexicons derived from concise content such as tweets. Given the brevity and character constraints of tweets, they may not always convey sentiments or discussions comprehensively. This can sometimes cause the model to misinterpret the sentiment roles of some emoji within longer complicated contexts. Furthermore, the constantly changing dynamics of platforms such as Twitter, which regularly introduces new emoji, changing slang, and cultural shifts, pose additional challenges for classifiers designed based on such data. This ever-evolving linguistic environment necessitates active adaptability from classifiers, requiring regular updates of its lexicons. In addition, the adaptability and complexity of our lexicon-based model, which are its strengths, can also bring challenges, such as slower performance, higher computational demands, and difficulties in making it work with larger data. Another layer of complexity is present in the sensitivity of the model. On the one hand, this sensitivity is advantageous, as it can capture even subtle nuances of sentiment. However, it also carries the risk of reacting strongly to data noise or outliers. Besides that, like all sentiment analysis models, there is a constant concern of bias, which can arise from cultural, linguistic, individual subjectivity, or other factors present in the design of the model.

In general, reliance mainly on lexicons and external resources for sentiment analysis models can be a double-edged sword, potentially impacting performance during times of resource shortages.

9.4 Recommendations and Future Work

To enhance sentiment analysis in Arabic social networks, our study of Arabic tweets using the emoji-role-based sentiment model marked a notable advance. Yet, as highlighted earlier,

our method, while promising, has limitations. Addressing these limitations requires different strategies.

The first suggestion is to use a variety of data sources, from complete tweet threads[1] to YouTube comments and WhatsApp chats, providing a comprehensive perspective on digital Arabic language patterns. By merging these data with the specific sentiment indicators using our emoji-role-based sentiment model, we can craft a representative training dataset for improved Arabic social media sentiment analysis classifiers.

Moreover, the advent of recent advanced learning models, such as BERT and GPT[2], when integrated with our emoji sentiment lexicon, promises improved sentiment insights, especially in emoji-laden content. Combining external knowledge with our lexicon could improve sentiment analysis by adding deeper context. Using various methods, such as layered models, feedback loops, combined analyses, transfer learning, and human-machine interaction, might revolutionise how we understand sentiments of digital communication.

In addition, exploring the many Arabic dialects requires specialised training methods, focused models for each dialect, and continuous data collection. By including our emoji-role-based lexicon, we can create models that understand local language variations and recognise how emoji convey sentiments in these dialects.

This work combines technology and language in a detailed way. With the help of our emoji-role-based sentiment lexicon, we aim to shape future research. We hope that other researchers will update the lexicon with new digital trends and dive deeper into how emotions are expressed online across different languages and platforms. This study has a wider impact than just understanding sentiment and highlights the complexities of today's online communication. The knowledge encompassed here can help businesses, researchers, and psychologists understand how people communicate in the digital age. It also offers

[1]The series of replies and discussions that stem from an initial tweet.

[2]Generative Pre-trained Transformer.

language experts a new way to study the evolution of the Arabic language, online habits, cultural differences, and complex online interactions.

This research acts as a roadmap for those who analyse social media networks. It emphasises the importance of emoji in expressing sentiment in Arabic and underscores the need to continuously update Arabic sentiment analysis models to the evolving nature of online communication.

Appendix A

Emoji's Scores-to-Labels Sentiment Scale

Applying Satthar, Evans, and Uchyigit [3]'s method, we first, needed a training dataset to assign boundaries of sentiment classes, where the classes have a natural sentiment order. For that, we randomly selected 579 emoji from our lexicon and let five Arabic-speaking annotators annotate them. We adapted Hakami, Hendley, and Smith [38] sentiment annotation process. For each emoji, at least three annotators agree on its sentiment label. This resulted in 287 emoji labelled as *Neutral*, 179 emoji labelled as *Positive*, and 86 emoji labelled as *Negative*. To ensure that each sentiment class had an equal number of emoji, we selected only 86 emoji for each label. Thus, the total emoji were 258 emoji. For each sentiment class, minimum (i.e., Min) and maximum (i.e., Max) boundaries should be set. In our dataset, the Min and Max boundaries for each class were as follows:

- **Negative** Class: $[Min = -0.934065934065934, Max = 0.1538461538461538]$.
- **Neutral** Class: $[Min = -0.5, Max = 0.8205128205128205]$.
- **Positive** Class: $[Min = 0.0675675675675675, Max = 0.8695524578136464]$.

Afterwards, the calculation of upper and lower boundary values of each sentiment class at

a time in sentiment order should be conducted. For instance, in a three-class classification, boundary values calculation should be applied for negative (1^{st} class), then neutral (2^{nd} class) and then positive (3^{rd} class). Then, the optimal cut-off value between each two boundaries should be determined to delimit the classes. To compute the cut-off value for a multi-class problem, it is necessary to first reduce it into a standard binary class problem. This can be done by selecting two classes, the $(n)^{th}$ order class and the $(n+1)^{th}$ order class, and computing the cut-off values between them. Documents belonging to these two classes are selected from the training dataset and run through a semantic classifier to obtain numerical scores for each document in each class. The maximum score for the $(n)^{th}$ class, $Max_{(n)}$, and the minimum score for the $(n+1)^{th}$ class, $Min_{(n+1)}$, are considered to calculate the cut-off value, $C_{n/n+1}$. It should be noted that the score ranges for the two classes may overlap, and $Max_{(n)}$ may be greater than $Min_{(n+1)}$.

In our dataset, the first two classes were *Positive-to-Neutral*, where *Positive* is the upper class and *Neutral* is the lower class. Thus, there were 18 possible cut-offs (0.06, 0.0625, 0.07, 0.12, 0.17, 0.22, 0.27, 0.32, 0.37, 0.42, 0.47, 0.52, 0.57, 0.62, 0.67, 0.72, 0.77, 0.82) ranged between the minimum of the *Positive* class (i.e., 0.06) and the maximum of the *Neutral* class (i.e., 0.82). The grey bar in Figure A.1-(A) visualize them clearly. The second two classes were *Neutral-to-Negative*, where *Neutral* is the upper class and *Negative* is the lower class. There were 16 possible cut-offs (-0.5, -0.45, -0.4, -0.35, -0.3, -0.25, -0.2, -0.15, -0.09, -0.0625, -0.06, -0.04, 0.01, 0.06, 0.11, 0.16) ranged between the minimum of the *Neutral* class (i.e., -0.5) and the maximum of the *Negative* class (i.e., 0.16). The grey bar in Figure A.1-(B) visualize them clearly.

Different PR curves were plotted for candidate cut-off values between these score ranges to determine the cut-off value that produces the best performance. A PR curve demonstrates how well the classifier system can categorize using the candidate cut-off as the class boundary, for various combinations of the two classes. The dataset is divided into k subsets with an equal number of documents in each subset. Each subset contains $(n)^{th}$ class documents and

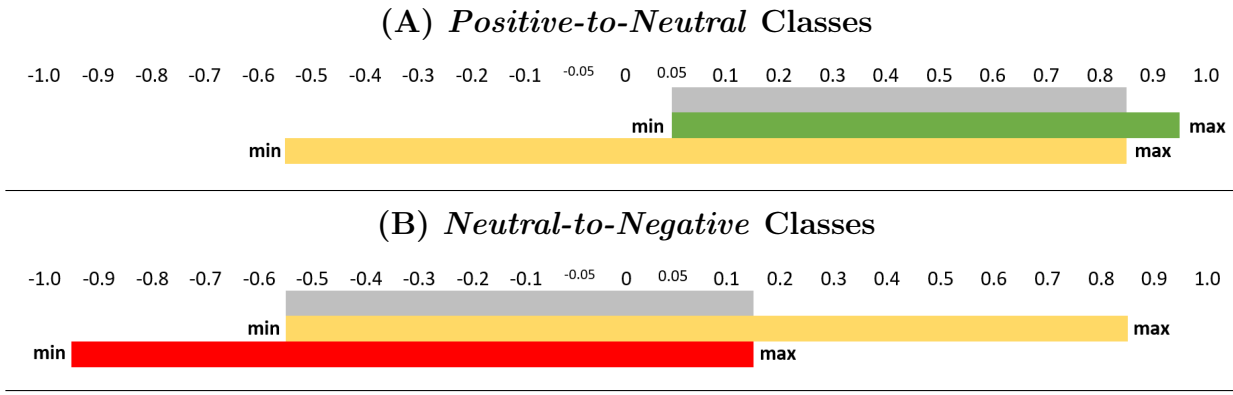
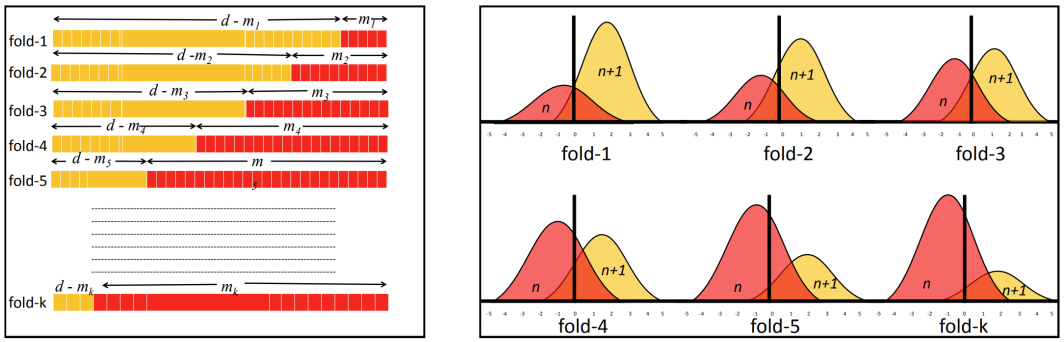


Figure A.1: The Representation of All The Possible Cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* Classes for Emoji Scores-to-Labels Sentiment Scale.

