Sentiment Analysis and Stance Detection in Arab versus non-Arab English News Comments

(Ingy Farouk Emara – Associate Professor of Linguistics at MIU University)

Abstract

This paper conducts sentiment analysis and stance detection on Arab and non-Arab Facebook comments associated with news articles likely to evoke anger, fear, sadness, and happiness emotions. The study found that both human and automated methods largely aligned in sentiment classification, assigning negative sentiment to comments on the articles evoking negative emotions and positive sentiment to discussions of the happiness-evoking article, yet they differed in the sentiment intensity values assigned to the comments associated with each emotion. Hyland's (2005) stance model was also applied to explore stance or attitude towards the articles' topics. The analysis revealed that both groups of commenters showed a predominant 'against' stance in discussions of topics evoking fear and sadness and a predominant 'in favor of' stance in the topic evoking happiness, but the two groups significantly differed in their stances towards the topic evoking anger, since it raised a controversial political issue. The paper recommends the use of the stance framework in future sentiment analysis for more accurate opinion mining results.

Keywords: sentiment analysis, stance detection, Arab versus non-Arab comments

تحليل المشاعر وتحديد المواقف في تعليقات العرب وغير العرب على الأخبار باللغة الإنجليزية

ملخص

تُجري هذه الورقة تحليلًا للمشاعر وتحديدا للمواقف في تعليقات المستخدمين العرب وغير العرب على فيسبوك، المرتبطة بمقالات إخبارية يُرجّح أن تثير المشاعر الإنسانية الأساسية مثل الغضب والخوف والحزن والسعادة. وبالاستعانة بنهجي الدراسة البشري والآلي، توصلت الدراسة إلى أن النهجين يتوافقان إلى حد كبير في تصنيف المشاعر، حيث تم تصنيف المشاعر السلبية بدقة في التعليقات على المقالات التي أثارت الغضب والخوف والحزن، والمشاعر الإيجابية في التعليقات المرتبطة بالسعادة، ولكن أظهرت الدراسة اختلافا بين المنهجين في تقييم شدة المشاعر المرتبطة بكل شعور في المجموعتين. كما تطبّق الدراسة نموذج Hyland (2005) للمواقف لتحليل التراكيب اللغوية التي تُمثل المواقف أو الاتجاهات تجاه المواضيع المطروحة. وتُظهر النتائج أن كلا المجموعتين من المعلّقين أبدوا موقفًا سائدًا "ضد" في مناقشة المواضيع التي تثير الخوف والحزن، وموقفًا "مؤيدًا" في الموضوع المرتبط بالسعادة. ومع ذلك، اختلفت المجموعتان بشكل ملحوظ في مواقفهما من الموضوع المرتبط بالغضب، نظرًا لأنه أثار قضية سياسية مثيرة للجدل. وتقترح الدراسة توظيف إطار تحليل المواقف ضمن تحليل المشاعر في الأبحاث المستقبلية للحصول على نتائج أكثر دقة في استخراج الآراء.

الكلمات المفتاحية: تحليل المشاعر، اكتشاف المواقف، تعليقات العرب وغير العرب

Sentiment Analysis and Stance Detection in Arab versus non-Arab English News Comments

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Introduction

The use of natural language processing (NLP) has been extensively studied in opinion mining research over the past decade. Opinion mining investigates people's opinions, attitudes and emotions towards individuals, topics and events (Razali et al., 2021). Both sentiment analysis and stance detection are subtasks of opinion mining, the former aiming to determine whether a text has positive, negative or neutral sentiment, and the latter targeting whether a speaker's/ writer's attitude towards a particular topic is in favor, against or neutral (Hercig et al., 2018). Previous research shows that though sentiment labeling can be beneficial in detecting stance, sentiment alone is not sufficient to determine whether a speaker/ writer is in favor of or against a topic (Mohammad et al., 2017).

The current study aims to perform sentiment analysis and stance detection on English-language news comments made by Arab and non-Arab Facebook users. The selected comments reflect social media users' reactions to topics that evoke the four basic human emotions: anger, fear, sadness, and happiness (Ekman, 1992; Gu et al., 2019). The users' language is analyzed in terms of sentiment polarity and intensity, which are assessed by both human evaluators and the LIWC-22 automated tool. Additionally, the stance model proposed by Hyland (2005) is applied in the analysis to identify the writers' attitudes toward the article topics through the examination of linguistic markers such as hedges, boosters, attitude markers, and self-mentions.

