# Emoji Sentiment Roles for Sentiment Analysis: A Case Study in Arabic Texts


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## Abstract

Emoji (the digital pictograms) are crucial features for textual sentiment analysis. However, analysing the sentiment roles of emoji is very complex. This is due to its dependency on different factors, such as textual context, cultural perspective, interlocutor's personal traits, interlocutors' relationships or a platforms' functional features. This work introduces an approach to analysing the sentiment effects of emoji as textual features. Using an Arabic dataset as a benchmark, our results confirm the borrowed argument that each emoji has three different norms of sentiment role (negative, neutral or positive). Therefore, an emoji can play different sentiment roles depending upon context. It can behave as an emphasizer, an indicator, a mitigator, a reverser or a trigger of either negative or positive sentiment within a text. In addition, an emoji may have neutral effect (i.e., no effect) on the sentiment of the text.


## 1 Introduction

Human social interaction consists not only of verbal exchanges, but also of non-verbal signals such as head-nods, facial expressions, gestures, posture, eye-movements or tone of voice. In text-based communication, it has been argued that many of these nonverbal cues are missed, which potentially makes the communication ambiguous and leads to misunderstandings (Kiesler et al., 1984). To mitigate this issue in textual messages, people tend to use many kinds of surrogates, such as emoticons (e.g. ":)" or ":(" ), and emoji (like 😊 and 😞). Carey (1980) categorized these nonverbal cues in text-based communication into five types: vocal spelling, lexical surrogates, spatial arrays, manipulation of grammatical markers, and minus features. Among these, emoticons and emoji are considered as examples of spatial arrays, that make a significant contribution to the interpretation of the textual contents' sentiment.

Sentiment analysis is used to discover opinions, emotions and attitudes in textual contents. Accordingly, Evans (2017) defined emoji as a form of developed punctuation (the way of encoding nonverbal prosody cues in writing systems) that supplements the written language to facilitate the writer's articulation of their emotions in text-based communication. Also, Miller et al. (2017) considered the use of emoji to be understood as analogically encoded symbols that are sensitive to a sender-receiver relationship, and that are fully integrated with the accompanying words (i.e., visible acts of meaning (Bavelas and Chovil, 2000)).

The view adopted in this work is that the visual representation of an emoji is a feature that influences the writer's choice of emoji (Wicke and Bolognesi, 2020; Hakami et al., 2022). As a result, it can affect wider stretches of text and so the emoji often tend to co-occur with 'negative' ('bad', 'unpleasant'), neutral ('non-emotional', 'mixed-emotional'), or 'positive' ('good', 'pleasant') collocates. These collocates can be either words or other emoji. This is similar to what discourse analysts call the "contextual valence shifters" (Polanyi and Zaenen, 2006). Contextual valence shifters are factors which assess a writer's attitude towards an event being described. This assessment relies on the lexical choice of the writer (i.e., the roles of the chosen words in the expressed texts), and the organization of the text. For example, Polanyi and Zaenen (2006) state that words often shift the valence of evaluative terms through their presuppositions. The adverb "barely", for instance, when it comes with the word "Sufficient" changes it sentiment from positive "Sufficient" into negative "barely sufficient". The later presupposes that better was expected.

Thus, in order to discover the sentiment roles of emoji within the body of a text, we need to investigate their general emoji-sentiment co-existence behaviors. To this end, we started our study by in-



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vestigating all of the possible sentiment states that might occur when comparing the same text with and without emoji. Accordingly, we defined a set of emoji roles in the sentiment analysis of the accompanying texts. Then, we analyzed the results to verify the existence of opposite sentiment roles for each emoji considered in the study – represented by means of visible acts of meaning.

The rest of this paper is organized as follows. Section 2 reviews related work upon which we build; Section 3 presents the study's design; Section 4 presents the results analysis and discussion. Finally, in Section 5 we draw conclusions from this work along with highlighting its limitations as well as some recommendations for future work.

## 2 Related Work

Walther and D'addario (2001) studied the sentiment impacts of emoticons in computer-mediated communication (CMC). For the first time, they proposed to study emoticons and plain verbal messages as a whole. They studied the impacts of positive and negative emoticons on positive and negative verbal messages. In the paper, it is reported that positive emoticons increase the positivity of positive verbal messages, but negative emoticon do not increase the negativity of negative messages. They found that while the emotional valence of text (e.g., "I am happy") tends to be more important than any accompanying emoticons with respect to interpretation, a negative emoticon (e.g., the *Frowning Face*: ☹️) can significantly change the interpretation of the message. Following the same approach, Derks et al. (2008, 2007) studied the sentiment impacts of more types of emoticons in various social contexts, and reported similar results. By applying similar approaches, the influences of emoticons on a person's perception (Ganster et al., 2012), and the effects of emoticons in task-oriented communication (Luor et al., 2010) were also studied. Lo (2008) provided additional evidence that emoticons affect interpretation, showing that the same text can be perceived as either happy or sad depending on which emoticon accompanies it.