$(n+1)^{\text{th}}$ class documents in different proportions, as is illustrated in Figure A.2.



(a) Folds containing mixtures of 2 document classes

(b) Example histograms and cut-off points for different balances between n^{th} and $n+1^{th}$ classes in different folds

Figure A.2: k-fold Class Mixtures To Produce PR Curves For Each Cut-off Candidate [3].

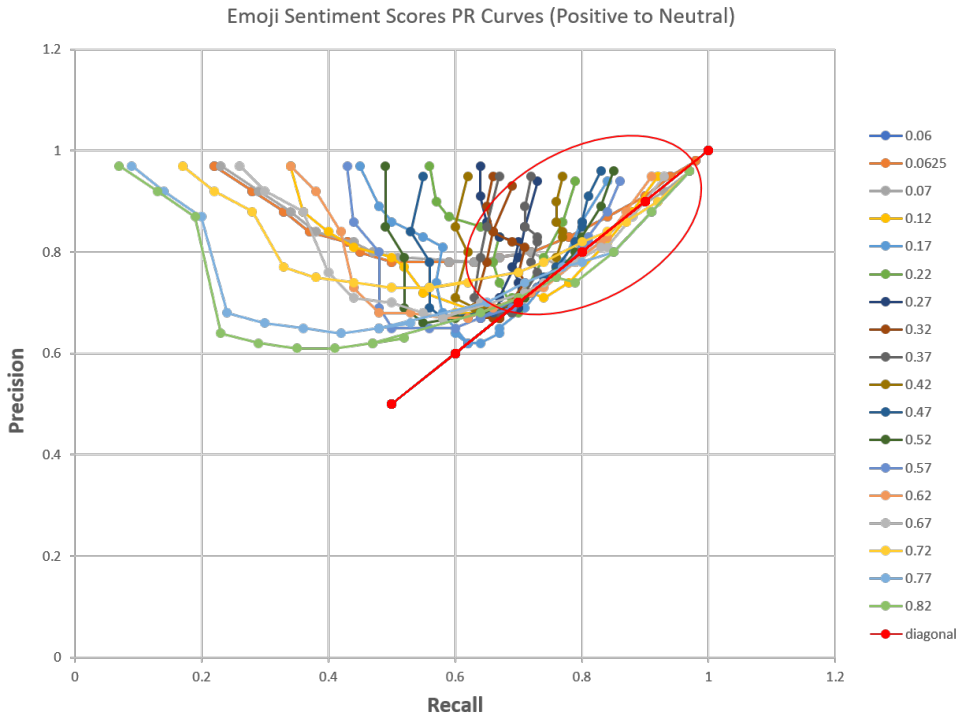
In our case, for each possible cut-off value in *Positive-to-Neutral* classes, we calculated precision and recall value for 17 sub-training datasets, each subset containing a mixture of 86 positive and neutral emoji. Also, the same has been applied for each possible cut-off value in *Neutral-to-Negative* classes. We calculated precision and recall values for 17 sub-training datasets, each subset containing a mixture of 86 neutral and negative emoji. The precision and recall scores for each class for a given cut-off value are different for each subset, so we calculate the macro-average precision and recall across the two classes, and plot the different precision/recall values for a single cut-off value across all the folds. Figure A.3-(A)

displays the PR curves for all the 18 possible cut-offs between **Positive** and **Neutral** sentiment classes. Likewise, Figure A.3-(B) displays the PR curves for all the 16 possible cut-offs between **Neutral** and **Negative** sentiment classes.

The best cut-off value produces high and almost equal values of precision and recall, and the PR curve of the best cut-off value lies in the top right-hand corner of the graph, as well as close to the diagonal line ($p = r$). Initially, the expectation was that the best PR curve could be selected through visual inspection. However, in practice, while this method is effective in eliminating unsuitable candidates, the final selection is also aided by generating plots of the average recall and precision for each PR curve. The ideal cut-off value will have a PR curve as close to the diagonal, and as far towards the top right corner as possible. As can be seen in Figure A.3, although the general trend is for all the curves to be in the top right half of the graph, many of them deviate significantly from the diagonal line. We focused on the six curves closest to the diagonal (by visual inspection), for further analysis. The six candidate cut-off values remaining after this step were 0.06, 0.0625, 0.07, 0.12, 0.17 and 0.22 for the *Positive-to-Neutral* classes; and they were -0.15, -0.09, -0.06, -0.0625, -0.04 and 0.01 for the *Neutral-to-Negative* classes.

Then, we calculated the averaged precision and recall values of each of the candidate cut-off values and plotted these in a scatter plot as is seen in Figure A.4. To validate these cut-off values, we also compared F1 scores for the candidate cut-off values from these macro-averaged recall and precision values. We only considered the candidate values with the highest F1 scores. Table A.1 shows that the cut-off with value 0.0625 has the maximum F1 core value in *Positive-to-Neutral*; and that the cut-off with value -0.0625 has the maximum F1 score value in *Negative-to-Neutral* classes. From this, we concluded that the best cut-off value for the first two classes *Positive-to-Neutral* (i.e., $C_{Positive/Neutral}$) was 0.0625; and the best cut-off value for the second two classes *Neutral-to-Negative* (i.e., $C_{Neutral/Negative}$) was -0.0625 as is shown in Figure A.5.

(A) *Positive-to-Neutral* Classes



(B) *Neutral-to-Negative* Classes

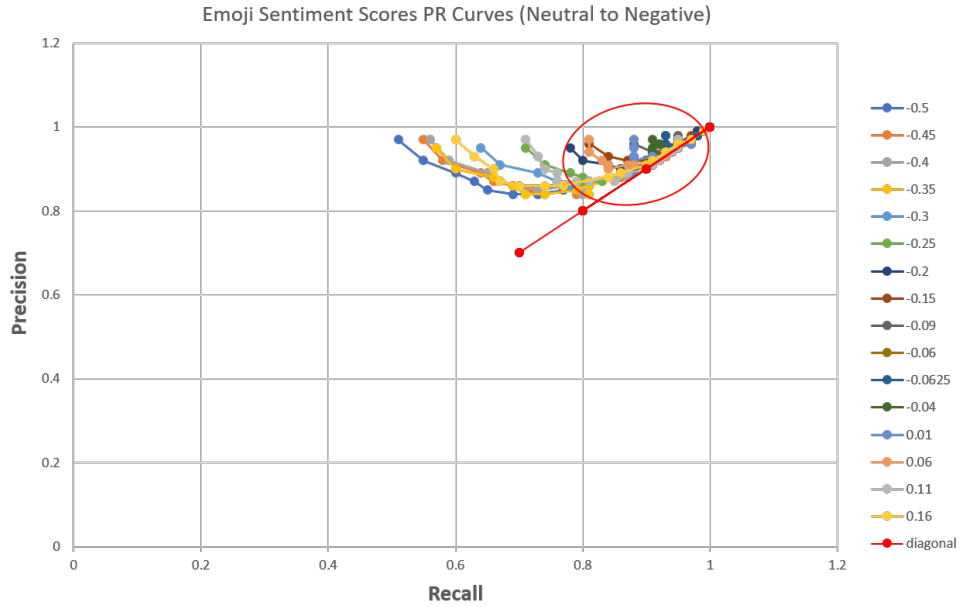
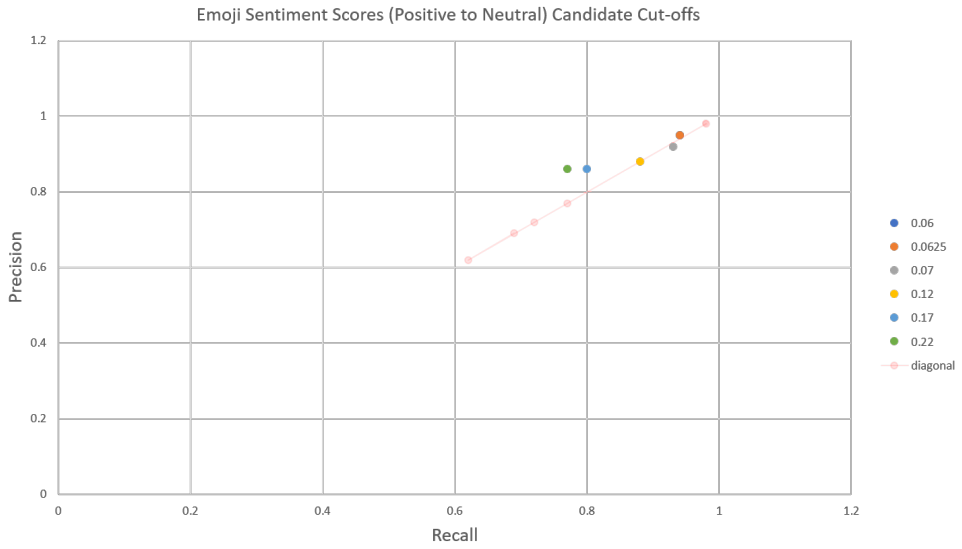


Figure A.3: The Precision-Recall (PR) Curves for All The Possible Cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* Classes for Emoji Scores-to-Labels Sentiment Scale.

