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Emoji are Effective Predictors of User's Demographics

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***Abstract*—Social media platforms like Twitter provide rich data that can offer insights into various aspects of users' behavior. In this study, we explore the potential of emoji usage as a means for demographic prediction. Leveraging a Twitter dataset of 18,689 users, annotated with gender and ethnicity labels, we analyze the proportion of tweets containing emoji across different demographic groups. We identify significant variations in emoji usage, with women utilizing emoji more frequently than men and users of African descent displaying a higher tendency for emoji usage compared to users of European descent. Moreover, we investigate the most distinctive emoji for each group, revealing intriguing patterns that are closely tied to the cultural and demographic backgrounds of users. Building upon these findings, we employ machine learning models with different feature extraction techniques to predict users' gender and ethnicity. Our results demonstrate the predictive power of emoji, outperforming traditional text-based features. Furthermore, our study provides evidence that emoji usage can be a valuable resource for inferring user demographic characteristics on social media platforms, contributing to our understanding of user behavior in digital environments.**

***Index Terms*—Emoji, Demographic Prediction, User Profiling**

I. INTRODUCTION

Emoji are utilized as ideograms in digital communication tools like social media and mobile apps. They can be used to convey the meaning of a word, phrase, or sentence in just one symbol, and can even replace entire sentences in a more engaging and meaningful way [1]. In recent times, emoji have become incredibly popular across the globe. In fact, the Oxford English Dictionary named an emoji as the "word of the year" in 2015 [2]. There are currently over 3,000 emoji in the Unicode Standard, which is the system used to encode and display characters on electronic devices. The range of emoji includes everything from smiley faces and food items to animals, transportation, and more [1]. Although various studies have been conducted on emoji in different fields, the nature of their usage in social media and their ability to predict demographic characteristics are still relatively unexplored research areas. Even though emoji may sound only emotional and impulsive, they may convey a more deep meaning beyond the emotional information. According to various studies [3]–[5], people utilize emoji like national flags, profession symbols, and skin-toned emoji to convey their identity in online communication. Additionally, research [6] suggests that if sufficient data is available, emoji can be used to gauge the level of development in a country. This demonstrates the potential of emoji as a significant means to deduce users' identity.

Numerous studies have demonstrated the potential of machine learning algorithms to detect personal information about users from their social media accounts. These studies have focused on various aspects, such as gender, age, location, political bias, and even sexual orientation. For instance, Al Zamal et al. [7] used Twitter data to predict users' gender and age, while Jurgens et al. [8] investigated the use of location data for user profiling. Similarly, Jernigan and Mistree [9] showed that sexual orientation could be predicted from Facebook data. Notably, these studies demonstrated that such personal information could be inferred even when users tried to hide their demographic and personal data. This underscores the importance of considering various social media signals, such as text, networks, and activity, to gain insights about users. In this context, our study aims to explore the potential of emoji, an increasingly popular form of online communication, to provide insights into users' demographic and personal data.

This paper investigates the emoji usage on Twitter across different gender and ethnicity groups, and their predictive power for inferring users demographic information. We base our study on a dataset that contains around 20k Twitter users labelled with both corresponding gender and ethnicity [4]. The tweets timeline of those users were collected, including the emoji each user use in their tweets. Initially, we apply a quantitative analysis regarding the differences in emoji usage by different genders and ethnicities. Later, we explore the possibility of predicting users' gender and ethnicity using emoji signals solely, and compare performance to using more advanced features for classification, such as users' tweets text, which has been demonstrated to be effective in previous

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[1] https://unicode.org/emoji/charts/

research [10]–[12].

The two main research questions we seek to answer are:

- **RQ1** Are there differences between emoji usage among different demographic groups?
- **RQ2** Can emoji be an enough signal to infer user's attribute? (e.g. gender and ethnicity)?