Regarding emoji, Herring and Dainas (2017) identified eight mutually exclusive pragmatic functions of graphicons (i.e., emoticons, emoji, stickers, GIFs, images, and videos) use (reaction, action, tone modification, mention, riff, narrative sequence, ambiguous, and other) in comments on Facebook groups, taking the discourse context into account. The results of their analysis showed that emoji were the most used graphicon and also expressed the widest range of pragmatic functions, especially reaction and tone modification. On the other hand, Hu et al. (2017) identified seven intentions underlying emoji use (expressing sentiment, strengthening messages, adjusting tone, expressing humour, expressing irony, expressing intimacy, and describing content) and had respondents rate how likely they were to use 20 individual emoji to express each intention. According to (Hakami et al., 2020), an emoji when used in an Arabic language context, and perhaps in other langauges as well, can be a true sentiment indicator, a multi-sentiment indicator, an ambiguous sentiment indicator, or a no-sentiment indicator.

## 3 Study Design

The objective of this work is to construct an approach to the analysis of the sentiment effects of emoji in textual content. We intended to analyse these effects through the differentiation in the sentiment labels of texts with and without emoji. Besides the labels, we also intended to investigate the nuance impact of emoji on the sentiment, like negativity mitigation or positivity emphasis, by analysing the sentiment intensity of the texts (i.e., their sentiment scores). Generally, the change in a text's sentiment with and without emoji inclusion implies the impact of that emoji on that 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-positive***. However, if the sentiment of the text changes after adding emoji from positive to negative, then the sentiment state will be ***Reverse-to-negative***. We assumed that there are seven possible emoji sentiment states that might occurs in such a comparison. Comparing these states with the sentiment of the emoji itself will lead us to know the emoji sentiment role in a text. Presumably, there are eleven possible sentiment roles that an emoji can have within a text. Figure 1 summaries our model used in this study. A detailed description of how we obtained these states and roles and how the result analysis has been done follows.

### 3.1 Dataset Benchmark

Our consideration was on data that is from a social media platform, containing emoji, written in the Arabic language, multi-dialect and multi-aspect.

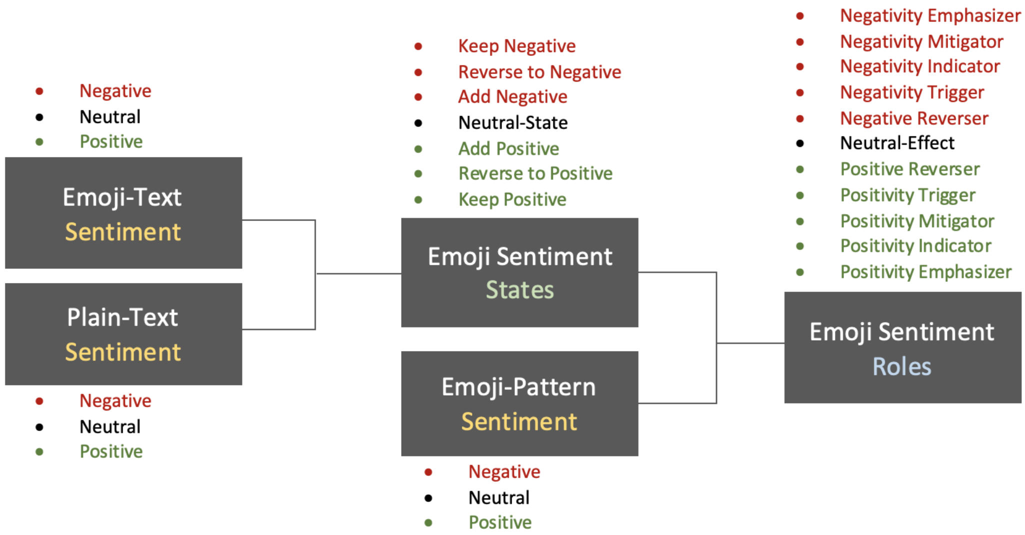



Figure 1: Model of analysis.

Collecting, cleaning and preparing a great deal of raw data for sentiment annotation in a short time is impossible. Thus, we targeted 14 different public datasets of Arabic social media containing 144,196 tweets from the Twitter platform that meet our criteria. The data details are stated comprehensively in Hakami et al. (2021). We refer to the resulting dataset as the Emoji-Text dataset. Then, we extracted and remove all of the emoji from the Emoji-Text dataset to get the same texts without the emoji. We refer to this as the Plain-Text dataset. From Emoji-Text dataset, we extracted 1034 unique emoji forming a total of 24,364 different emoji patterns.

### 3.2 Sentiment Annotation Process

Manual annotation is complex and expensive. We utilized four automatic Arabic sentiment classifiers as follows. The mechanism of preparing Arabic texts containing emoji for automatic sentiment annotation by some of these tools (i.e., Mazajak, CAMeL and ASAD) was adopted from Hakami et al. (2021).