(A) *Positive-to-Neutral* Classes



(B) *Neutral-to-Negative* Classes

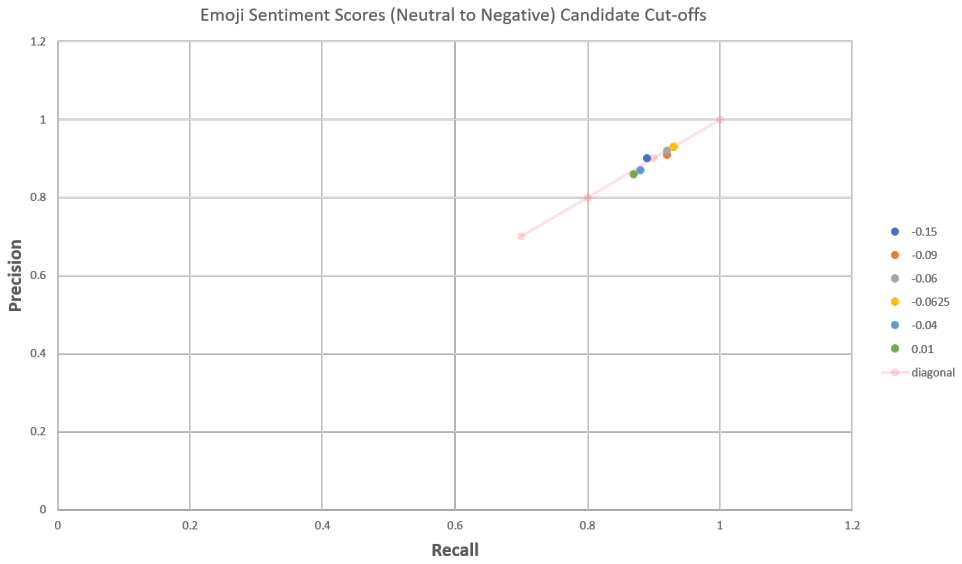


Figure A.4: PR curves for the candidate cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for emoji scores-to-labels sentiment scale.

Table A.1: Average Precision, Recall and F-score measures for candidate cut-off values for emoji scores-to-labels sentiment scale.

Positive-to-Neutral Classes				**Neutral-to-Negative Classes**			
Cut-offs	*Precision*	*Recall*	*F1*	**Cut-offs**	*Precision*	*Recall*	*F1*
0.06	0.95	0.94	0.93	-0.15	0.9	0.89	0.90
0.0625	**0.95**	**0.94**	**0.93**	-0.09	0.91	0.92	0.92
0.07	0.92	0.93	0.92	-0.06	0.92	0.92	0.92
0.12	0.88	0.88	0.88	**-0.0625**	**0.93**	**0.92**	**0.93**
0.17	0.86	0.8	0.83	-0.04	0.87	0.88	0.89
0.22	0.86	0.77	0.8	0.01	0.86	0.87	0.86

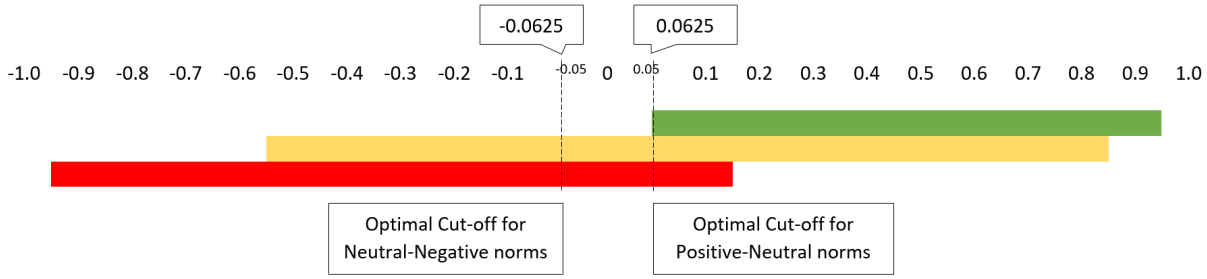


Figure A.5: Emoji's Scores-to-Labels Sentiment Scale

These cut-off values were then used to map the numerical scores in our lexicon to the three sentiment classes, negative, neutral, and positive, in an optimal way. We assign the sentiment labels to the emoji in our lexicon based on Equation A.1, as follows:

$$Emoji_i_Label = \begin{cases} \textbf{positive}, & \text{if } (\textbf{0.0625} < Emoji_i_Score \leq \textbf{1}) \\ \textbf{neutral}, & \text{if } (\textbf{-0.0625} \leq Emoji_i_Score \leq \textbf{0.0625}) \\ \textbf{negative}, & \text{if } (\textbf{-1} < Emoji_i_Score \leq \textbf{-0.0625}) \end{cases} \tag{A.1}$$

Emoji with sentiment score i, where -1 $\leq i <$ -0.0625, was classified as negative. Emoji with sentiment score i, where $1 \geq i >$ 0.0625, was classified as positive. Lastly, an emoji was classified as neutral when its sentiment score i was in the range where -0.0625 $\leq i \leq$ 0.0625.

Appendix B

Words' Scores-to-Labels Sentiment Scale

Using the calibration method described in Appendix-A, we selected two Arabic words sentiment lexicons: the *Arabic Senti-Lexicon*[1] [267] and the *NileULex*[2] [268]. These lexicons were combined to form a training dataset that was used to establish the boundaries of the sentiment classes. The resulting dialectic sentiment lexicon comprises a total of 2,140 Arabic words. To ensure that each sentiment class had an equal number of words, we selected only 28 words for each label, making 84 words in total. For each sentiment class, a minimum (i.e., Min) and maximum (i.e., Max) boundaries have been established as follows:

- **Negative** Class: $[Min = -0.8787878787878788, Max = 0.4096385542168674]$.
- **Neutral** Class: $[Min = -0.5, Max = 0.5]$.
- **Positive** Class: $[Min = -0.365079365079365, Max = 0.7051282051282052]$.

The calculation of upper and lower boundary values of each sentiment class at a time in sentiment order was carried out as follows. The first two classes were *Positive-to-Neutral*, where *Positive* is the upper class and *Neutral* is the lower class. There were 20 possible cut-offs (-0.37, -0.32, -0.27, -0.22, -0.17, -0.12, -0.07, -0.02, 0.01, 0.06, 0.0625, 0.11, 0.16, 0.21,

[1] https://github.com/almoslmi/masc
[2] https://github.com/NileTMRG/NileULex

0.25, 0.31, 0.36, 0.41, 0.46, 0.51) ranged between the minimum of the *Positive* class (i.e., -0.37) and the maximum of the *Neutral* class (i.e., 0.51). The grey bar in Figure B.1-(A) clearly visualises them. The second two classes were *Neutral-to-Negative*, where *Neutral* is the upper class and *Negative* is the lower class. There were 20 possible cut-offs (-0.5, -0.45, -0.4, -0.35, -0.3, -0.25, -0.2, -0.15, -0.1, -0.0625, -0.05, 0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40) ranged between the minimum of the *Neutral* class (i.e., -0.5) and the maximum of the *Negative* class (i.e., 0.50). The grey bar in Figure B.1-(B) clearly visualises them.