Answering such questions allows on one hand to understand social behaviour of online communities and demographics groups through the interpretation of their emoji usage, which contributes to the large lines of research about emoji usage on social media. Additionally, it reveals how emoji can be misused to unveil personal information about users identity, which contributes to the work related to online users information prediction highlighting additional threats to privacy online.

II. Related Work

Emoji are small images or icons that convey emotions, attitudes, or ideas, and are used to complement or replace text in online conversations. We explore here emoji analysis from two distinct perspectives. Firstly, we investigate how emoji can be utilized to understand the social and behavioral patterns of online users. Specifically, we examine the relationship between emoji and personality traits, sentiment, emotions, and social network structures. Secondly, we focus on a more specialized application of emoji analysis, namely, predicting user demographics. This involves examining the association between the usage of specific emoji and the demographic characteristics of users. By analyzing the relationship between emoji and demographic factors, researchers can develop algorithms that can accurately predict user age, gender, or other demographic features.

A. Emoji usage

Analysing emoji usage have attracted increasing attention upon the emergence of social media [6], [13]–[16]. Researchers have been looking into varying reasons and impacts of Emoji usage, such as sentiment and semantic analysis of emoji usage [17]–[19], relation between emoji and online language [20]–[22], the role of emoji in detecting users' gender, skin colour or age [4], [23]–[25], or simply the role in identifying users' affiliation and identity [5], [26]. novak2015sentiment were among the first to provide an emoji sentiment lexicon of the most frequently used emoji in Twitter. They investigated the sentiment of emoji extracted from 1.6 million tweets in 13 European languages. In the Emoji Sentiment Ranking, the sentiment of each emoji were measured by referring to the sentiment polarity of the tweets. Most emoji were identified as positive, while the sentiment ranking of emoji were similar in between all languages. Similarly, barbieri2016cosmopolitan emphasised on the semantic comparison of emoji usage in different languages. They indicated that the overall semantics of the emoji in their chosen subset is identical across different languages whereas some emoji are interpreted differently by certain languages. These make emoji capable of transporting the message meaning across different language barriers. preisendorfer2018social found that the 140 character limit of twitter posts make it difficult for emotions to be expressed. On the other hand, emotions, which are a typographic display of a facial representation in emoji, were found to be more accurate when it comes to conveying users sentiment. [27] suggested an emotion-aware framework that predicts emoji sentiment incorporate emotional information for emoji prediction tasks. They rendered a reasonable performance in emotion detection, by analyzing the correlation between emoji and emotions. Studies about emoji usage can also play a significant role in our understanding of the influence of online media content into influencing the user consumer behavior. For example, [28] examined how the interaction between emoji (emotional vs semantic) and social media content (aesthetic experience vs promotion) influenced consumer engagement in digital communication of tourism brands. The results showed that, for aesthetic experience content, emotional emoji elicited more consumer engagement than semantic emoji did. Moreover, emotional emoji increased consumer engagement by eliciting a higher level of emotional responses for aesthetic experience content, whereas semantic emoji enhanced consumer engagement by generating greater credibility for promotion content. Such findings have practical implications for social media marketers in the marketing industry, helping them make informed decisions about the effective use of emoji and content to enhance consumer engagement.

Apart from the semantics and interpretations of emoji, some studies focused on the relationship between emoji usage and demographic attributes. ljubevsic2016global analyzed the spatial distribution of emoji using millions of geo-encoded tweets containing emoji. By applying a correlation analysis between emoji distributions and World Development Indicators, they demonstrated that emoji usage can reflect the living conditions in different regions all over the world. Similarly, an analysis of the emoji usage on smartphones has been performed by using a large amount of data from a popular emoji keyboard, indicating that the frequencies and the categories of emoji are considered to be a strong signal of the cultural differences between smartphone users [29]. robertson2018self,robertson2020emoji focused on the use of Skin Tone Modified Emoji (STME) in Twitter (i.e., emoji with different gradients of skin colour). They analysed the connection between ethnicity and STME usage through the analysis of more than half a billion tweet. They found that darker-skinned profile photos are more likely to use STME, with the emoji's skin color being more close to the skin tone of the profile's photo. hand2022interactions explored the increasing presence of emoji alongside written language in interpersonal communication. They specifically investigated the impact of negative-face emoji on perceptions of message tone and senders' mood. Their findings revealed a negativity effect, suggesting that negative-face emoji influenced the emotional interpretation of messages.