#### 3.2.1 Mazajak Sentiment Classifier

Mazajak (Abu Farha and Magdy, 2019) is the first online Arabic sentiment analyser, it is based on a deep learning model built on a convolutional neural network (CNN) followed by a long short-term memory (LSTM). This analyser provides different functionalities for Arabic sentiment analysis including two modes for raw text processing: the batch mode and the online API, which is what we used. The results were one of the sentiment annotations: positive, negative or neutral.

#### 3.2.2 CAMeL Sentiment Tool

CAMeL Tools (Obeid et al., 2020) is a collection of open-source tools for Arabic NLP in Python. It provides utilities for many NLP tasks, including sentiment analysis. The system has two sentiment analysis models. We used the default model that was generated by fine-tuning the AraBERT language model (Antoun et al., 2020). This sentiment model returns one of the three sentiment labels: positive, negative, or neutral as an output for Arabic text annotation.

#### 3.2.3 ASAD Sentiment Classifier

Arabic Social media Analysis and unDerstanding (ASAD) toolkit (Hassan et al., 2021) is an online tool of seven individual modules, one of which is for sentiment analysis. This toolkit is made available through a web API and a web interface where users can enter text or upload files. 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.

#### 3.2.4 Lexicon-based Sentiment Classifier

All of the above mentioned tools classify the texts with sentiment labels not scores. Therefore, we adopted the lexicon-based Logit-scale sentiment scoring technique (Lowe et al., 2011) as a fourth automatic sentiment annotator used in this analysis

| | Plain-Text Sentiment (PT) | Emoji-Text Sentiment (ET) | Emoji Sentiment State |
|---|---|---|---|
| **Negative Norm** | Negative | Negative | Keep Negative |
| | Positive | Negative | Reverse to Negative |
| | Neutral | Negative | Add Negative |
| **Neutral Norm** | Neutral | Neutral | Neutral-State |
| **Positive Norm** | Positive | Positive | Keep Positive |
| | Negative | Positive | Reverse to Positive |
| | Neutral | Positive | Add Positive |

Table 1: Summary of all possible emoji sentiment states within texts.

model.

Any lexicon-based approach involves calculating 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 needed two Arabic-language-based sentiment lexicons: one for words, and one for emoji. The word sentiment lexicon used was based on the Ar-SeLn (Badaro et al., 2014) lexicon, a publicly available, large-scale Arabic word sentiment lexicon, where each word is annotated with a sentiment score. We augmented this by adding a set of words (with their sentiment scores) from our dataset that was not in the Ar-SeLn lexicon. The sentiment scores of the added words were calculated using the same approach that was applied by Kralj Novak et al. (2015) for emoji. We ended up with a word sentiment lexicon with 178,620 unique words, each with their corresponding sentiment score. For emoji, we used Arab-ESL[1] (Hakami et al., 2021), a publicly available Arabic emoji sentiment lexicon (i.e., extracted from Arabic texts), where each emoji is annotated with sentiment score and label. This lexicon contains 1,034 unique emoji.

To calculate the sentiment scores, we computed an index for the sentence from the scored sentiment components (i.e., words and emoji) using the Logit scale approach, as follows: $S = log(\sum Pos + 0.5) - log(\sum Neg + 0.5)$, where, $Pos$ is the list of the positive components' scores; $Neg$ is the list of the negative components' scores; and 0.5 is a smoother to prevent log(0). This formula tends to have the smoothest properties and is symmetric around zero (Lowe et al., 2011).

The approach of Hakami et al. (2021) was followed to convert the resulting sentiment scores into sentiment labels. We classified three scaled-groups of sentiment scores under three sentiment norms (negative, neutral and positive). Text with sentiment score $i$, where -$\infty \leq i <$ -0.0625, was classified as negative. Text with sentiment score $i$, where $\infty \geq i >$ 0.0625, was classified as positive. Lastly, a text was classified as neutral when its sentiment score $i$ was in the range -0.0625 $\leq i \leq$ 0.0625.

Separately, we calculated the sentiment score and label of each emoji pattern in each text using the same approach of calculating scores and labels for the sentences.

### 3.3 Annotation Reliability and Agreement Test

The majority voting approach was used to ensure that the data was annotated reliably by the algorithms. First, we only considered those texts where the sentiment matched for all the annotations on both positive and negative norms, both for texts with and without emoji. Then, for neutrality agreement, we considered the texts where their sentiment was produced by the lexicon-based statistical approach and was agreed by at least one of the other annotations. This resulted in 35,668 texts reliably annotated with sentiment.

To test the agreement between the aggregated sentiment annotation results by the machines and a manual annotation, we used Cohen's Kappa agreement tests (McHugh, 2012) on a sample of 2,567 texts. These texts were annotated manually. The test resulted in $\kappa$ = 0.8601 which is a high consensus degree. Further, we used the same sample to check the accuracy of the annotation and it was 0.93.

