

# A Context-free Arabic Emoji Sentiment Lexicon (CF-Arab-ESL)

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## Abstract

Emoji can be valuable features in textual sentiment analysis. One of the key elements of the use of emoji in sentiment analysis is the emoji sentiment lexicon. However, constructing such a lexicon is a challenging task. This is because interpreting the sentiment conveyed by these pictographic symbols is highly subjective, and differs depending upon how each person perceives them. Cultural background is considered to be one of the main factors that affects emoji sentiment interpretation. Thus, we focus in this work on targeting people from Arab cultures. This is done by constructing a context-free Arabic emoji sentiment lexicon annotated by native Arabic speakers from seven different regions (Gulf, Egypt, Levant, Sudan, North Africa, Iraq, and Yemen) to see how these Arabic users label the sentiment of these symbols without a textual context. We recruited 53 annotators (males and females) to annotate 1,069 unique emoji. Then we evaluated the reliability of the annotation for each participant by applying sensitivity (Recall) and consistency (Krippendorff's Alpha) tests. For the analysis, we investigated the resulting emoji sentiment annotations to explore the impact of the Arabic cultural context. We analyzed this cultural reflection from different perspectives, including national affiliation, use of colour indications, animal indications, weather indications and religious impact.

**Keywords:** Emoji, Lexicon, Arabic, NLP, Sentiment Analysis, Social Media

## 1. Introduction

Emoji are pictographic characters that people use in text-based communication to address the issue of the lack of nonverbal cues (e.g. facial expressions, body language, and voice tones) in text communication. The unseen coding skeleton for emoji is the Unicode standard, which is the foundation for text in all modern writing systems. Currently, there are more than three thousand emoji in the Unicode standard list. Each emoji has a point code in a Unicode transformation format (e.g., U+1F602), and a name (e.g., 'face with tears of joy'), but they lack a standard graphical appearance. To generate the graphical appearance (e.g., 😊), each platform has to render the UTF point codes to produce emoji. As a consequence, the shape, the colour, and the availability of emoji differs across platforms.

The accessibility of emoji in almost all social media platforms leads the users to adopt them to, for instance, initiate/close conversations, indicate celebration, express approval of a message, signal task fulfilment or to respond to thanks/complimenting expressions (Al Rashdi, 2018). Linguistically, researchers have found that emoji can be used to disambiguate the intended sense (Riordan, 2017), manipulate the original meaning (Donato and Paggio, 2017; Njenga, 2018), infer some contextual information (Dresner and Herring, 2010; Skovholt et al., 2014), add sentiment to a message as a writer (Shiha and Ayvaz, 2017) and to ease the understanding of the expressed sentiment as a reader (Dresner and Herring, 2010; Skovholt et al., 2014). This has led natural language processing (NLP) researchers to realise the importance of emoji as sentiment features in text and to include them in their analysis.

Sentiment analysis has become an important tool in classifying and interpreting text. It has important applications in social media analysis, consultation systems, text classification and many other areas. Sentiment analysis can be defined as a process that analyses text and builds an in-

terpretation of the sentiment that it is intended to convey. Usually, this is a two dimensional measure from negative to positive and often it is mapped to just three values: negative, neutral or positive. Studies on emoji within textual context mainly focus on three areas: the usage of emoji, their meaning and the sentiment they convey.

According to Hakami et al. (2020), emoji can be a true sentiment indicator, which is the conventional assumption of most existing sentiment analysis approaches with emoji. This is the approach used by most of the existing work and of implementations of software to perform sentiment analysis of text with embedded emoji. However, some of the most frequently used emoji also occur with many other, unconventional, roles. They may act as either multi-sentiment indicators or as ambiguous sentiment indicators. This is because, depending on the context, emoji sometimes have a very negative effect, and sometimes a very positive one. Furthermore, in some cases, the sentiment of an emoji can be neglected within a text. They may be dominated by the sentiment of the text or be dominated by the sentiment of the other emoji in that text. In this case, such emoji are considered as No-sentiment indicators.