Emoji are also used as a way to reflect user cultural identity. barbieri2018gender demonstrated that emoji usage is heavily correlated with the user's gender and skin tone. Through the analysis of two billion US tweets, they found that the stereotypes of ethnicity and gender significantly affect the use of the skin tone modifiers, emoji changing the most when switching the skin tone were in the main hand gestures, while the ones changing the most when switching the gender tone are in the job roles, such as Teacher emoji (👩‍🏫) for female users or Police Officer emoji (👮‍♂️) for male users. In the context of employment and nationalities, previous studies have examined the usage of emoji of different social network users, such as Twitter and Instagram. These investigations have highlighted the role of emoji in representing individuals' self-identity, including their country of origin, occupation, and sometimes even their sexual orientation [5], [30], [31].

B. Demographic Prediction

There have been numerous studies focusing on predicting personal information about online users, including demographic attributes such as gender and age [7], [10], [32], ethnicity [10], [11], [33], and user location [8], [34], [35]. While earlier studies have primarily focused on using emoji to predict emotions and sentiments from text, which involves extracting a sentiment value from the text using the detected emoji [19], [27], [36], [37], our study takes a different approach. We aim to uncover personal and demographic traits of users based on their emoji usage. Rather than solely focusing on emotions, we explore how emoji can provide insights into individuals' characteristics and preferences. In this section, we discuss research conducted on predicting user demographics using general profile textual data, with a specific emphasis on the use of Emoji words.

One common approach for predicting user demographics involves the use of classification models based on users' names to determine gender and ethnicity [11], [38]–[40]. Studies suggest that discrete attributes such as first names and usernames can be valuable resources for predicting demographics, particularly for specific user groups. In a study by bhagvati2018word, three popular deep learning models were trained using 18,000 names from different regions, demonstrating that LSTM combined with an appropriate embedding technique achieved the highest performance in gender classification. Furthermore, some studies have utilized user-posted images [41] or the follower network of users [32], [42] to predict demographics. preoctiuc2018user focused on predicting user-level ethnicity, achieving state-of-the-art out-of-sample accuracy by extracting five linguistic features from users' tweets for four prominent racial groups in America.
Demographic prediction can also be accomplished using geo-tagged tweets. In the study by montasser2017predicting, models were trained on geo-tagged tweets to make predictions about demographics. This suggests that geo-tagged tweets can provide valuable insights into the demographics of specific geographic regions. Deep learning models have also been employed to predict demographics based on user posts. In sezerer2019gender, an RNN model with an attention mechanism was developed to predict the gender of Twitter users using their tweets. Further advancements have been made in demographic prediction using deep learning models. For example, sezerer2018gender focused on gender prediction from tweets by utilizing a combination of CNN and attention mechanisms. In their approach, each tweet was inputted into a CNN, which generated an attention vector corresponding to that specific tweet.

There have been only limited research that use emoji to make demographic predictions. chen2018through have made the first effort to predict user gender from emoji. In [43], 1370 features have been extracted based on the user's frequency and preference of emoji. The features were fed into five different machine learning models commonly used for demographic prediction. They also provided a comparison between the emoji models and text models, and finally found that the model solely based on emoji usage achieves a comparable performance of text model in terms of gender prediction.

In this study, we try to explore demographic prediction, namely gender and ethnicity, using emoji signals on a large scale dataset and compare its performance to state-of-the-art baselines using users' textual data in their social media posts. Our paper focuses on two main contributions. First, we analyze how emoji are used by different racial groups on Twitter. Second, we propose a prediction method to accurately predict user ethnicity and gender using state-of-the-art classifiers. These two areas have not been extensively studied in the existing literature, and our paper aims to fill this gap. By doing so, we hope to provide new insights into the use of emoji and how they relate to user characteristics, as well as contribute to the development of more accurate prediction models for user ethnicity and gender.