Previous research on sentiment analysis and stance detection extends over a wide range of domains including politics, films, health, tourism, business, culture and others (Darwish et al., 2017; Jaidka et al., 2018; M'Bareck, 2019; Al-Natour & Turetken, 2020; AlDayel & Magdy, 2021; Kastrati et al., 2021; Ibrahim et al., 2022; Weinzierl & Harabagiu, 2024). However, a gap in sentiment and stance analysis research exists in the scarcity of studies comparing the sentiment and stance of comments made by social media users from different ethnic backgrounds on topics evoking the basic human emotions. Though previous studies investigated linguistic differences between native and non-native users of English in social media interaction (Liddicoat, 2016; Ohiagu, 2020; Cahyanti et al., 2021); no work, to the best of the author's knowledge, has studied the sentiment and stance analysis of Arab versus non-Arab online comments in situations triggering the basic human emotions. Therefore, the contribution of this paper is to provide a quantitative-qualitative sentiment and stance analysis of the comments made by social media users claiming an Arab identity and those claiming a non-Arab identity in four contexts triggering the basic emotions of anger, fear, sadness and happiness. The analysis also aims to detect whether the socio-ideological identities of social media users have an impact on the way they express emotions in the English language.

The study aims to address the following research questions:

1. What sentiment intensity is detected in the social media comments made by Arab versus non-Arab users on topics evoking the four basic emotions of anger, fear, sadness and happiness?
2. What stance is reflected in the news comments through the use of linguistic stance markers, revealing the writers' attitudes toward articles that evoke the four basic emotions?
3. What are the ideological implications underlying Arabs' and non-Arabs' news comments?

By answering the research questions above, this paper explores how sentiment and stance can be extracted from text using both automatic and human annotation methods. The paper is structured into five main sections: section 1 introduces the study highlighting the research gap and research questions, section 2 provides a review of the relevant literature, section 3 outlines the methodology employed, section 4 presents the findings, discussion and implications, and finally, section 5 wraps up with the conclusion.

2. Literature Review

Research on sentiment analysis has lately gained increased attention in the fields of politics, business, health and more. In a study of political tweets regarding local gun policy in the United States, M'Bareck (2019) found that the political sentiment was significantly more negative on Twitter than on news media as the former showed more negative emotions of fear and agitation, while the latter demonstrated a neutral sentiment in the news coverage of the topic. The study findings highlighted the power of social media to disseminate particular sentiments and emotions among users, which could, in turn, shape their attitudes towards governmental policies. In another study foregrounding the impact of social media on users' sentiment, Anspach and Carlson (2020) found that social media users were more likely to be emotionally influenced by the comments attached to news articles posted on social media than by the news articles themselves.

In the fields of business and marketing, Al-Natour and Turetken (2020) revealed that performing automatic sentiment analysis of online reviews could detect customers' sentiments and opinions regarding particular products and services as effectively as star ratings. In another study, Tunca et al. (2023) performed a sentiment analysis of opinion articles written about the metaverse between 2021 and 2022 on the Guardian website. The study concluded that almost two thirds of the articles showed a positive sentiment, one third showed a negative sentiment, and 9% were neutral, suggesting the power of online media to shape people' sentiments and perceptions. The positive sentiments were detected in the articles describing the metaverse's potential to provide users with beneficial virtual experiences, whereas the negative sentiments stemmed from the articles' concerns about misinformation and harmful content (Tunca et al., 2023). The relationship between sentiment and customer behavior was also investigated by Sun et al. (2024) who found that using language that implied positive sentiment when describing a product resulted in increased sales and higher customer satisfaction.

Sentiment analysis also proved useful in assessing public sentiment regarding health hazards and pandemics, such as COVID-19. Chandra et al. (2025) carried out a sentiment analysis of news articles from the Guardian website tackling the COVID-19 pandemic in its different stages. They found the news articles to be dominated by negative emotions associated with denial, sadness, annoyance and anxiety as they reflected people's fearful attitude at the time. The authors also found that, compared to news articles, social media posts tended to have more diversified sentiments towards the pandemic, with recurring examples of expressions showing positive sentiments like optimism and humor (Chandra et al., 2025).

A few studies examined the impact of gender and racial differences on sentiment analysis (Zhou & Srivastava, 2024; Nguyen et al., 2024), yet they did not compare how individuals from different ethnic backgrounds expressed sentiment in language. Zhou and Srivastava (2024) investigated gender and racial differences in sentiment analysis through interviews with individuals of different genders and ethnic backgrounds. Their findings showed that gender had an impact on the linguistic expression of sentiment with females displaying more emotional content, while race had no significant impact on sentiment expression. Nguyen et al. (2024) analyzed tweets for racial sentiments towards minority groups in the United States between 2011 and 2021 and found that tweets referencing black and Middle Eastern people had the highest values of negative sentiments.