Semantically, although some emoji may have a clear standard, defined meaning, there is, in practice, no constant, universal agreement on their interpretation. Their interpretation varies over time and across users. Many factors can affect the semantic interpretation of emoji: age, level of education, language etc. Indeed, the functional meaning of some emoji is culture-sensitive, and the sender-receiver cultural background is one of the essential contextualization aspects that can affect emoji-text sentiment analysis. For instance, the 'Thumbs Up' emoji (i.e., 👍) has a positive meaning in Asia and North America, while it can be interpreted as an insult in Iraq or Greece (i.e., means 'up yours') (Danesi, 2017).

<sup>51</sup> Eastern and Western cultures are different in their use of mouth versus eye cues when interpreting emotions (Gao

and VanderLaan, 2020). These researchers found that such differences extend to written para-linguistic signals such as emoji and, consequently, this has implications for digital communication. Also, although cultures might share similar emoji sentiment indications (i.e., with emoji that represent common human behaviours or basic emotions), there are other emoji where their sentiments might be affected by a cultural-specific aspect, such as those for food, symbols, and human activities (Hakami et al., 2021).

In this work, we present a context-free emoji sentiment lexicon for Arabic with 1,069 emoji. The lexicon is made freely available for research use<sup>1</sup>. We describe a preliminary study which analyses the impact of the Arabic culture on such an emoji sentiment annotation. 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 analysis of the results and the 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

Emoji can be treated as non-verbal emotional indicators within texts. This means that emoji are a valuable feature in sentiment analysis approaches. There has been some work that has utilized emoji in their sentiment analysis methodologies. This has been done in different languages, but little that has investigated their use in Arabic. Here we present an analysis of the research in sentiment analysis for Arabic that includes emoji (and/or emoticons) in their studies.

Refaee and Rieser (2014) investigated a distant supervision approach for both subjective and sentiment analysis of Arabic tweets. Two data-sets were manually and automatically annotated. Emoticons (i.e., a sequence of ASCII characters that represent nonverbal behaviors, such as facial expressions) were utilized to collect and annotate a data-set of Arabic tweets. Several features were used including bag-of-words (BOW) and both morphological and semantic features. Emoticons were considered as semantic features but were excluded when evaluating the automatically annotated data-set. The authors reported that the emoticon-based distant supervision approach to subjectivity and sentiment analysis in Arabic can perform significantly better than a fully supervised approach and can be useful for annotating larger amounts of data.

Hussien et al. (2016) utilised emoji to analyze emotions in Arabic texts. They claimed that training a classifier to detect emotions in automatically annotated tweets (based on emoji) is better than training it on manually annotated tweets. In their methodology, they collected 22,752 tweets with emoji, extracted the most frequently occurring emoji (58 emoji) and assigned a sentiment weight to each, based on the AFINN sentiments lexicon (Nielsen, 2011). Afterward, each emoji was categorized into one of the four emotion categories: joy, sadness, anger and disgust. For the automatic labelling approach, they labelled 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 which were human annotated into the four adopted emotional labels. Then, they applied two machine learning classification models (support vector machine and multinomial naive Bayes) on both automatically and manually labelled training data-sets. Finally, they evaluated each model’s results on a test data-set. Their results showed that the performance of the machine learning classifiers on the automatic labelled data (using emoji) outperformed the one with the manually labelled data.

Al-Azani and El-Alfy (2018b) aimed at analysing the impact of combining emoji-based features (including some emoticons) with text-based features on sentiment classification of Arabic texts. They used bag-of-words (BOW), latent semantic analysis (LSA) and word embedding as feature extraction models. The data-set they used was 1,101 tweets containing 120 emoji and emoticons. For sentiment classification, they applied a sequential minimal optimization-based support vector 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 a SVM, can produce good classification results.