### 3.4 Emoji Sentiment States and Roles

Based on the sentiment annotation of the texts (with and without emoji), our model of analysis consists

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

| Emoji Sentiment State | Text Sentiment Scores | Emoji Pattern Sentiment | Emoji Sentiment Role |
|---|---|---|---|
| | ETs > PTs | Negative | Negativity Emphasizer |
| | ETs > PTs | Neutral | Negativity Emphasizer |
| | ETs > PTs | Positive | Negativity Mitigator |
| | ETs = PTs | Negative | Negativity Indicator |
| **Keep Negative** | ETs = PTs | Neutral | Negativity Indicator |
| | ETs = PTs | Positive | Negativity Mitigator |
| | ETs < PTs | Negative | Negativity Indicator |
| | ETs < PTs | Neutral | Negativity Indicator |
| | ETs < PTs | Positive | Negativity Mitigator |
| | | Negative | Negativity Trigger |
| **Add Negative** | N/A | Neutral | Negativity Trigger |
| | | Positive | Negativity Mitigator |
| | | Negative | Negative Reverser |
| **Reverse to Negative** | N/A | Neutral | Negative Reverser |
| | | Positive | Negativity Mitigator |
| | | Negative | Negativity Trigger |
| **Neutral-State** | N/A | Neutral | Neutral-Effect |
| | | Positive | Positivity Trigger |
| | | Negative | Positivity Mitigator |
| **Reverse to Positive** | N/A | Neutral | Positive Reverser |
| | | Positive | Positive Reverser |
| | | Negative | Positivity Mitigator |
| **Add Positive** | N/A | Neutral | Positivity Trigger |
| | | Positive | Positivity Trigger |
| | ETs > PTs | Negative | Positivity Mitigator |
| | ETs > PTs | Neutral | Positivity Emphasizer |
| | ETs > PTs | Positive | Positivity Emphasizer |
| | ETs = PTs | Negative | Positivity Mitigator |
| **Keep Positive** | ETs = PTs | Neutral | Positivity Indicator |
| | ETs = PTs | Positive | Positivity Indicator |
| | ETs < PTs | Negative | Positivity Mitigator |
| | ETs < PTs | Neutral | Positivity Indicator |
| | ETs < PTs | Positive | Positivity Indicator |

Table 2: Summary of all possible emoji sentiment roles in the three sentiment norms: negative, neutral and positive. **ETs** means emoji-text sentiment score and **PTs** means plain-text sentiment score.

of seven sentiment states in which an emoji can occur. These states are: *Keep-positive*, *Keep-negative*, *Neutral-State*, *Add-positive*, *Add-negative*, *Reverse-to-positive* or *Reverse-to-negative*, as described in Table 1. These states are considered to be an intermediate phase in our model, transferring the analysis into exploring the emoji sentiment roles.

Knowing these intermediate sentiment states along with the sentiment of the emoji pattern leads to the identification of eleven possible sentiment roles that an emoji can have within a text. These roles are emphasis, indication, mitigation, reversing and triggering under each of the positive and negative sentiment norms. Furthermore, emoji could have a *no-effect* role reflecting the neutrality sentiment norm. Note that for the identification of some roles (i.e., emphasis, mitigation, and indication), knowing the sentiment scores of the texts (with and without emoji) was mandatory. Table 2 summarizes all of the possible emoji sentiment roles based on all of the possible cases between each of the sentiment states, along with the emoji sentiments.