Sentiment analysis has often been studied in relation to stance detection in order to analyze speakers' or writers' stance towards particular issues or individuals. AlDayel and Magdy (2021) indicate that current research uses two approaches for stance detection: sentiment-based, examining the sentiment expressed towards the stance object, and position-based, studying whether a text agrees or disagrees with a given claim. The first approach investigates stance through detection of sentiment towards a topic or an entity, such as Donald Trump, gun control, or feminism (Weinzierl & Harabagiu, 2024). The second approach examines stance towards a position statement or a claim such as 'We should disband NATO' (Kucuk & Can, 2021; Weinzierl & Harabagiu, 2024). However, it is advisable to incorporate both approaches in sentiment and stance detection research to account for both emotions and attitudes toward entities and claims (Weinzierl & Harabagiu, 2024), which is the approach adopted in the present study.

Inferring stance from language has often been associated with Hyland's (2005) stance markers as well as attitude-specific adjectives, adverbs and lexical items (Jaffe, 2009). Hyland's model of interaction is based on Halliday's (1994) classification of language as having three macro functions: ideational, interpersonal and textual. The model, with its emphasis on stance and engagement, addresses the interpersonal function since it identifies the relationship between the writer and the reader. The use of stance markers determines a writer's attitude towards a proposition or an entity as well as engages the readers or alienates them from the writer (Hyland, 2005).

The stance markers Hyland's model proposes are hedges, boosters, attitude markers and self-mentions. Hedges are grammatical or lexical devices showing tentativeness or uncertainty about a certain proposition, such as 'may', 'likely' and 'perhaps'. Boosters are linguistic devices showing certainty and solidarity with the audience, such as 'certainly' and 'unquestionably'. Attitude markers are adjectives, adverbs and other lexical items that convey feelings towards or opinions about a certain proposition, such as 'important' and 'harmful'. Self-mentions refer to showing self-presence or asserting one's point of view, as in using the personal pronouns 'I' and 'we' (Hyland, 2005).

Several studies have explored stance within sentiment analysis research, particularly through the examination of social media language. Barlett and Norrie (2015) studied stance towards immigration in England by examining the sentiment polarity of tweets related to immigration. They determined the 'against' stance through the presence of negative sentiment and considered the positive sentiment as an indication of an 'in favor' stance. Similarly, Gualda and Rebollo Diaz (2016) examined attitudes towards refugees in tweets from different languages and used the text sentiment measures as an indicator of stance towards refugees, labeling text with negative sentiment as 'against' and that with positive sentiment as 'in favor'. However, these two studies are considered suboptimal due to their reliance on sentiment alone to determine stance (AlDayel & Magdy, 2021).

Darwish et al. (2017) studied stance towards Muslims in tweets posted after the 2015 Paris attacks. The findings revealed that the majority of tweets expressed a positive stance toward Muslims, distinguishing them from the attackers. However, the stances or opinions conveyed were largely influenced by homophily and social influence.

AlDayel and Magdy (2021) used the SemEval stance detection dataset consisting of over 4000 tweets covering five topics: atheism, climate change, feminist movement, Hilary Clinton as a presidential candidate, and legalization of abortion. They found that the predominant sentiment polarity for the tweets was negative, but it did not always match with the stance. For example, 50% of the comments showed a negative sentiment towards climate change, but 59% of the tweets were in favor of the claim that climate change is a real concern (AlDayel & Magdy, 2021).

The preceding literature review establishes the theoretical framework for this study and summarizes key findings from various research efforts that have applied sentiment analysis and stance detection to online texts across different fields. The existing research lacks studies comparing the sentiment and stance of social media language used by individuals from different ethnic backgrounds, particularly Arabs and non-Arabs. Therefore, the current study aims to address this gap through the analysis presented in the following sections.

3. Methodology

To investigate how different cultural groups express sentiment and stance in online discourse, this study analyzes user-generated comments on social media news posts. The current section outlines the analytical framework and procedures used to carry out this investigation.

3.1 Research Design

The study adopts a mixed-methods approach, combining quantitative and qualitative sentiment analysis to examine comments made by Arab and non-Arab users on social media news articles. The primary objective is to compare sentiment intensity and stance expression across the two groups. Sentiment analysis is used to assess the emotional tone and intensity of the emotions underlying the comments, while the qualitative component focuses on identifying and interpreting linguistic patterns that reflect different stances. The analysis of linguistic patterns indicating different stances is based on Hyland's stance model (2005), with emphasis on the stance markers of hedges, boosters, attitude markers and self-mentions.