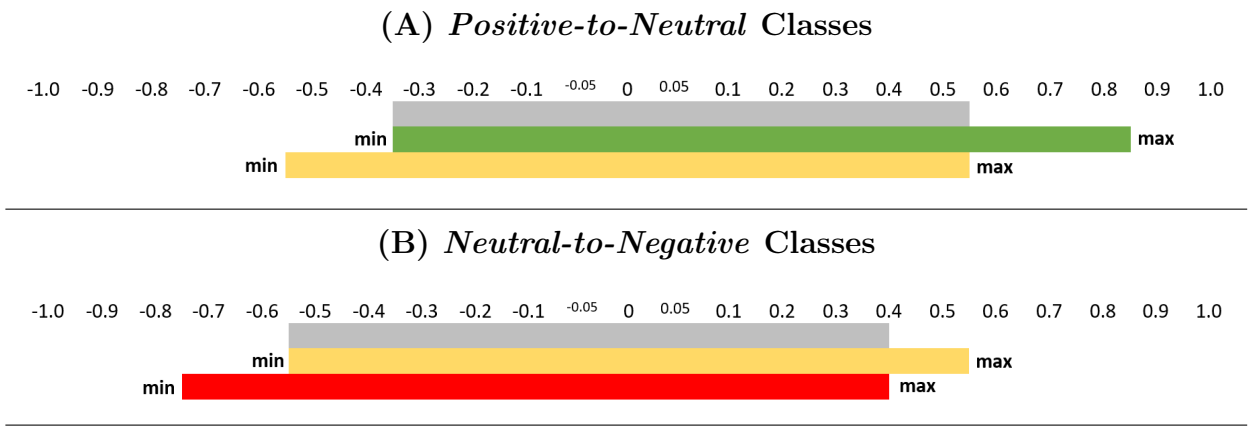


Figure B.1: The representation of all the possible cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for words scores-to-labels sentiment scale.

For each possible cut-off value in *Positive-to-Neutral* classes, we calculated the precision and recall value for 5 sub-training datasets, each subset containing a mixture of 28 positive and neutral emoji. Furthermore, the same has been applied for each possible cut-off value in the *Neutral-to-Negative* classes. We calculated precision and recall values for five subtraining datasets, each subset containing a mixture of 28 neutral and negative emoji. The precision and recall scores for each class for a given cut-off value are different for each subset, so we calculate the macro-average precision and recall across the two classes, and plot the different precision/recall values for a single cut-off value across all the folds. Figure B.2-(A) displays the PR curves for all the 20 possible cut-offs between **Positive** and **Neutral** sentiment classes. Likewise, Figure B.2-(B) displays the PR curves for all 22 possible cut-offs between **Neutral** and **Negative** sentiment classes. The ideal cut-off value will have

a PR curve as close to the diagonal and as far towards the top right corner as possible. As can be seen in Figure B.3, although the general trend is that all curves are in the upper right half of the graph, many of them deviate significantly from the diagonal line. We focused on the six curves closest to the diagonal (by visual inspection) for further analysis. The six candidate cut-off values remaining after this step were 0.16, 0.21, 0.25, 0.31, 0.36 and 0.41 for the *Positive-to-Neutral* classes; and they were -0.35, -0.3, -0.25, -0.2, -0.15 and -0.1 for the *Neutral-to-Negative* classes.

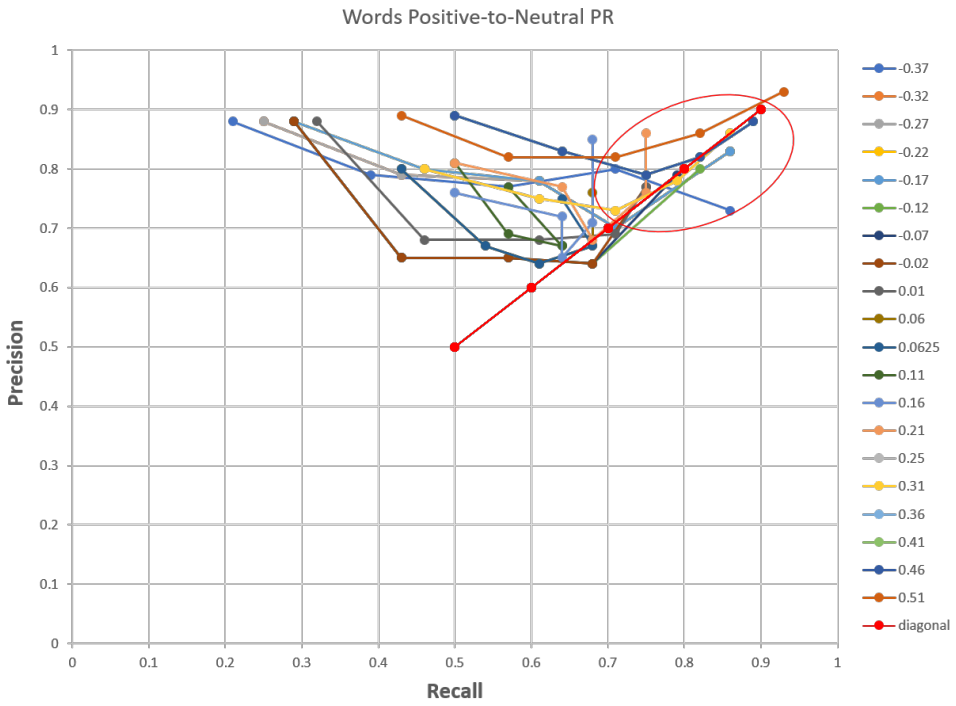
We, then, calculated the averaged precision and recall values of each of the candidate cut-off values and plotted them in a scatter plot as seen in Figure B.3. To validate these cut-off values, we also compared F1 scores for the candidate cut-off values of these macro-averaged recall and precision values. We only considered the candidate values with the highest F1 scores. Table B.1 shows that the cut-off with value 0.25 has the maximum F1 score value in *Positive-to-Neutral*; and that the cut-off with value -0.25 has the maximum F1 score value in *Negative-to-Neutral* classes. We concluded that the best cut-off value for the first two classes *Positive-to-Neutral* (i.e., $C_{Positive/Neutral}$) was 0.25; and the best cut-off value for the second two classes *Neutral-to-Negative* (i.e., $C_{Neutral/Negative}$) was -0.25 as is shown in Figure B.4.

Table B.1: Average Precision, Recall and F-score measures for candidate cut-off values for words scores-to-labels sentiment scale.

Positive-to-Neutral Classes				**Neutral-to-Negative Classes**			
Cut-offs	*Precision*	*Recall*	*F*1	**Cut-offs**	*Precision*	*Recall*	*F*1
0.16	0.7	0.66	0.64	-0.35	0.8	0.77	0.76
0.21	0.73	0.66	0.68	-0.3	0.83	0.82	0.82
0.25	**0.77**	**0.74**	**0.86**	**-0.25**	**0.83**	**0.82**	**0.82**
0.31	0.8	0.68	0.85	-0.2	0.77	0.73	0.74
0.36	0.77	0.68	0.82	-0.15	0.75	0.66	0.74
0.41	0.8	0.66	0.82	-0.1	0.79	0.64	0.73

These cut-off values were then used to map the numerical scores in our lexicon to the three sentiment classes negative, neutral and positive, as shown in Figure B.4. We assign these sentiment labels based on Equation B.1, as follows:

(A) *Positive-to-Neutral* Classes



(B) *Neutral-to-Negative* Classes

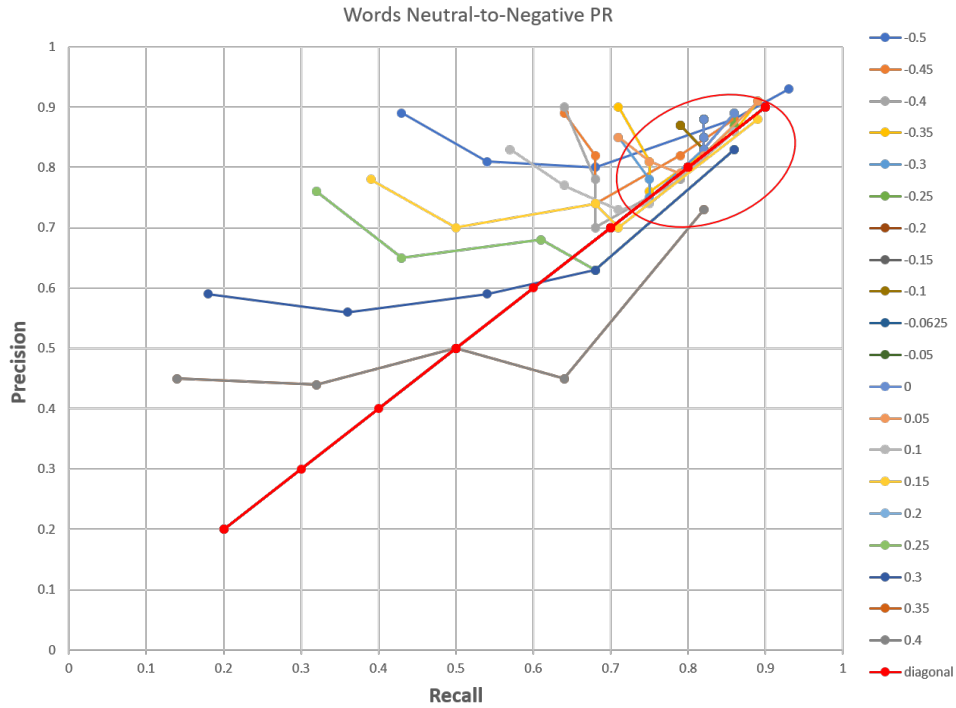
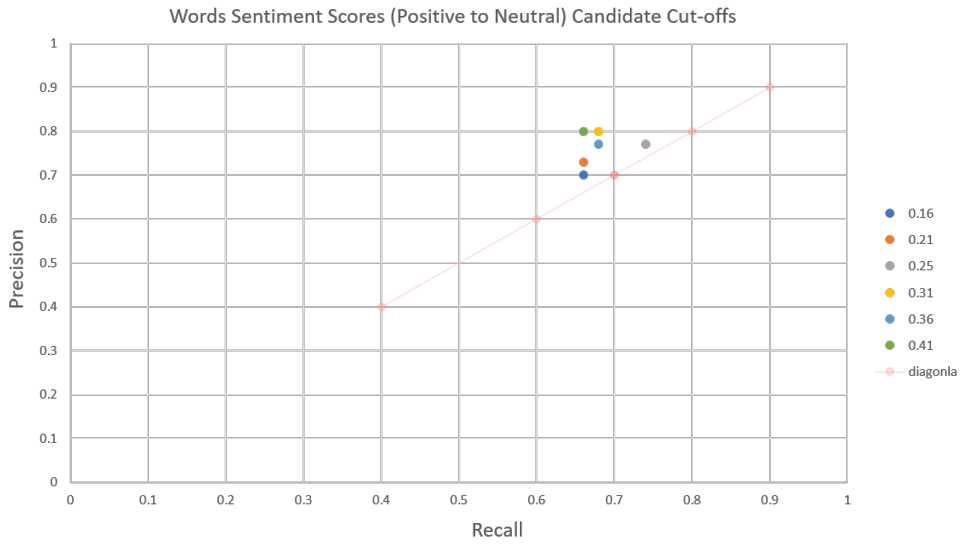