In other work, Al-Azani and El-Alfy (2018) 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 a Bootstrap Aggregating (Bag-ging) algorithm and a Synthetic Minority Oversampling Technique (SMOTE) to build and combine multiple models from the training data-set. Three different classifiers were evaluated as single and ensemble classifiers: naive Bayes, k-NN, and decision trees. The performance was evaluated and compared on three data-sets with a varying imbalance ratio ranging from two to more than seven. This study concluded that the proposed approach performs better than other approaches in most of the considered cases.

Al-Azani and El-Alfy (2018c) extended their previous work mentioned above by expanding the dataset with more instances from 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), multi-nomial naive Bayes (MNB), stochastic gradient descent (SGD), sequential minimal optimization-based support vectors 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, relying on their extended data-set, Al-Azani and El-Alfy (2018a) empirically evaluated two state-of-the-art

<sup>1</sup><https://github.com/ShathaHakami/Context-Free-Arabic-Emoji-Sentiment-Lexicon>

models of deep recurrent neural networks to detect sentiment polarity of Arabic micro-blogs using emoji as features. In this work, 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 LSTM and GRU based models significantly outperformed other classifiers with a slight difference between them with best results attained when using bidirectional GRU.

Abdellaoui and Zrigui (2018) used ten subjective emoji from the Euro-ESL (Kralj Novak et al., 2015) along with the Arabic word sentiment lexicon Ar-SeLn (Badaro et al., 2014) to construct and annotate a large-scale dataset for Arabic sentiment analysis. Their process used a dataset of Arabic tweets with a vocabulary of 602,721 distinct entities. They named their dataset TEAD and released a subset of it for public use.

From another research perspective, hate speech and offensive language in Arabic texts has been analyzed using emoji (Husain, 2020). The study’s approach was based on applying intensive pre-processing techniques to their data-set before processing it further and feeding it into the classification model. One of these techniques was converting emoji and emoticons into their Arabic labels (i.e., their official Unicode names) and using them as sentiment features to train their Linear SVM-based classifier for hate speech and offensive language detection. Their results reported better performance than another model that did not consider emoji conversion.

Similarly, Mubarak et al. (2022) employed the paralinguistic information embedded in the emojis to collect a large number of offensive texts containing hate speech and vulgar or violent content. Then, they used their data-set as a benchmark for detecting offensive and hate speech using different transformer architectures. For evaluation, they used a different data-set that had been collected separately. They found that the data collected using emoji captures universal characteristics of offensive language. Further, as a benefit of using emoji, their findings showed the common words used in offensive communications, common targets for hate speech and specific patterns in violent tweets. This study also highlighted the common classification errors due to the need to understand the context, consider cultural-background and the presence of sarcasm among others.

It is worth mentioning that almost all of the work listed here agreed on the need for an Arabic-specific emoji sentiment lexicon and they recommended constructing such a lexicon upon which to build their further work. Thus, our work is trying to fulfil this target.

### 3. STUDY DESIGN

The objective of this work, is to construct a context-free Arabic emoji sentiment lexicon, annotated manually by Arabic native speakers. This was done through the following steps.

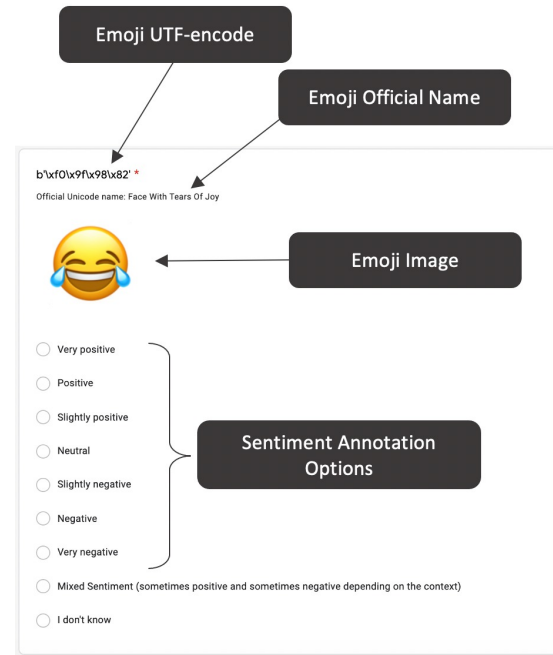


Figure 1: The interface for context-free emoji sentiment annotation.