3.2 Data Collection Procedures

The data collected is comprised of 712 comments, 206 made by Arabs and 506 made by non-Arabs, attached to 4 news articles triggering the four basic human emotions of anger, fear, sadness and happiness. The total number of words analyzed is 17600, with 5919 from Arab comments and 11681 from non-Arab comments. To analyze the emotion of anger, a CNN article published in February 2025 discussing Trump's proposal to evacuate Gaza for reconstruction was examined. For the emotion of fear, an Al Jazeera article covering the COVID-19 outbreak from April 2020 was selected. Sadness was represented by an Al Jazeera article about the drowning of a Moroccan boy in a well following unsuccessful rescue attempts, published in February 2022. Lastly, happiness was analyzed through an Al Jazeera article celebrating the Moroccan football team's victory in the World Cup, published in December 2022. These four articles were chosen based on their potential to evoke the four basic emotions, the volume of user comments they generated (i.e. each had no less than 1000 words of comments), and the presence of both Arab and non-Arab user names as commenters.

The comments were divided into Arab and non-Arab based on the identity of the writer as shown by the choice of name. Comments made by users with clear Arabic names were considered Arab comments although the author acknowledges that there is no definitive evidence confirming the users' ethnic background. These users were treated as Arab mainly because they chose to present themselves with an Arab identity. It is also recognized that some individuals with likely Arabic names may be non-Arab Muslims; however, since their comments largely reflected Arab-aligned perspectives, they were included in the Arab group. On the other hand, non-Arab comments were those posted by users who chose to disclose a non-Arab identity through their choice of name.

To collect the data, the four selected news articles were retrieved from their respective newspaper Facebook pages, and all 'relevant comments' were copied into Word documents. For each article, two separate files were created: one containing comments from users with Arabic names and the other from users with non-Arabic names. A data cleaning process followed, during which irrelevant elements—such as names, dates, emojis, special characters, non-English lexical items, and non-meaningful words—were removed. Accordingly, 8 documents were prepared for sentiment analysis, 4 comprising Arab comments on the articles evoking the 4 basic emotions and 4 comprising non-Arab comments on the same articles. The non-Arab comments outnumbered the Arab ones, especially in the CNN article about the Israeli-Palestinian conflict, which could be attributed to the deletion of some Arab comments from 'mostly relevant' due to Facebook moderation of anti-Semitic comments. In order to obtain consistent values from the two groups of comments, regardless of the different data size, percentages of word frequencies were used in the analysis.

3.3 Data Analysis Tools

The data was examined using both quantitative and qualitative methods to uncover linguistic patterns related to sentiment and stance. Quantitatively, the analysis employed the LIWC-22 sentiment analysis tool alongside human annotation. LIWC-22 was used to assess sentiment polarity, generate scores for positive and negative sentiment, and identify dominant emotions within each text. Human annotation was conducted by two evaluators—the author and a fellow PhD holder in linguistics—who manually counted the number of positive and negative words, as well as words associated with each of the four basic emotions. To ensure reliability, the average of their results was used. The words classified as positive or negative fell into four grammatical categories: nouns (e.g., *heaven*), verbs (e.g., *bless*), adjectives (e.g., *safe*), and adverbs (e.g., *proudly*). Following this, a qualitative analysis was carried out to identify sentiment-related features that were overlooked by the automated tool and to interpret the writers' attitudes towards the article topics through the use of stance markers. The step of human annotation was necessary in the quantitative-qualitative analysis to detect the linguistic differences in sentiment expression between Arabs and non-Arabs with more accuracy. The human evaluators annotated the texts by coding sentiment attributes and subsequently inputted the texts into the AntConc corpus analysis tool to investigate the relevant linguistic patterns within their context.

4. Results and Discussion

This section presents the findings from the data analysis conducted through both automated and manual sentiment analysis methods. The automated results were generated using the LIWC-22 software, which assesses sentiment polarity and intensity. In contrast, the manual analysis involved human evaluation of sentiment intensity, along with the identification and interpretation of the frequency and significance of stance markers.

4.1 Sentiment Intensity in Arab versus Non-Arab Comments

Sentiment intensity refers to the strength or degree of emotion expressed in a text, indicating whether the overall tone is predominantly positive, negative, or neutral. Table 1 below shows the sentiment intensity values for Arab and non-Arab comments in response to the four articles, each of which elicited one of the four basic emotions: anger, fear, sadness, and happiness. The sentiment intensity is calculated by LIWC-22 automatic sentiment analysis tool and shows that all the comments on the 3 articles representing topics triggering the negative emotions of anger, fear and sadness had more negative than positive emotions, except for the non-Arab comments on the article triggering fear, which had equal values for both negative and positive emotions. It also shows that the article representing the topic likely to evoke happiness had more positive than negative emotions as detected by the program. In terms of emotion intensity differences between the two groups, Arab comments expressed more positive emotion than non-Arab comments in discussions related to death. This was primarily due to the frequent use of positively connoted terms such as mercy, heaven, and paradise. Conversely, non-Arab comments exhibited more positive emotion in discussions related to the other three topics—anger, fear, and happiness. Arab comments, on the other hand, conveyed more negative emotion in discussions of topics related to anger and death, while non-Arab comments were more negative in response to topics evoking fear and happiness. Although the sentiment intensity values calculated by LIWC-22 were effective in determining the overall sentiment polarity of most articles (i.e., whether they were generally positive or negative), the tool sometimes failed to distinguish between inherently positive words used sarcastically or negatively and genuinely positive expressions. As a result, table 1 shows relatively high positive emotion scores even in discussions of negative topics, due to the tool's misclassification of sarcastic phrases—such as "super misleading"—as positive.