| | | Negative | | | | | Neutral | Positive | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Emoji | Freq. | Emphasizer | Indicator | Mitigator | Reverser | Trigger | Neutral-Effect | Trigger | Reverser | Mitigator | Indicator | Emphasizer |
| 😂 | 3692 | 0.065276 | 0.043879 | 0.455309 | 0 | 0.003792 | 0.000271 | 0.06961 | 0.014355 | 0.000542 | 0.024919 | 0.322048 |
| 🙂 | 1045 | 0.180861 | 0.048804 | 0.461244 | 0 | 0.007656 | 0 | 0.055502 | 0.000957 | 0 | 0.004785 | 0.240191 |
| 😅 | 695 | 0.01983 | 0.082153 | 0.243626 | 0.001416 | 0.007082 | 0.001416 | 0.147309 | 0.021246 | 0.001416 | 0.008499 | 0.466006 |
| ✋ | 362 | 0.08311 | 0.093834 | 0.246649 | 0.002681 | 0.002681 | 0.002681 | 0.0563 | 0.010724 | 0.005362 | 0.016086 | 0.479893 |
| 😉 | 232 | 0.00823 | 0.069959 | 0.407407 | 0.004115 | 0.004115 | 0.004115 | 0.106996 | 0.004115 | 0.004115 | 0.016461 | 0.37037 |
| 👇 | 229 | 0.179167 | 0.3375 | 0.095833 | 0.004167 | 0.0125 | 0.033333 | 0.0375 | 0.004167 | 0.004167 | 0.083333 | 0.208333 |
| 😀 | 219 | 0.004348 | 0.056522 | 0.408696 | 0.004348 | 0.008696 | 0.004348 | 0.082609 | 0.004348 | 0.004348 | 0.013043 | 0.408696 |
| 🥀 | 207 | 0.366972 | 0.03211 | 0.009174 | 0.004587 | 0.03211 | 0.009174 | 0.004587 | 0.004587 | 0.252294 | 0.247706 | 0.036697 |
| 🌚 | 201 | 0.283019 | 0.033019 | 0.226415 | 0.004717 | 0.037736 | 0.009434 | 0.080189 | 0.014151 | 0.004717 | 0.023585 | 0.283019 |
| 🖤 | 176 | 0.208556 | 0.048128 | 0.02139 | 0.005348 | 0.037433 | 0.005348 | 0.026738 | 0.005348 | 0.385027 | 0.106952 | 0.149733 |
| 🤣 | 158 | 0.017751 | 0.12426 | 0.491124 | 0.005917 | 0.011834 | 0.005917 | 0.118343 | 0.017751 | 0.005917 | 0.011834 | 0.189349 |
| 😴 | 129 | 0.071429 | 0.014286 | 0.521429 | 0.007143 | 0.007143 | 0.007143 | 0.071429 | 0.007143 | 0.007143 | 0.028571 | 0.257143 |
| 🙈 | 100 | 0.036036 | 0.099099 | 0.234234 | 0.009009 | 0.018018 | 0.009009 | 0.081081 | 0.009009 | 0.009009 | 0.027027 | 0.468468 |
| 😋 | 91 | 0.009804 | 0.058824 | 0.254902 | 0.009804 | 0.019608 | 0.019608 | 0.186275 | 0.009804 | 0.009804 | 0.009804 | 0.411765 |
| 😚 | 80 | 0.021978 | 0.032967 | 0.241758 | 0.010989 | 0.010989 | 0.010989 | 0.032967 | 0.032967 | 0.010989 | 0.010989 | 0.582418 |
| 😗 | 72 | 0.012048 | 0.084337 | 0.204819 | 0.012048 | 0.012048 | 0.012048 | 0.024096 | 0.012048 | 0.012048 | 0.024096 | 0.590361 |
| 😜 | 70 | 0.012346 | 0.111111 | 0.506173 | 0.012346 | 0.012346 | 0.012346 | 0.037037 | 0.024691 | 0.012346 | 0.012346 | 0.246914 |
| 🏃 | 56 | 0.014925 | 0.164179 | 0.119403 | 0.014925 | 0.029851 | 0.014925 | 0.164179 | 0.014925 | 0.014925 | 0.014925 | 0.432836 |

Figure 2: Example of the probability distribution of eleven emoji sentiment roles for eighteen emoji from our data-set.