#### 3.1. Emoji Selection

A collection of 1,034 emoji extracted from the context-sensitive Arabic emoji sentiment lexicon Arab-ESL <sup>2</sup> (Hakami et al., 2021) was used. These emoji have been extracted from 14 different Arabic datasets that contain tweets from the Twitter platform. The tweets have a variety in dialect, aspect, topic, and emoji used within the text. In addition, we added 35 extra emoji that we believe are important to be included in this lexicon. In total, we ended up with 1069 emoji.

#### 3.2. Annotation Interface Setup

To perform an easier and more efficient emoji sentiment annotation, it was important to set up a user-friendly annotation interface. This was done using *Google Forms*, an online web-based survey administration service provided by *Google*. We created two sets (each with five forms): one with the emoji’s official names and the other without. Each set containing all of the 1069 emoji. We think that by adding official names (i.e., emoji descriptions), the uncertainty towards an emoji’s meaning will be decreased. However, only a subset of the participants were provided with the forms that contained the emoji descriptions; to test whether this procedure is beneficial for emoji sentiment annotation.

To provide a consistent representation of the emoji’s graphical appearance, the Apple platform emoji rendering was used throughout. We uploaded the emoji to the forms as images rather than using the locally rendered Unicode characters. This is to unify the visual appearance and the displayed size of the emoji on the various web browsers

<sup>2</sup><https://github.com/ShathaHakami/Arabic-Emoji-Sentiment-Lexicon-Version-1.0>

Negative Emoji	Annotator ID	🙄	😞	😓	😞	$\kappa$ -Alpha	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	🤔	🤔	🤔	🤔	$\kappa$ -Alpha	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	❤️	❤️	💖	💖	$\kappa$ -Alpha	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

Table 1: A sample showing reliability and validation test results for human annotators. The annotations in blue are outliers.

and operating systems used by the annotators. Consequently, we converted each emoji’s official name into its UTF-encoding and used it as an emoji identifier within the forms. This is to ease identifying and extracting each emoji with all of its corresponding annotations by all annotators after the entire annotation task is 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”. Two extra options were added, which are “Mixed Sentiment” and “I don’t know”. Figure 1 illustrates the details of the annotation interface.

### 3.3. Participants Recruitment and Annotation Process

We recruited participants from all over the Arabic regions. Some of the participants were directly asked to volunteer while others were hired via Khamsat<sup>3</sup>, the largest Arabic marketplace for digital services. Initially, we recruited 83 native Arabic speakers, males and females, from the Gulf, Egypt, Levant, Sudan, Magharib, 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 on the informed consent; 27 participants did not completed all the five forms; one was dyslexic; and one failed in the self-agreement annotation tests and was considered as an unreliable annotator. Thus, the total number of approved participants was 53 (28 females, and 25 males).

As a post-sentiment-annotation procedure, in the last form (i.e., the fifth form), we asked the participants the following. First, to provide us with the five emoji that they used most. Second, to answer a question regarding the impact of

including the emoji’s official names along with their symbols in the emoji sentiment annotation process. The answer options to this question were: “Partially important”; “Very important”; “Not important”; and “Causing a confusion”.

#### 3.3.1. Demographics 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 issues (i.e., dyslexia and colour blindness) and social media usage. We also asked about the currently used device, operating system, and browser, as part of the technical setup for the annotation task. After providing their demographic information, each participant was asked to agree or disagree to the use of the provided information for the purpose of scientific research.