Table 1 Sentiment intensity of Arab and non-Arab comments

Article	**Emotion Evoked/ by Commenters**	**Positive Emotions**	**Negative Emotions**
Gaza's Evacuation	Anger/Arabs	0.35	0.78
	Anger/Non-Arabs	0.51	0.62
COVID-19	Fear/Arabs	0.17	0.35
	Fear/Non-Arabs	0.56	0.56
Rayan's Death	Sadness/Arabs	0.57	2.00

Article	Emotion Evoked/ by Commenters	Positive Emotions	Negative Emotions
	Sadness/Non-Arabs	0.16	1.74
Morocco's Win	Happiness/Arabs	5.54	0.20
	Happiness/Non-Arabs	5.58	0.26

The LIWC and human classifications of negative emotions associated with the articles evoking anger, fear and sadness are shown in table 2 below. The given values show that the automated tool could correctly detect the dominant emotion in most comments, except for the non-Arab comments on the article likely to evoke anger where the tool assigned more values for the emotion of fear. This occurred due to the incorrect classification of words that did not have a negative meaning as negative terms implying fear as in the word 'stress' meaning 'emphasize' that was incorrectly labeled as fear-related.

Table 2 Frequencies of negative emotion words calculated by LIWC and human annotators

Article	Emot-ion	LIWC-Measured Anger	Human-Measured Anger	LIWC-Measured Fear	Human-Measured Fear	LIWC-Measured Sadness	Human-Measured Sadness
Gaza Evacu-ation	Anger/ Arab	**0.18**	3.36	**0.33**	0.31	**0**	0.13
	Anger/ Non-Arab	**0.19**	1.85	**0.12**	0.29	**0.16**	0.15
COVID-19 Spread	Fear/ Arab	**0**	1.91	**0.17**	2.48	**0**	0.57
	Fear/ Non-Arab	**0**	2.45	**0.19**	2.45	**0.19**	0.75
Death of Rayan	Sad/ Arab	**0**	0	**0**	0	**1.57**	3.16
	Sad/ Non-Arab	**0**	0	**0**	0	**1.58**	2.87
MoroccoVictory	Happy/ Arab	**0**	0.76	**0**	0	**0**	0
	Happy/ Non-Arab	**0**	0.8	**0**	0	**0**	0

There were significantly higher counts in human measures than in LIWC measures of positive and negative emotion words, which implies the automatic tool's tendency to ignore a significant number of emotion words either due to their absence from its dictionary or due to their association with other categories in the system like the category of religion or politics. For example, the expression 'ethnic cleansing' was not counted as a negative word by the program as it was listed under the category of culture rather than the category of negative words.

4.2 Stance Detection in Arab versus Non-Arab Comments

This section analyzes the linguistic representation of stance in the Arab and non-Arab comments associated with the four news articles according to Hyland's stance model. The analysis of stance, or writers' attitude is based on both automatic and human ratings of stance markers in the collected texts. The LIWC-22 tool was used to calculate frequencies of pronouns, especially the self-mentions, and to list words of high frequency occurrence in the articles. The human evaluators then conducted a qualitative analysis of the values provided by the automated tool, along with those manually counted, to achieve more accurate stance detection and better classification of context-dependent meanings. Table 3 below presents the percentage of words indicating stance in the comments associated with each article.

Table 3 Percentage of stance in Arab versus non-Arab comments

Article	Emotion by Commenters	In favor	Neutral	Against
Gaza's Evacuation	Anger/ Arabs	0	0	100
	Anger/Non-Arabs	29.08	1.66	69.26
COVID-19 Spread	Fear/ Arabs	0	0	100
	Fear/ Non-Arabs	0	0	100
Death of Rayan	Sadness/ Arabs	0	0	100
	Sadness/ Non-Arabs	0	0	100
Morocco's Football Victory	Happiness/ Arabs	96	0	4
	Happiness/ Non-Arabs	87.76	4.08	8.16

The table above shows that the article about Gaza's evacuation, likely to evoke anger, elicited the comments with the most significant different stances. The articles about COVID-19 and Rayan's death, likely to evoke fear and sadness, elicited comments that shared the same stance, being against the incidents of the virus breakout and the boy's death. The article about Morocco's football win, likely to evoke happiness generated comments that were mostly in favor of the achievement. The few ‘against’ stances in the Arab comments criticized celebrating the third position and wished the team would win first or second position. The ‘against’ remarks in the non-Arab comments were mainly criticizing Morocco as an under-developed country, or the fact that they celebrated the win as the win of an Arab rather than an African country. As the comments on Gaza’s evacuation displayed the greatest variation in stance, they will be examined in detail below with a focus on their use of stance markers. Table 4 shows the percentage of the stance markers used by the Arab and non-Arab social media users in their comments about the topic of Gaza’s evacuation.