### 3.5 Emoji Roles Probability Distribution

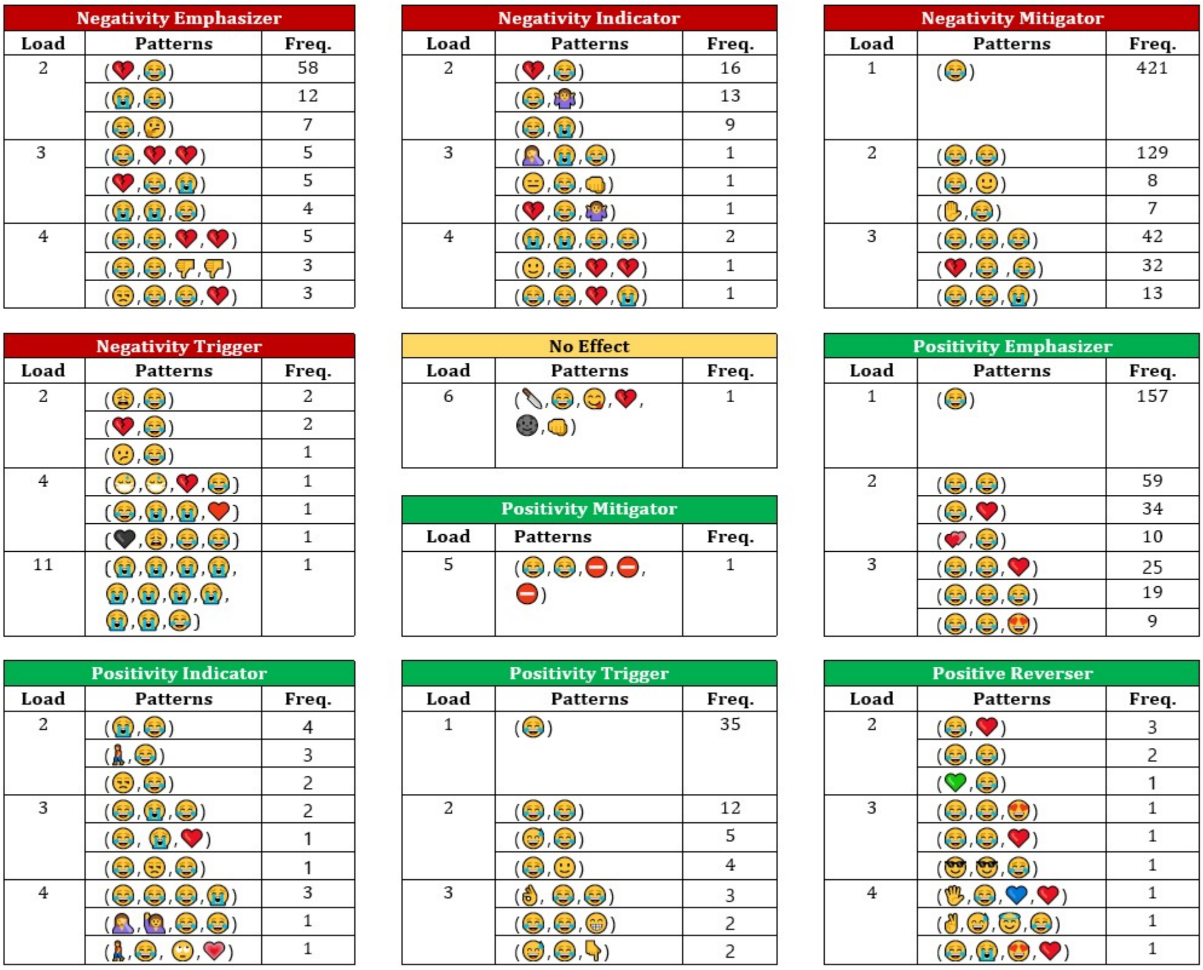
After identifying the emoji sentiment role in each text in our dataset, we calculate the frequency distribution of all of the sentiment roles for each emoji. We start by identifying the frequency with which each emoji is associated with each sentiment role. The following equation captures the distribution of the set of sentiment roles for an emoji across the dataset, as follows: $N(c), \sum N(c) = N$. 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 *negative emphasizer*, *negative indicator*, *negative mitigator*, *negative reverser*, *negative trigger*, *no-effect*, *positive trigger*, *positive reverser*, *positive mitigator*, *positive indicator*, or *positive 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: $p_c = \frac{N(c)}{N}$. Since we were dealing with small samples, we used the Laplace estimate (also known as the rule of succession) (Good, 1965) as it is recommended to estimate the probability: $p_c = \frac{N(c)+1}{N+k}$ , where **k** is the cardinality of the sentiment roles ($k = 11$ sentiment roles in our case). Figure 2 shows examples of the probability distribution $\mathbf{p_c}$ of the sentiment roles for some emoji.

| Emoji Sentiment Role | Occurrence Freq. |
|---|---|
| Positivity Emphasizer | 16,589 |
| Negativity Emphasizer | 12,451 |
| Negativity Mitigator | 3,091 |
| Positivity Trigger | 888 |
| Negativity Indicator | 750 |
| Negativity Trigger | 668 |
| Positivity Mitigator | 617 |
| Positivity Indicator | 449 |
| Positive Reverser | 111 |
| Negative Reverser | 27 |
| Neutral-Effect | 27 |
| Total | 35,668 |

Table 3: Summary of the resulted emoji sentiment roles in our data-set.

## 4 Results Analysis and Discussion

In the analysis, we found eleven of the defined sentiment roles within the dataset, as shown in Table 3. Due to the space limitations, we present a detailed analysis only for the case of the "Face With Tears of Joy" emoji (i.e., 😂). Results were analyzed based on three criteria: the emoji load (i.e., the number of the emoji in each text); the sentiment of the co-occurring emoji (emoji pattern) and the sentiment intensity (sentiment score) of the emoji pattern. The "Face With Tears of Joy" emoji (i.e., 😂) is defined as a positive emoji in Arab-ESL.



| Negativity Emphasizer | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 2 | (💔,😂) | 58 |
| | (😭,😂) | 12 |
| | (😂,🤔) | 7 |
| 3 | (😂,💔,💔) | 5 |
| | (💔,😂,😭) | 5 |
| | (😭,😭,😂) | 4 |
| 4 | (😂,😂,💔,💔) | 5 |
| | (😂,😂,👎,👎) | 3 |
| | (😒,😂,😂,💔) | 3 |

| Negativity Indicator | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 2 | (💔,😂) | 16 |
| | (😂,🤷) | 13 |
| | (😂,😭) | 9 |
| 3 | (🤦,😭,😂) | 1 |
| | (😑,😂,👊) | 1 |
| | (💔,😂,🤷) | 1 |
| 4 | (😭,😭,😂,😂) | 2 |
| | (🙂,😂,💔,💔) | 1 |
| | (😂,😂,💔,😭) | 1 |

| Negativity Mitigator | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 1 | (😂) | 421 |
| 2 | (😂,😂) | 129 |
| | (😂,🙂) | 8 |
| | (✋,😂) | 7 |
| 3 | (😂,😂,😂) | 42 |
| | (💔,😂 ,😂) | 32 |
| | (😂,😂,😭) | 13 |