#### 3.3.2. Emoji Annotation

Each of the five forms contained around 200 emoji, which are drawn from 1,069 emoji in total. Each participant was asked, independently, to complete the five forms within seven days. They were asked to select one 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 (see Figure 1). The annotation process was estimated at roughly 21 seconds per emoji, which is about 50 minutes per form. The whole data collection task was completed by all participants within a period of six weeks.

### 3.4. Validity and Reliability Annotation Tests

To test an individual annotator’s self-agreement, we used the Recall for sensitivity measure (Su, 1994), and the Krippendorff’s Alpha ( $\kappa$ -Alpha) for consistency measurement (Krippendorff, 2004). We applied these measurements, for

<sup>3</sup><https://khamsat.com/>

Emoji	Emoji Class	N	P_negative	P_neutral	P_positive	Sentiment Score	Sentiment Label
💔	Heart	53	0.767857	0.178571	0.053571	-0.714286	negative
😞	Facial Expression	53	0.553571	0.339286	0.107143	-0.446429	negative
😂	Facial Expression	53	0.017857	0.125000	0.857143	0.839286	positive
❤️	Heart	53	0.017857	0.053571	0.928571	0.910714	positive
👉	Body Language	53	0.120000	0.800000	0.080000	-0.040000	neutral
👈	Body Language	53	0.056604	0.849057	0.094340	0.037736	neutral

Table 2: A sample of the context-free Arabic emoji sentiment lexicon. **N** denotes the number of times an emoji has been annotated. **P\_negative**, **P\_neutral**, and **P\_Positive** denote the relative frequency probability  $p_c$  in negative, neutral, and positive sentiment classes, respectively.

each annotator, on the three sentiment label norms: negativity, neutrality, and positivity. We chose the following groups of emoji: (😞, 😞, 😞, 😞), (🕒, 🕒, 🕒, 🕒), and (❤️, ❤️, ❤️, ❤️), for negativity, neutrality, and positivity self-agreement tests, respectively. If either the Recall value or the  $\kappa$ -Alpha value for an annotator, in any of the three sentiment norms, is less than 0.75, then we considered the annotator as unreliable, and her/his annotation results as invalid. Thus, such an annotator will be excluded from the analysis. Table 1 displays a sample of the results of the two tests.

### 3.5. Sentiment Scores and Labels Calculation

To associate each emoji with each sentiment class, 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 applied to the 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.

The sentiment score calculation was applied by following the approach of Kralj Novak et al. (2015). We started by identifying the frequency with which each emoji is associated with human sentiment annotation labels (negative, neutral and positive). Equation (1) captures the sentiment distribution for the set of sentiment annotations for an emoji across annotators, as follows:

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

**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*, *neutral* or *positive*. From the above we formed a discrete probability distribution:

$$(p_-, p_0, p_+), \sum_c p_c = 1 \quad (2)$$

The components of the distribution, i.e.,  $p_-$ ,  $p_0$ , and  $p_+$  denote the negativity, neutrality, and positivity of the emoji, respectively.  $p_c$  are the probabilities that are estimated from relative frequencies as follows:

$$p_c = \frac{N(c)}{N} \quad (3)$$

Since we are dealing with small samples (i.e., the maximum **N** is 53, which is the maximum number of annotation agreed on a sentiment class), we used the Laplace estimate (also known as the rule of succession) Good (1965) to estimate the probability as follows:

$$p_c = \frac{N(c) + 1}{N + k} \quad (4)$$

**k** is the cardinality of the sentiment class, where  $k = 3$ , in our case. Table 2 shows some examples of  $p_c$  in negative, neutral and positive sentiment classes for some emoji.

Lastly, the sentiment score  $\bar{S}$  of the emoji was computed as the mean of the distribution as follows:

$$\bar{S} = (-1 \cdot p_-) + (0 \cdot p_0) + (+1 \cdot p_+) \quad (5)$$

The approach of Hakami et al. (2021) was followed to convert the resultant sentiment scores into sentiment labels. We classified three scaled-groups of sentiment scores under three sentiment norms (negative, neutral and positive). 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  $-0.0625 \leq i \leq 0.0625$ . Table 2 shows some examples of sentiment scores and labels for some emoji in our lexicon.