Figure B.2: The Precision-Recall (PR) curves for all the possible cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for words scores-to-labels sentiment scale.

(A) *Positive-to-Neutral* Classes



(B) *Neutral-to-Negative* Classes

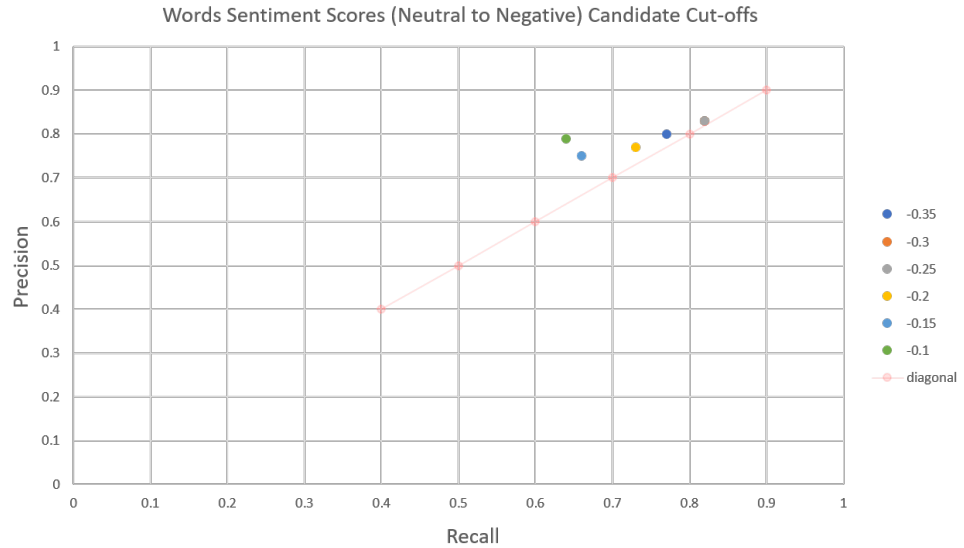


Figure B.3: PR curves for the candidate cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for words scores-to-labels sentiment scale.

$$Word_i_Label = \begin{cases} \textbf{positive}, & \text{if } (\textbf{0.25} < Word_i_Score \leq \textbf{1}) \\ \textbf{neutral}, & \text{if } (\textbf{-0.25} \leq Word_i_Score \leq \textbf{0.25}) \\ \textbf{negative}, & \text{if } (\textbf{-1} < Word_i_Score \leq \textbf{-0.25}) \end{cases} \tag{B.1}$$

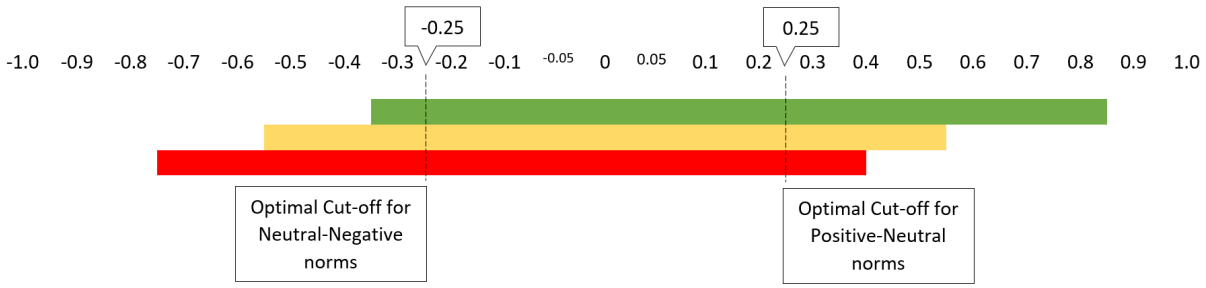


Figure B.4: Words' Scores-to-Labels Sentiment Scale.

Appendix C

Sentences' Scores-to-Labels Sentiment Scale

The same calibration method as described earlier in Appendix-A was utilized in this case. The training set was selected from the gold standard data (i.e., described in Section 5.3.1) comprising a total of **252** Arabic Emoji-texts, which were divided into three distinct groups based on their sentiment: negative, neutral, and positive texts, each group consisting of 84 texts. This was to ensure that each sentiment class had an equal number of texts. The test set consisted of the same texts with sentiment scores calculated using Equation 6.11. For each sentiment class, the minimum (i.e. Min) and maximum (i.e. Max) boundaries have been set as follows:

- **Negative** Class: $[Min = -2.355848958733977, Max = 1.204220304401081]$.
- **Neutral** Class: $[Min = -1.4261652292780012, Max = 2.0156271067433815]$.
- **Positive** Class: $[Min = -0.8640465687120402, Max = 2.3037941875933226]$.

The calculation of upper and lower boundary values of each sentiment class at a time in

sentiment order was carried out as follows. The first two classes were *Positive-to-Neutral*, where *Positive* is the upper class and *Neutral* is the lower class. There were 32 possible cut-offs (-0.9, -0.82, -0.72, -0.62, -0.52, -0.42, -0.32, -0.22, -0.12, -0.02, 0.08, 0.18, 0.28, 0.38, 0.48, 0.50, 0.58, 0.68, 0.78, 0.88, 0.98, 1.08, 1.18, 1.28, 1.38, 1.48, 1.58, 1.68, 1.78, 1.88, 1.98, 2.02) ranged between the minimum of the *Positive* class (i.e., -0.92) and the maximum of the *Neutral* class (i.e., 2.02). The grey bar in Figure C.1-(A) clearly visualises them. The second two classes were *Neutral-to-Negative*, where *Neutral* is the upper class and *Negative* is the lower class. There were 40 possible cut-offs (-1.42, -1.32, -1.22, -1.12, -1.02, -0.92, -0.82, -0.72, -0.62, -0.50, -0.52, -0.42, -0.32, -0.22, -0.12, -0.02, 0.08, 0.14, 0.19, 0.24, 0.29, 0.34, 0.39, 0.44, 0.49, 0.54, 0.59, 0.64, 0.69, 0.74, 0.79, 0.84, 0.89, 0.94, 0.99, 1.04, 1.09, 1.14, 1.19, 1.24) ranged between the minimum of the *Neutral* class (i.e., (-1.42) and the maximum of the *Negative* class (i.e., 1.20). The grey bar in Figure C.1-(B) clearly visualise them.

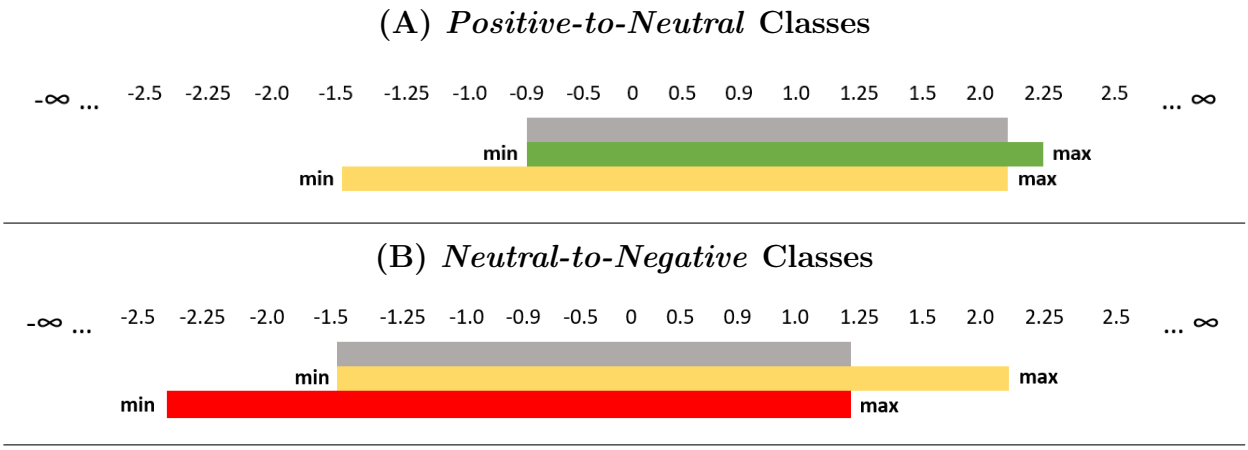


Figure C.1: The representation of all the possible cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for sentences scores-to-labels sentiment scale.