| Negativity Trigger | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 2 | (😩,😂) | 2 |
| | (💔,😂) | 2 |
| | (😕,😂) | 1 |
| 4 | (😷,😷,💔,😂) | 1 |
| | (😂,😭,😭,❤️) | 1 |
| | (🖤,😩,😂,😂) | 1 |
| 11 | (😭,😭,😭,😭, 😭,😭,😭,😭, 😭,😭,😂) | 1 |

| No Effect | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 6 | (🔪,😂,😋,💔, 🌚,👊) | 1 |

| Positivity Mitigator | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 5 | (😂,😂,⛔,⛔, ⛔) | 1 |

| Positivity Emphasizer | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 1 | (😂) | 157 |
| 2 | (😂,😂) | 59 |
| | (😂,❤️) | 34 |
| | (💕,😂) | 10 |
| 3 | (😂,😂,❤️) | 25 |
| | (😂,😂,😂) | 19 |
| | (😂,😂,😍) | 9 |

| Positivity Indicator | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 2 | (😭,😂) | 4 |
| | (🚶,😂) | 3 |
| | (😒,😂) | 2 |
| 3 | (😂,😭,😂) | 2 |
| | (😂, 😭,❤️) | 1 |
| | (😂,😒,😂) | 1 |
| 4 | (😂,😂,😂,😭) | 3 |
| | (🤦,🙋,😂,😂) | 1 |
| | (🚶,😂, 🙄,💗) | 1 |

| Positivity Trigger | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 1 | (😂) | 35 |
| 2 | (😂,😂) | 12 |
| | (😅,😂) | 5 |
| | (😂,🙂) | 4 |
| 3 | (👌, 😂,😂) | 3 |
| | (😂,😂,😁) | 2 |
| | (😅,😂,👇) | 2 |

| Positive Reverser | | |
|---|---|---|
| **Load** | **Patterns** | **Freq.** |
| 2 | (😂,❤️) | 3 |
| | (😂,😂) | 2 |
| | (💚,😂) | 1 |
| 3 | (😂,😂,😍) | 1 |
| | (😂,😂,❤️) | 1 |
| | (😎,😎,😂) | 1 |
| 4 | (🖐,😂,💙,❤️) | 1 |
| | (✌,😅,😇,😂) | 1 |
| | (😂,😭,😍,❤️) | 1 |

Figure 3: Examples of the emoji loads and patterns of the different sentiment roles that are played by the "Face With Tears of Joy" emoji (i.e., 😂).

However, our observations reveal that this emoji plays different sentiment roles including each of the three sentiment norms: positive, negative and neutral.

In the positive norm, the "Face With Tears of Joy" emoji is found, in some cases by itself (i.e., the emoji load = 1), playing roles such as: *positivity emphasizer* and *positivity trigger*, as shown in Figure 3. Besides the mentioned positive roles, this emoji also co-occurs with other positive emoji (e.g., ❤️, 💚, 💙, 😍, 😎, 👌 and ✌) to play roles such as: *positivity indicator* and *positive reverser*. Examples 6, 7, 8, 9 and 10 in Figure 4 illustrate this emoji acting as a *positivity emphasizer*, *positivity indicator*, *positivity mitigator*, *positive reverser* and *positivity trigger*, respectively. In these examples, we could conclude some positive meanings from the stated texts, like encouragement, complement, humour, and positive response; based on the positive sentiment roles of the co-existing emoji.

The "Face With Tears of Joy" emoji has been found 421 times by itself playing a *negativity mitigator* role within negative text (which has a sense of positivity)(see Figure 3) but it has not been found, when standing alone, playing any other roles in the negative sentiment norm. For behaving negatively, this emoji was always found co-occuring with other negative emoji (like 😭, 💔, 😒, 🖤, 🤦, and 😷). Examples 1, 2, 3 and 4 in Figure 4 illustrate this emoji taking the role of a *negativity emphasizer*, *negativity indicator*, *negativity mitigator* and *negativity trigger*, respectively. In these examples, we could infer some negative meanings from the relevant texts, like sarcasm, bullying, complaining and regret, based on the negative sentiment roles of the co-occuring emoji.