## 4. Results and Discussion

### 4.1. Demographic Information Results

As is shown in Figure 2, the largest group of participants was from the Gulf region with 45%. The age of the majority of the participants (86%) was in the range 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 were living in their native countries (75%); and all of them were highly educated. For the annotation, as is demonstrated in Table 3, 74% of the participants used a mobile phone while 26% used a personal laptop. Furthermore, 53% undertook the annotation using the *iOS* operating system, and 47% used the *Chrome*

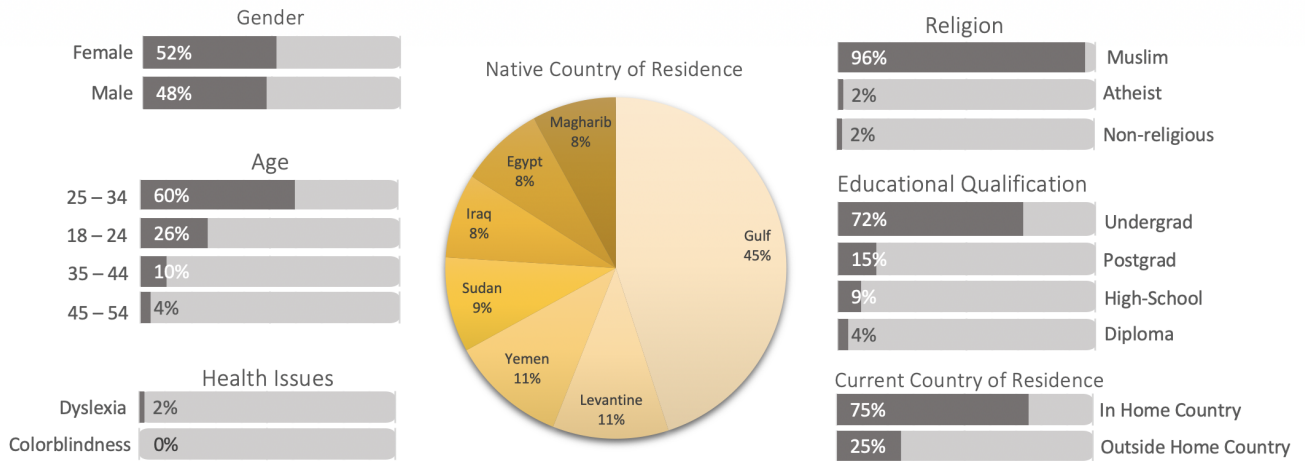


Figure 2: Summary of participants' demographic information.