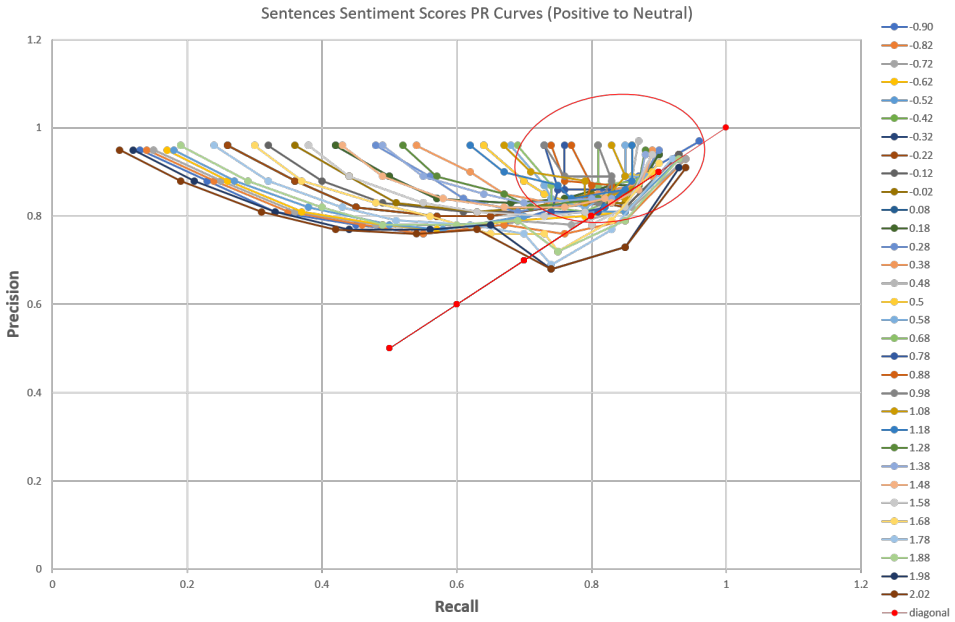
For each possible cut-off value in the *Positive-to-Neutral* classes, we calculated the precision and recall value for 9 sub-raining datasets, each subset containing a mixture of 84 positive and neutral emoji. Furthermore, the same has been applied for each possible cut-off value in *Neutral-to-Negative* classes. We calculated precision and recall values for 9 sub-training datasets, each subset containing a mixture of 84 neutral and negative emoji.

The precision and recall scores for each class for a given cut-off value are different for each subset, so we calculate the macro-average precision and recall across the two classes, and plot the different precision/recall values for a single cut-off value across all the folds. Figure C.2-(A) displays the PR curves for all the 32 possible cut-offs between **Positive** and **Neutral** sentiment classes. Likewise, Figure C.2-(B) displays the PR curves for all 40 possible cut-offs between **Neutral** and **Negative** sentiment classes. The ideal cut-off value will have a PR curve as close to the diagonal and as far toward the top right corner as possible. As can be seen in Figure C.2, although the general trend is that all curves are in the upper right half of the graph, many of them deviate significantly from the diagonal line. We focused on the six curves closest to the diagonal (by visual inspection) for further analysis. The six candidate cut-off values remaining after this step were 0.5, 0.58, 0.68, 0.78, 0.88, and 0.98 for the *Positive-to-Neutral* classes; and they were -0.72, -0.62, -0.5, -0.52, -0.42 and -0.32 for the *Neutral-to-Negative* classes. We then calculated the macro-average precision and recall values of each of the candidate cut-off values and plotted them in a scatter plot as is seen in Figure C.3.

To validate these cut-off values, we also compared f-scores for the candidate cut-off values from these macro-averaged recall and precision values. We only considered the candidate values with the highest F1. Table C.1 shows that the cut-off with value 0.5 has the maximum value of F1 in *Positive-to-Neutral*; and that the cut-off with value -0.5 has the maximum F1 value in *Negative-to-Neutral* classes. From this, we concluded that the best cut-off value for the first two classes *Positive-to-Neutral* (i.e., $C_{Positive/Neutral}$) was 0.5; and the best cut-off value for the second two classes *Neutral-to-Negative* (i.e., $C_{Neutral/Negative}$) was -0.5 as is shown in Figure C.4.

These cut-off values were then used to map the numerical scores for text b in our dataset to the three sentiment classes negative, neutral, and positive. We assign these sentiment labels

(A) *Positive-to-Neutral* Classes



(B) *Neutral-to-Negative* Classes

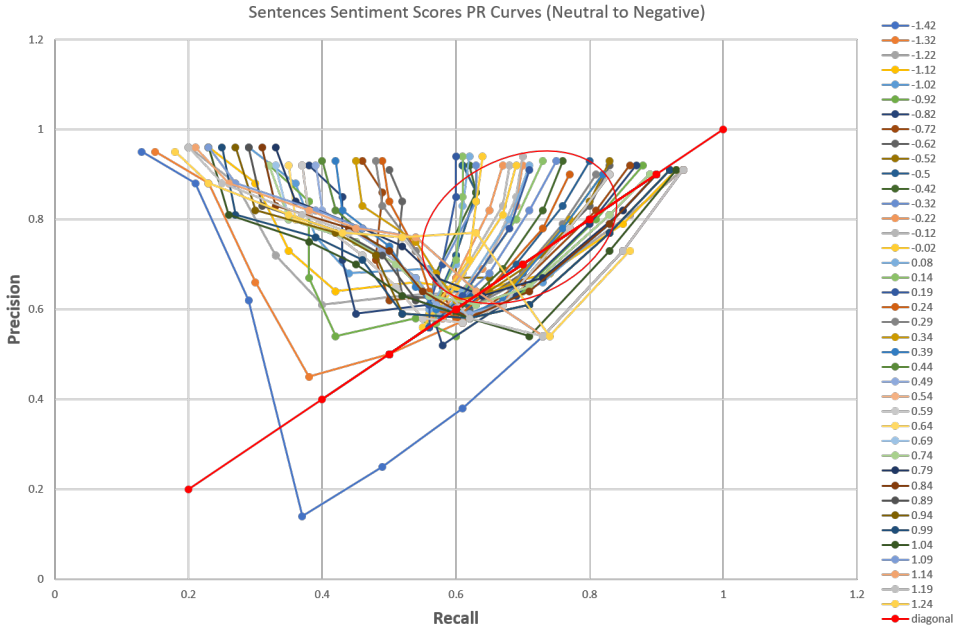
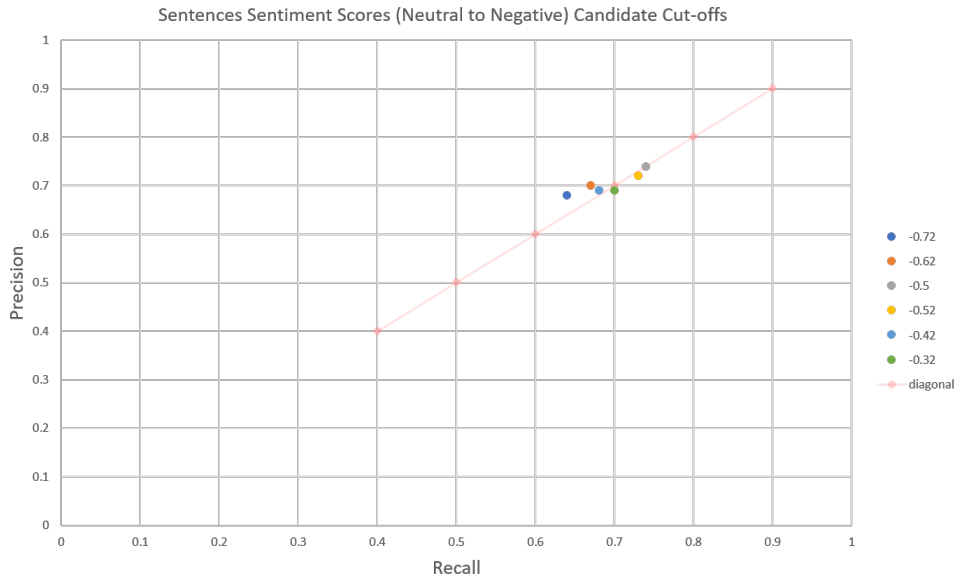


Figure C.2: The Precision-Recall (PR) curves for all the possible cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for sentences scores-to-labels sentiment scale.