Moreover, we found one case where this emoji played the *Neutral-effect* sentiment role. This is shown in Example 5 in Figure 4. The combination of the mixed sentiments of the text and the emoji used within it, makes the message become neutral. Thus, none of the contained emoji has a

| Example No. (Sentiment) | Text | Emoji Role | Text Meaning |
|---|---|---|---|
| Example 1 (negative) | انا مش عارف الناس ال عماله تنزل صور الكليه والدنيا بتمطر وتقولك ما احلاها وكم انتي جميله متروح تتجوزها يا متخلف😒😂؟<br>I don’t know why everybody is taking pictures and flirting the college in such a rainy day and say: “How lovely it looks”. Why don’t you go and marry it, idiot 😒😂? | Negativity Emphasizer | Sarcasm |
| Example 2 (negative) | مني طنشيها لو فيها خير كان سكتت علي طول جابت حرب البسوس 😂 توقع هي من قبيله جحدر الله يستر عليها 😫.<br>Mona, ignore her. If she is wise enough, she could have remained silent, but she immediately mentioned the Al-Basus war 😂 I think she is from the Jahdar tribe 😫. | Negativity Indicator | Bullying |
| Example 3 (negative) | مش كفايا طول الصيف متبهدلين 😒؟ بطلو قر بقي😂😂.<br>Wasn't enough that we had been working all the summer 😒? Stop mention it 😂😂. | Negativity Mitigator | Complaint |
| Example 4 (negative) | ماهو انا الي كتبت😂😩<br>It was me who wrote it 😂😩. | Negativity Trigger | Regret |
| Example 5 (neutral) | كل شوي القي متابعه من شيخ روحاني وتخسيس الوزن مدري من قايلهم اني دبه مسحووره👊💔🌚🔪😋😂<br>Every minute I receive a following request from either a spiritual sheikh account or a weight losing account. I don’t know who tells them that I am fat and bewitched 👊💔🌚🔪😋😂 | Neutral-Effect | Mixed Emotions |
| Example 6 (positive) | افضل تغريده لك منذ ولادتك بالتويتر😂👌<br>This is the best tweet that you have written since you born in Twitter 😂👌 | Positivity Emphasizer | Encouragement |
| Example 7 (positive) | كل شي منك جميل يا جميل 😂😂😂😭<br>Everything from you is beautiful 😂😂😂😭 | Positivity Indicator | Complement |
| Example 8 (positive) | بسرعه محمد صلاح 😂😂 بنوزع فولوباك يومي ⛔⛔⛔ عاده عايز تبطلها<br>Hurry up Mohammed Salah 😂😂 We daily provide follow requests ⛔⛔⛔ a habit you want to get rid of. | Positivity Mitigator | Random |
| Example 9 (positive) | تخوفي وبس رعب اللهم ياكافي💚😂<br>Not only you are scary, but you are also terrifying; Oh, my dear God💚😂. | Positive Reverser | Humor |
| Example 10 (positive) | سنوات 😂😂😂😂<br>Years 😂😂😂😂 | Positivity Trigger | Positive Response |

Figure 4: Examples of the different sentiment roles that are played by the "Face With Tears of Joy" emoji (i.e., 😂).

distinguished sentiment effect on this text.

Note that, in our model, the sentiment intensity of the co-existing emoji is an important factor in determining an emoji’s sentiment role in a text. Furthermore, emoji sentiment intensity is affected by the emoji load in a text. For instance, in Figure 4, Example 1 has two emoji (😂 and 😒), while Example 3 has the same emoji with different load (i.e., three emoji) ( 😂, 😂 and 😒). The intensity of the 😒 emoji is -0.6879562 (the minus sign represent the negativity not the score value), which is higher than the intensity of the 😂 (0.2724255). Therefore, the emoji with higher intensity dominates the one with lower intensity, making the 😂 emoji become a *negativity emphasizer* through this pattern with (-0.0404245) sentiment intensity [2]. On the other hand, because of the duplication of the 😂 emoji in Example 3 (i.e., a negative text), its positive intensity in this specific text becomes higher than the negative intensity of the 😒 emoji in a way that makes the 😂 emoji play a *negativity mitigator* sentiment role via this emoji pattern [3].

[2]Log[(0.2724255+0.5) - (-0.6879562+0.5)] = -0.0404245
[3]Log[(0.5448510+0.5) - (-0.68795620+0.5)] = 0.2092938

## 5 Conclusions and Future Work

This study objectively depicts all the possible emoji sentiment roles that researchers interested in sentiment analysis might encounter when they are dealing with emoji within textual contents. We have investigated the sentiment roles of emoji within textual content, by investigating their general emoji-sentiment co-occurence behaviours. Accordingly, we defined a set of emoji roles in the sentiment analysis of the accompanying texts. Then, we analyzed the results to confirm the existence of opposing sentiment roles for each emoji considered in the study. To this end, we concluded that an emoji can be an emphasizer, an indicator, a mitigator, a reverser or a trigger of negative or positive sentiments; in addition, each emoji might have a sense of no-sentiment-effect that reflects the neutral sentiment norm. Nevertheless, investigating, deeply, the impact of the emoji sentiment roles stated here, on the semantics of texts should be considered in the future. In addition, an extended and detailed analysis is needed for the other common emoji rather than just for the “Face With Tears of Joy" emoji. Besides, a study on how the presence of emoji might affect the performance of fine-tuned sentiment classification models for Arabic can be one of the future considerations. Finally, we recommend reproducing this work with different languages in order to understand the similarities and differences of the emoji sentiment roles across different cultures and languages.

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