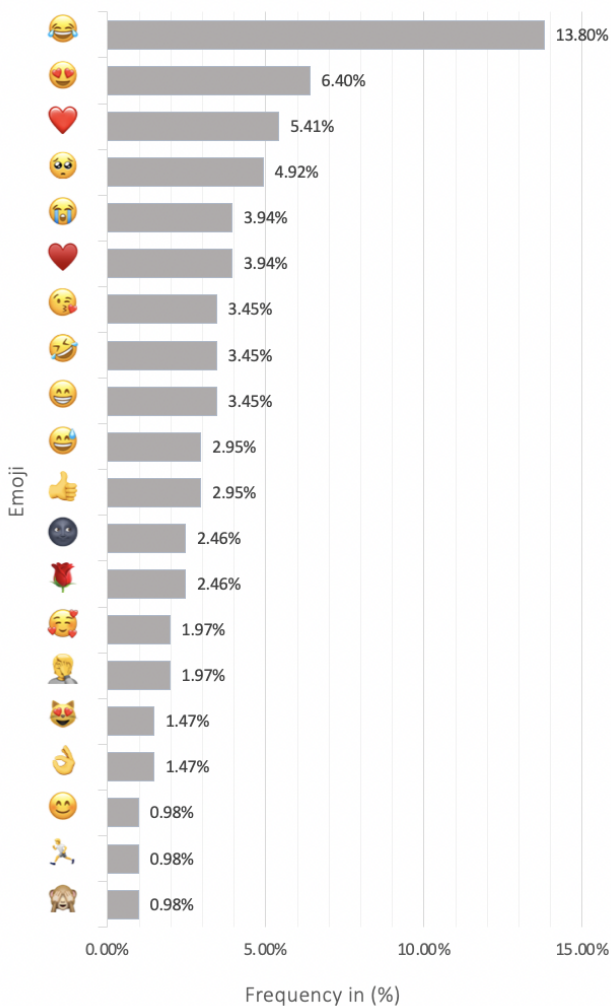


Figure 3: The most 20 commonly used emoji.

quent emoji used by the participants is (😂); while the least frequent used emoji are (😊, 🏃, and 🙇).

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%

Table 3: Technical setup for the annotation by the participants.

#### 4.2. Sentiment Annotation Results

Regarding the inclusion of emoji descriptions (i.e., emoji official names) during the sentiment annotation process, 53% of the participants reported that this was partially important, 25% that it was very important, 17% that it was not important, and only 5% of them that it was confusing.

In these, context free, emoji sentiment annotations, Arabic users (perhaps like other users from different cultures) agreed on a specific sentiment for a subset of emoji that obviously represent that sentiment. For example, our participants agreed on the positivity of positive facial expressions represented by emoji like: 😂, 😊, and 😎; as well as their agreement on the positivity of (almost) any emoji containing a heart in its graphical representation, like: 🥰, 🍷, 🍷, 🍷, 🍷, 🍷, 🍷, and 🍷. Furthermore, positive concepts such as motherhood, represented by emoji like 'Breastfeeding' (i.e., 🍼) and 'Pregnant Woman' (i.e., 🤰); or childhood that is represented by emoji like 'Baby' (i.e., 👶) and 'Baby Bottle' (i.e., 🍼), were annotated as positive. Likewise, our

web browser. The most frequently used social media platform was *WhatsApp* with 16%, and the least used was the *SMS* with 7%. Lastly, Figure 3 shows that the most fre-

Emoji	Unicode Name	Sentiment Label
	Saudi Arabia	positive
	Egypt	positive
	Morocco	positive
	Tunisia	positive
	Kuwait	positive
	United Arab Emirates	positive
	Qatar	positive
	Oman	positive
	Iraq	positive
	Yemen	positive
	Algeria	positive
	Jordan	positive
	Lebanon	positive
	Sudan	positive
	Libya	positive
	Syria	positive
	Bahrain	positive
	Palestinian Territories	positive

Table 4: The flag emoji of Arabic countries in our lexicon.

annotators agreed on the negativity of the negative body language emoji, like: 👎, 🙅, 🙄, and 🙊. Also, emoji that represent prohibition symbols, such as 🚫, 🚳, 🚫, and 🚫 were annotated as negative.

Focusing on the Arabian cultural effect on how our participants perceived emoji, we recognized interesting sentiment annotation results.

First, since all of our annotators are Arabic native speakers, they annotated all Arabic countries’ flags with positive sentiment as a sense of national affiliation. Table 4 displays all of the emoji of Arabic countries’ flags (i.e., 18 emoji flags) in our lexicon.

Second, usually, black color indicates negativity in Arabic culture. Therefore, we found emoji rendered in black colour like ‘Black Heart’ (i.e., 🖤), ‘Black Flag’ (i.e., 🚩), and many meaningless symbols, such as ‘Black Circle’ (i.e., ⬤), ‘Black Medium Square’ (i.e., ◼), ‘Black Medium-Small Square’ (i.e., ◼) were annotated as negative.

Third, there are many animals that indicate positivity in Arabic culture, such as camel (i.e., 🐪), lion (i.e., 🦁), horse (i.e., 🐎), and eagle (i.e., 🦅), which are annotated as positive for the emoji representing them. In contrast, there are other animals that indicate negativity in Arabic culture,

such as snake (i.e., 🐍), pig (i.e., 🐷), and lizard (i.e., 🦎), and emoji representing them were annotated as negative by the Arabic annotators.