(A) *Positive-to-Neutral* Classes



(B) *Neutral-to-Negative* Classes

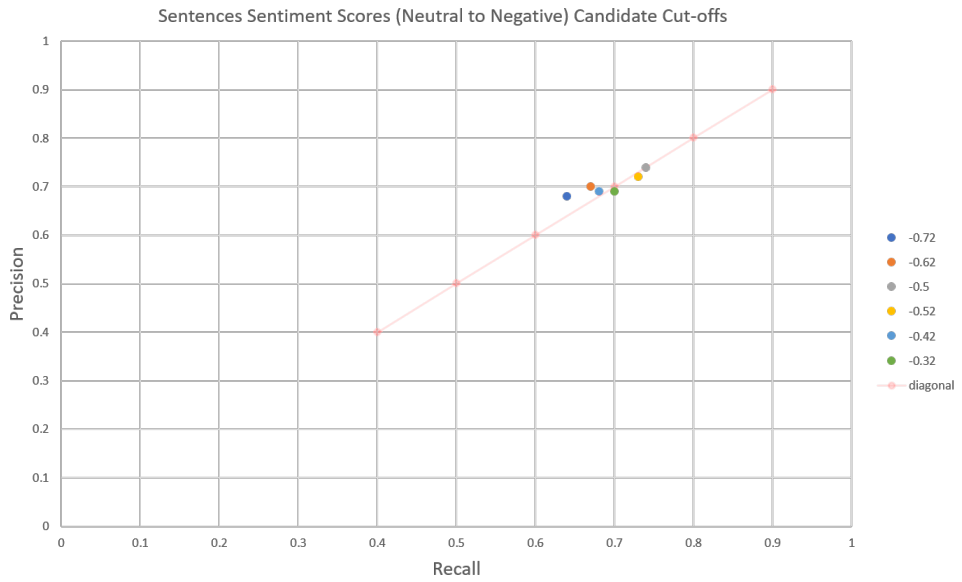


Figure C.3: PR curves for the candidate cut-offs in *Positive-to-Neutral* and *Neutral-to-Negative* classes for sentences scores-to-labels sentiment scale.

Table C.1: Average Precision, Recall, and F-score measures for candidate cut-off values for sentences scores-to-labels sentiment scale.

Positive-to-Neutral Classes				**Neutral-to-Negative Classes**			
Cut-offs	*Precision*	*Recall*	*F1*	**Cut-offs**	*Precision*	*Recall*	*F1*
0.5	**0.76**	**0.76**	**0.76**	-0.72	0.68	0.64	0.62
0.58	0.76	0.75	0.75	-0.62	0.7	0.67	0.65
0.68	0.74	0.74	0.74	**-0.5**	**0.74**	**0.74**	**0.73**
0.78	0.73	0.73	0.73	-0.52	0.72	0.73	0.7
0.88	0.74	0.74	0.74	-0.42	0.69	0.68	0.68
0.98	0.75	0.74	0.74	-0.32	0.69	0.7	0.69

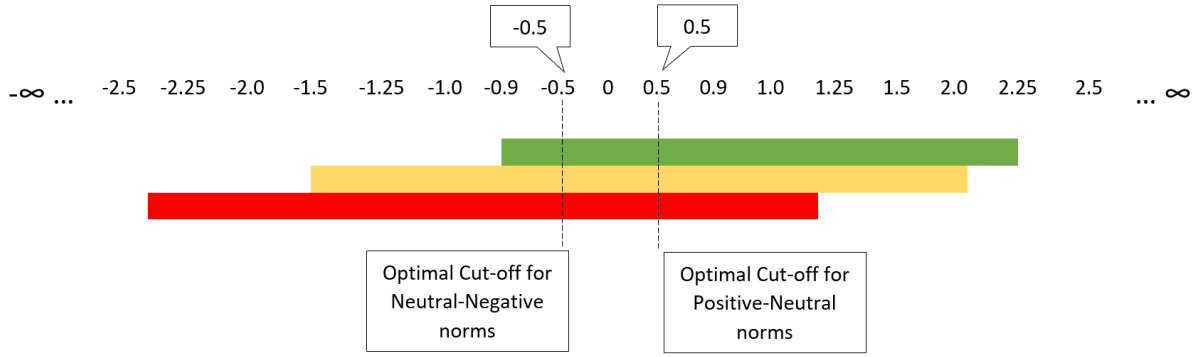


Figure C.4: Sentences' Scores-to-Labels Sentiment Scale.

based on Equation C.1, as follows:

$$Sentence_i_Label = \begin{cases} \textbf{positive}, & \text{if } (\textbf{0.5} < Sentence_i_Score \leq \infty) \\ \textbf{neutral}, & \text{if } (\textbf{-0.5} \leq Sentence_i_Score \leq \textbf{0.5}) \\ \textbf{negative}, & \text{if } (-\infty < Sentence_i_Score \leq \textbf{-0.5}) \end{cases} \tag{C.1}$$

Appendix D

Context-Sensitive vs. Context-Free Arabic Emoji Lexicons Analysis Results

Table D.1: Statistical Analysis Results for Comparisons between Context-Sensitive and Context-Free Lexicons (Part I).

#	Emoji Class	Sentiment Label	Emoji Size	Cohen Kappa (κ)	Root Mean Square Error (RMSE)		
					Both	Context-Sensitive	Context-Free
1	**All Emoji**	Total	459	0.4841926902715469	0.4017986309707579	0.2829644092571804	0.12794157230141803
2		Negative	121	0.02336448598130836	0.3127737605835312	0.2278212852175457	0.09736755810816526
3		Neutral	29	-0.05994152046783641	0.40822481842119573	0.28941595245657487	0.12478538439188758
4		Positive	309	-0.009489732420659758	0.4311197363313213	0.30125042539626756	0.13835239818782313
5	**Object**	Total	78	0.25878999049730755	0.38783005581374624	0.2704763341208047	0.1264705368308392
6		Negative	13	-0.2264150943396228	0.41527339584540746	0.3149582251219189	0.10861764678120112
7		Neutral	4	-0.6000000000000001	0.44901741816458146	0.3357350383854931	0.1226808955332339
8		Positive	61	0	0.37730288287326447	0.2549775284370961	0.13019659923002141
9	**Symbol**	Total	75	0.5124113475177305	0.3318013277691432	0.2346377816608424	0.10553946954970791
10		Negative	29	-0.05454545454545445	0.2969386338234663	0.2023056513040014	0.10239373308099192
11		Neutral	8	0.06976744186046513	0.24216483358109805	0.17252234308536066	0.07607436825022897
12		Positive	38	-0.08333333333333326	0.3710140660819146	0.26675956318171773	0.11297940843725005
13	**Nature**	Total	72	0.21182266009852213	0.40186395770300937	0.29396059872562463	0.1167355112814583
14		Negative	6	-0.19999999999999996	0.38663816054236794	0.2918553619161502	0.10175392268599184
15		Neutral	5	-0.13636363636363624	0.5883208891776284	0.4150149843062526	0.17924028749656887
16		Positive	61	0	0.38411218412762554	0.281956266802936	0.11150228717621441
17	**Facial Expression**	Total	99	0.6596562184024266	0.44110843427925955	0.30778539859759596	0.1414776235190049
18		Negative	57	-0.01183431952662728	0.2967516734666815	0.21561328143162217	0.0928158401964214
19		Neutral	1	0	0.5599779490000001	0.3935128735147059	0.16646507548529416
20		Positive	41	0	0.5828861004470836	0.4004181643312536	0.18888780935483854

Table D.2: Statistical Analysis Results for Comparisons between Context-Sensitive and Context-Free Lexicons (Part II).