Table 4 Percentage of stance markers used by Arab and Non-Arab commenters

Commenters	Hedges	Boosters	Self-Mentions	Attitude Markers
Arabs	0.34	1.94	0.23	5.14
Non-Arabs	0.75	1.54	0.65	4.57

The values show that both Arabs and non-Arabs used more boosters showing certainty like ‘really’, ‘absolutely’, ‘very’ and ‘sure’ than hedges like ‘perhaps’, ‘maybe’ and ‘I guess’. This implies that both groups were sure about their stance towards the article evoking anger, which was mainly against a proposition (e.g. evacuating Gaza) or a person (e.g. Trump). This agrees with previous research which found anger and happiness emotions to entail a sense of certainty whereas fear and sadness were more associated with uncertainty (Kapucu et al., 2024). As for self-mentions, the Arabs used less first person pronouns than the non-Arabs, which was also shown in LIWC’s calculation of pronouns in all comments associated with the four articles. In all articles, the Arabs used less of the pronoun ‘I’ and more of the collective pronoun ‘we’ than non-Arabs, which reveals that they showed more collectivism and less individualism than non-Arabs. A similar observation was made by Alhadlaq and Alnuaim (2023) who compared sentiment analysis of Arabic and Spanish tweets after translating them into English and found that the Arabs showed more collectivism through the use of personal plural pronouns.

As for the attitude markers, represented by lexical items suggesting a specific attitude, the Arabs outnumbered the non-Arabs in the number of attitude markers used. Though the predominant emotion in Arabs’ and non-Arabs’ comments was negative, as found by both human and automatic sentiment analysis methods, the two groups did not show the same stance against the same proposition or individual. For example, in the Arabs' comments, the 'against' stance was predominant towards people (e.g. Trump) and claims (e.g. evacuating Gaza), yet the in the non-Arab comments, the writers expressed a different stance orientation showing a stance against Palestinians and in favor of Trump in about 25% of the comments. This indicates that sentiment analysis alone is insufficient for accurately detecting stance, and that stance should be examined within both its immediate and broader context to achieve more reliable results. The next section describes the attitude markers used to indicate sentiment and stance in Arabs and non-Arabs comments, which in turn highlights ideological differences between the two groups.

4.3 Ideological Significance of Attitude Markers in Arab vs. Non-Arab Comments

In order to investigate the ideological differences in stance expression between Arabs and non-Arabs in news comments, the author coded the negative emotion words in each group of comments according to the most frequent themes and compared the themes across the two groups. In addition, the presence of high-frequency words, calculated by LIWC, was also examined to detect similarities and/or differences among Arab and non-Arab social media users.

The most frequent semantic representations of emotion in the article on Gaza's evacuation, likely to evoke anger, were related to states (or persons) that cause harm, result from harm, are irrational, rejected, deceitful or conquering. States that cause harm are represented by words such as 'destroy,' 'attack,' 'force,' and 'terrorize'; states that result from harm are represented by words like 'suffer,' 'lose their homes,' and 'are threatened'; irrational states are conveyed through words like 'crazy,' 'mad,' and 'lunatic'; rejected states appear in terms like 'hate,' 'refuse,' and 'condemn'; deceitful states are expressed through words like 'mislead,' 'deceive,' and 'misinform'; and conquering states are depicted with words like 'conquer,' 'invade,' and 'take over.' Figure 1 below shows the frequencies of these states that semantically represent anger-evoked negative words in Arab and non-Arab comments.