Fourth, rainy weather is considered positive in Arabic regions. Hence, we found that all emoji representing rainy or cloudy weather like ‘Cloud’ (i.e., ☁), ‘Cloud with Rain’ (i.e., ☔), ‘Cloud with Lightning and Rain’ (i.e., ⚡☔), and ‘Sun Behind Cloud’ (i.e., ☁☀); besides objects related to rain that are represented in emoji like ‘Umbrella with Rain Drops’ (i.e., ☔) and ‘Closed Umbrella’ (i.e., 🌂) were annotated positively.

Fifth, since the majority of the participant were Muslim, the Islamic religious impact was reflected in their sentiment annotation of some emoji. For example, emoji that represent Islamic religious rituals like ‘Prayer Beads’ (i.e., 🕌), ‘Woman with Headscarf’ (i.e., 🧕), and ‘Palms Up Together’ (i.e., 🙌); or Islamic temples like ‘Mosque’ (i.e., 🕌), and ‘Kaaba’ (i.e., 🕌) were annotated as positive.

On the other hand, pork (i.e., the culinary name for the meat of the domestic pig) is prohibited to be eaten in Islam. Thus, we found that all the emoji that represent the pig animal (🐷); any part of it (i.e., its face 🐷 and its nose 🐷); or its related species (i.e., boar 🐷) were annotated as negative. Similarly, drinking alcoholic beverages is prohibited in Islam. Thus, the ‘Beer Mug’ emoji (i.e., 🍺) was annotated as negative. However, we noticed that there are another three alcoholic drinks emoji named as ‘Wine Glass’ (i.e., 🍷), ‘Tumbler Glass’ (i.e., 🍹), and ‘Cocktail Glass’ (i.e., 🍸), which were annotated as neutral, neutral, and positive, respectively. This is, probably, due to either their neutral graphical appearances that might look like non-alcoholic drinks; or their neutral names that might indicate non-alcoholic drinks as well. We should clarify here that the non-alcoholic mixed-fruits drinks can be called ‘Cocktail’ in Arabic regions. Moreover, the sentiment annotation results show that the glasses-clink celebration behavior as it is represented by emoji such as ‘Clinking Glasses’ (i.e., 🍷) and ‘Clinking Beer Mugs’ (i.e., 🍺) was annotated as positive; even though these emoji are actually representing alcoholic drinks.

## 5. Conclusion and Future Work

In this work, we constructed a context-free sentiment emoji lexicon, annotated by 53 Arabic native speakers, from most Arabic regions. The sentiment annotation process, along with the annotators’ personal characteristics are described in detail. We analyzed the resulting annotations to see how Arabic cultural-background was reflected in the sentiments of the annotated emoji. We discussed this cultural effect regarding national affiliation, colour indication, animal indication, weather indication, and religious impact.

This work is limited to an analysis of manual sentiment annotations of stand-alone emoji out of any context. In the future, it would be interesting to compare this resulting context-free lexicon with a context-sensitive emoji sentiment lexicon, in the Arabic language. This kind of comparison can help understanding the differences between how the sentiment of an emoji is perceived when it is stand-

alone and how it is interpreted differently, when it is presented in an accompanying context. Another limitation is the recruitment of a small number of participants as representatives for a specific Arabic region. Similar future investigations with more participants would be advantageous. In the future, we intend to make the resulting emoji sentiment lexicon more fine grain for further, focused and detailed analytical studies of emoji within the Arabic language. In addition, the lexicon provided in this study may also be informative for Arabic socio-linguistics researchers interested in emoji usage and sentiment expression on social media by Arabic users. Also, the correlation between sentiment and meaning of emoji evolves over time. It might be important to explore the change in the meaning of controversial emoji, and how they are affected by the corresponding social processes.

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