#	Emoji Class	Sentiment Label	Emoji Size	Cohen Kappa (κ)	Root Mean Square Error (RMSE)		
					Both	Context-Sensitive	Europ
21	**Flag**	Total	28	0.3450292397660818	0.2783190469146903	0.216284072216103	0.07135162214691837
22		Negative	2	1	0.2529156518358389	0.21326418039406034	0.06493490501334286
23		Neutral	3	0.25	0.3586079666025772	0.2561379291276196	0.10712979920710143
24		Positive	23	0	0.2682625334398834	0.2107979930965225	0.06583445843842615
25	**Food**	Total	19	0.28301886792452824	0.5274965369117485	0.3738722573375841	0.15864208140040148
26		Negative	1	1	0.2893813073584906	0.17505138007491677	0.11432992728357384
27		Neutral	0	NaN	NaN	NaN	NaN
28		Positive	18	0	0.5376418568142094	0.38189482595642454	0.16074610027364294
29	**Body Language**	Total	51	0.39370629370629373	0.3823259036040414	0.2591217848912102	0.13372582396022173
30		Negative	10	-0.11111111111111116	0.27627288506792863	0.20163431365647888	0.09544331600732506
31		Neutral	7	0	0.3965726242614932	0.27161828856028875	0.13033357093149678
32		Positive	34	0	0.4055015750482896	0.27123625703680426	0.14369189383158154
33	**Human Activity**	Total	14	0.06666666666666665	0.5656876390468644	0.3995233460008837	0.17475480697690587
34		Negative	1	0	0.2912223134150944	0.17043185714789127	0.12079045626720314
35		Neutral	1	0	0.1621417796862745	0.10395927594117649	0.05818250374509801
36		Positive	12	0	0.6033886722113109	0.42766908030735756	0.18474619026162428
37	**Place**	Total	5	0	0.7334668377365667	0.5026981902752369	0.23289502760956524
38		Negative	0	NaN	NaN	NaN	NaN
39		Neutral	0	NaN	NaN	NaN	NaN
40		Positive	5	0	0.7334668377365667	0.5026981902752369	0.23289502760956524
41	**Heart**	Total	18	0.7272727272727273	0.2518520931147013	0.15417417134361344	0.11454765961960985
42		Negative	2	0	0.17613028532147992	0.20682362295670262	0.06840183539780229
43		Neutral	0	NaN	NaN	NaN	NaN
44		Positive	16	1	0.2597699496306491	0.146266479828972	0.11906494332568146

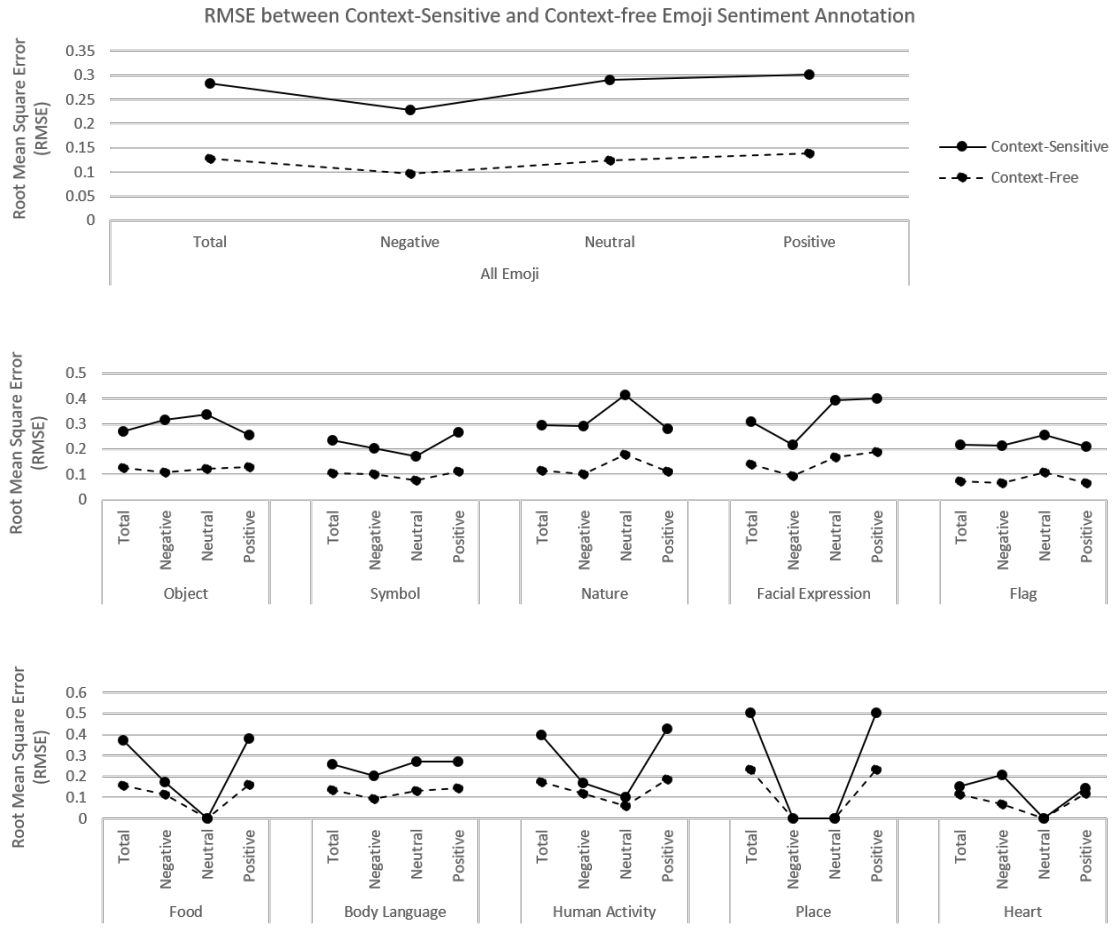


Figure D.1: Root Mean Square Error (RMSE) Values changes between Context-Sensitive and Context-Free Emoji Sentiment Annotation.

(A) Similar Emoji

	Emojis	Unicode_Name	Arabic_Name	Class	Score_Sens	Score_free	Euclidean_Distance
1		Starstruck	وجه مبتسم بعيون نجمه	Facial Expression	0.871186	0.870370	0.000847
2		Hibiscus	زهره الخبازي	Nature	0.804939	0.803571	0.002060
3		Rose	ورده	Nature	0.859694	0.857143	0.002592
4		Expressionless Face	وجه بلا تعبير	Facial Expression	-0.600071	-0.600000	0.004767
5		Pouting Face	وجه يشناط غضبا	Facial Expression	-0.862091	-0.857143	0.004952
6		Face With Symbols On Mouth	وجه يشتم	Facial Expression	-0.904110	-0.909091	0.004983
7	MA	Morocco	علم المغرب	Flag	0.525060	0.520000	0.005913
8		Birthday Cake	كعكه عيد الميلاد	Food	0.886943	0.892857	0.005921
9		Person Fencing	شخص يبارز	Human Activity	0.545455	0.549020	0.006129
10		Umbrella With Rain Drops	مظله مع قطرات المطر	Object	0.619632	0.611111	0.008541
11		Place Of Worship	رمز مكان للعباده	Symbol	0.583333	0.590909	0.009272
12		Confounded Face	وجه مرتبك	Facial Expression	-0.829825	-0.839286	0.009480
13		Glowing Star	نجمه متوهجه	Nature	0.789849	0.780000	0.010004
14		Paw Prints	اثار اقدام حيوان	Nature	0.171429	0.170213	0.010066
15		Exploding Head	راس متفجر	Facial Expression	-0.589744	-0.600000	0.010284
16		Triangular Flag	علم مثلث	Flag	-0.009901	0.000000	0.012913
17		Up Arrow	سهم للاعلى	Symbol	0.241379	0.229167	0.013405
18		Eightthirty	الساعه الثامنه و النصف	Object	0.142857	0.145833	0.014146
19		Red Triangle Pointed Down	مثلث احمر يشير للاسفل	Symbol	-0.266990	-0.270833	0.015192
20		Joystick	عصا العاب	Object	0.400000	0.387755	0.016154

(B) Different Emoji

	Emojis	Unicode_Name	Arabic_Name	Class	Score_Sens	Score_free	Euclidean_Distance
1		Cowboy Hat Face	وجه قبعه رعاه البقر	Facial Expression	-0.615385	0.865385	1.480788
2		Person Biking	شخص يقود دراجه	Human Activity	-0.637681	0.773585	1.411269
3		Watermelon	بطيخ	Food	-0.614035	0.773585	1.387659
4		Ram	حمل	Nature	-0.718750	0.641509	1.360263
5		Person Taking Bath	شخص يستحم	Human Activity	-0.571429	0.754717	1.326196
6		Cow	بقره	Nature	-0.722222	0.596154	1.318399
7		Pregnant Woman	امراه حامل	Human Activity	-0.466667	0.830189	1.296998
8		Ewe	نعجه	Nature	-0.769231	0.480769	1.250006
9		Moneymouth Face	وجه المال	Facial Expression	-0.387755	0.846154	1.234107
10		Camping	تخييم	Nature	-0.500000	0.705882	1.205974
11		Monkey Face	وجه القرد	Nature	-0.600000	0.571429	1.171429
12		Face Savoring Food	وجه متلذذ	Facial Expression	-0.326375	0.839286	1.165890
13		Grinning Squinting Face	وجه ضاحك مغمض العينين	Facial Expression	-0.411270	0.732143	1.143506
14		Rolling On The Floor Laughing	يتدحرج على الارض من الضحك	Facial Expression	-0.344764	0.785714	1.130713
15		Turtle	سلحفاه	Nature	-0.700000	0.423077	1.123133
16		Jeans	جينز	Object	-0.583333	0.509434	1.092783
17		Locomotive	قاطرة	Object	-0.545455	0.540000	1.085459
18		Rescue Workers Helmet	خوذه عامل انقاذ	Object	-0.600000	0.480769	1.080771
19		Grinning Face	وجه ضاحك	Facial Expression	-0.329591	0.750000	1.079670
20		Dog	كلب	Nature	-0.789855	0.274510	1.064520

Figure D.2: Examples of the *L2* Distance Values between Emoji Annotated Within and Out of Contexts.

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