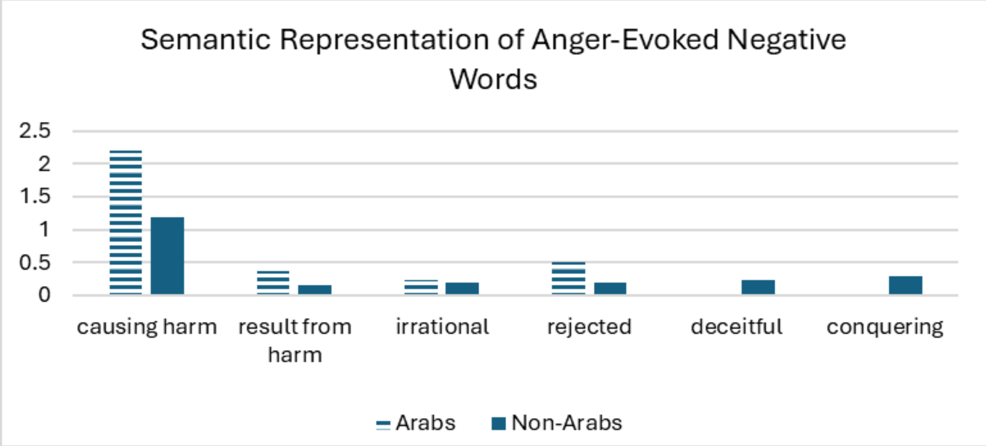

Figure 1 Semantic representation of anger-evoked negative words in Arab vs non-Arab comments

The above graph shows that the most frequently occurring negative expressions in Arabs' comments on Gaza's evacuation are related to states causing harm and resulting from harm as well as the state of rejecting the current situation. This implies that the Arabs were taking a more defensive stance, condemning the American policies and expressing their anger by describing the violence inflicted upon the Palestinians, aiming to win the world's support to stand against their evacuation. The non-Arabs, on the other hand, used more negative expressions criticizing the American president's policies as irrational and deceitful. They also referred to America and its allies as 'conquering and invasive' of other peoples' lands, which reflects a sense of power and a confrontational rather than a defensive identity. However, a number of non-Arabs also showed a negative stance towards the opposite side; that is, the Palestinians. This was shown in comments like 'Gaza wants to play victims', 'Look at the terrible situation Hamas has put you in' and 'The US should help destroy terrorists', and a positive stance towards Trump and his decisions as shown in 'Trump just wants to make it better to make peace' and 'God bless Trump'.

The significant differences between Arabs and non-Arabs in the high-frequency words associated with Gaza's evacuation were related to the use of the words (God, Christian, Muslim, Jew, Zionist, Hamas, terrorist, displacement, rebuild, international and dream). Figure 2 shows the distribution pattern of these words in Arabs vs non-Arabs' comments.

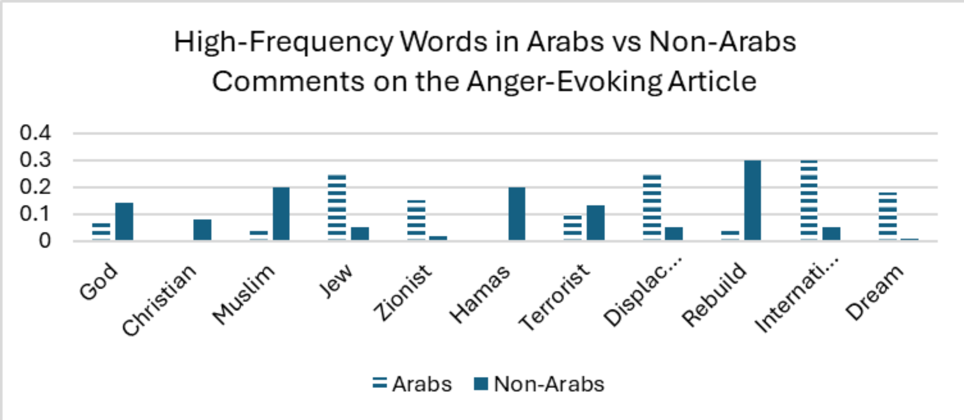

Figure 2 High-frequency words in Arabs vs non-Arabs' comments on the anger-evoking article

Figure 2 shows that the Arab commenters used a significantly higher number of the words (Jews, Zionists, displacement, international and dream), while the non-Arabs used a higher number of the words (God, Christian, Muslim, Hamas, terrorist and rebuild). This implies that the Arabs tended to associate the American policies against Palestinians with the policies of Israel, which, for many Arabs, is associated with Judaism and Zionism. The non-Arabs, on the other hand, treated Israel as simply a country trying to secure its existence in the region, regardless of its religious disposition. The Arabs used the word 'displacement' more to refer to the plan to dislocate the Palestinians and expel them from their own land for the benefit of Israel, while the non-Arabs described the process as an attempt to evacuate the inhabitants to 'rebuild' Gaza to make it a more livable place. The Arabs, again, implied a defensive attitude, trying to call for the 'international' forces to help the Palestinians to achieve their 'dream' of freedom, while the non-Arabs showed a more offensive and confrontational attitude by describing the 'Hamas' militant group in Palestine as a 'terrorist Muslim' group that is responsible for all the resulting chaos. The analysis of the comments on the article about Gaza is the most detailed in the current paper since the comments gathered were significantly more than those associated with the other three articles.

In the article about the outbreak of COVID-19, likely to evoke fear, the most frequent negative expressions in the comments were related to the themes of chaos, fear, death, infection, incompetence and deceit. The values of these themes' frequencies were close in Arab and non-Arab comments, with more Arab comments mentioning chaos-related expressions (1.7% compared to 1.3%) and more non-Arab comments criticizing the incompetence and deceitful practices of governments in reporting numbers of infections (1.3% compared to 0.19%). This supports the previous finding that shows Arabs as more defensive, commenting on the outcomes of destructive and chaotic states, while non-Arabs tend to be more cynical and more likely to freely criticize their governments' policies.

In the article about the drowning of the Moroccan boy, Rayan, most negative words belonged to the themes of sorrow, hard times, and death, with more Arabs mentioning sorrow-related words (3.8% compared to 2.8%). This implies that Arabs felt more sorrow as the killed boy was Arab, and they seemed to identify more with him. A significant finding about the comments on this article is that the words 'parents' and 'family' were mentioned 17 times (2.8% of total words) in Arab comments but did not occur at all in the non-Arab comments. This suggests that Arabs tended to place a higher value on family relationships compared to non-Arabs, and that they felt a deeper sympathy for parents who lost a child.

As for the article about Morocco's victory in World Cup 2022, likely to evoke happiness, the common themes in Arabs' and non-Arabs' comments were pride, praise for the players, congratulating the winners, achievement and merit. The values were close between Arabs and non-Arabs with the difference mainly in the Arabs' more use of words related to pride (1.5% compared to 1.2%), praise for the players (4.3% compared to 3.15%) and merit or emphasizing that the players truly deserved the victory (0.97% compared to 0.4%). This suggests that Arabs showed more pride in the victory as the winning team shared their Arab background.

A significant finding about the use of religious words, especially words referring to God (or the Arabic name of God 'Allah') was shown by both LIWC and human annotators. Words referring to God were significantly higher in Arabs' comments associated with the articles evoking fear (1.14% compared to 0%), sadness (3.8% compared to 1%) and happiness (1.19% compared to 0.2%), which implies that Arabs have a more religious nature and tend to call on God when feeling scared (seeking help), sad (seeking comfort) or happy (expressing gratitude). The same finding was observed by Germano and Miller (2015) who found that the speech produced by Arabs of different faiths in North Africa and the Middle East was significantly influenced by religious references. However, the Arabs made less references to God in their angry comments related to Gaza's evacuation (0.07% compared to 0.14%), which implies that, out of respect for divinity, they avoided mentioning God in contexts that included insulting words criticizing people or policies. The same result was found by Abdel Hamid et al.

(2020) who concluded that Arab bilinguals used more religious words in contexts provoking fear, sadness and happiness than in contexts provoking anger.

4.4 Limitations and Recommendations for Future Research

The sentiment analysis of Arab and non-Arab comments presented in this paper faces several limitations. The first limitation is the relatively limited corpus of comments related to the four news articles. The author chose the four articles as representative of the four basic emotions of anger, fear, sadness and happiness, but a larger corpus is recommended in future research to obtain a more comprehensive overview of sentiment representation in language. Another limitation lies in the uncertainty regarding the cultural background of each comment writer. The author considered the comments written by users with Arab names as Arab comments since the users chose an Arab identity; yet, this was not enough evidence that the commenters were actually Arabs, and the same applies to non-Arab comments. Therefore, future research should explore methods for distinguishing the cultural background of users, possibly by obtaining legal consent to access information about their nationality or place of residence. A third limitation is the lack of available information about the age or gender of commenters. Future research could explore how age and/or gender may influence sentiment polarity and intensity as well as emotion expression in language.

5. Conclusion

This paper provides a sentiment and stance analysis of Arab versus non-Arab comments associated with articles likely to evoke the emotions of anger, fear, sadness and happiness. Both the LIWC-22 tool and human annotators assigned the same sentiment polarities; however, the human-calculated values were higher, as the automated tool appeared to overlook a significant number of emotion-related words—likely due to the broad categorization system within its lexicon. In terms of stance detection, the comments associated with the negative emotions of fear and sadness showed an overall ‘against’ stance, the comments associated with happiness showed an ‘in favor’ stance, and the comments associated with a controversial political conflict evoking anger showed contradicting stances between Arabs and non-Arabs.

As for the ideological implications of the sentiment analysis and stance detection of the data under study, the Arab comments were found to be more defensive and emotional, and to include more words related to family and religion. The non-Arab comments, on the other hand, were found to be more confrontational and critical, often questioning the honesty of individuals and the credibility of governments. To conclude, the present study conducts sentiment analysis and stance detection on Arab versus non-Arab texts to explore differences in emotional expression across cultural backgrounds. It also provides insights that could inform future sentiment analysis research, offering practices to improve accuracy in understanding emotional expression.

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