III. Data Preparation

Our study is based on a Twitter dataset provided by Robertson et al. (2020) [4]. The dataset consists of 19,874 Twitter users, each labeled with their gender and ethnicity. The gender labels include male and female, while the ethnicity labels include Asian, African, Hispanic, and European. The dataset was obtained through crowd-sourcing platform Figure-eight, where annotators labeled each user based on their profile picture. Only users with clear profile pictures that showed their gender and ethnicity, and with agreement from three annotators, were included in the dataset. It is worth noting that the four defined labels assigned to the r users in the are based on their physical traits rather than strict geographic or continental origins.

Using the Twitter API, we collected the timelines of these users. Some accounts were found to be deleted or converted to protected, resulting in a final dataset of 18,689 users. The demographic distribution of this dataset includes 9,531 females and 9,158 males, with 1,143 Asians, 7,693 African, 418 Hispanics, and 9,435 European.

In total, we collected approximately 40 million tweets from the timelines of these 18,689 users. We extracted the emoji that appeared in each user's timeline, and on average, 20% of the tweets contained at least one emoji. This corresponds to an average of 439 emoji per user. Table I provides a summary

	Total	Mean	Std
Users	18,689	na	na
Tweets	40,716,790	2,179	1,454
Tweets with emoji	8,203,910	439	549

TABLE I: Number of users in our data collection, and the number of tweets and tweets with emoji in total and per user

of the user and tweet statistics in our dataset.
In the following, we apply analysis to the differences in emoji usage among different demographics; then we explore using the emoji per user as a feature vector to predict the user's gender and ethnicity.

IV. EMOJI USAGE BY DEMOGRAPHICS

In this section, we investigate our RQ1; we conduct a descriptive analysis of emoji usage in different demographics. For each demographic group, we analyse the proportion of tweets containing emoji, the top used emoji, the most distinctive emoji of each group over the others. Although previous studies might have highlighted some of the findings we have in this section [6], [16], [44], [45], the analysis we present here is essential for motivating prediction work in the next section.

A. Proportion of Tweets with Emoji

As mentioned previously, we examined the proportion of tweets containing emoji in our dataset, and now we further explore this percentage across different demographic groups. Table II presents the mean and standard deviation of the percentage of tweets with emoji for each group.

The analysis reveals significant differences in emoji usage between females and males. A Z-test indicates that, on average, 23% of female tweets contain emoji, while the proportion is 18% for males. This finding suggests that females tend to use emoji more frequently than males.

Moreover, when considering ethnicity, we observed a noteworthy contrast in emoji usage between African and European users. African Twitter users incorporate emoji in almost 30% of their tweets, whereas European users use emoji in less than half that amount, around 13%. Asian and Hispanic users fall in between, with emoji appearing in approximately 21% and 20% of their tweets, respectively.

These results highlight the variation in emoji usage patterns among different demographic groups, indicating distinct preferences and cultural influences on emoji usage across genders and ethnicities.

These results are interesting and adds to some of the previous findings by other research studies. For example, robertson2018self show that African users are more keen to modify the emoji skin-tone in their tweets. Our findings shows that they are also keen significantly more than European users to use emoji in general.

B. Top Used Emoji

Figure 1 shows the general top 10 popular emoji. According to this chart, the ”Face with Tears of Joy” 😂 is by far the most popular emoji, which accounts for approximately 20 percent of the total usage. These result aligns with all previous studies since 2017 [6], [16], [44], [45], showing that this emoji consistently remains to be the most popular. The second (😭) and third (🤣) most popular emoji are still another form of Faces with tears of joy. It is noticeable that the top 10 most popular emoji account for nearly half of the overall proportion.

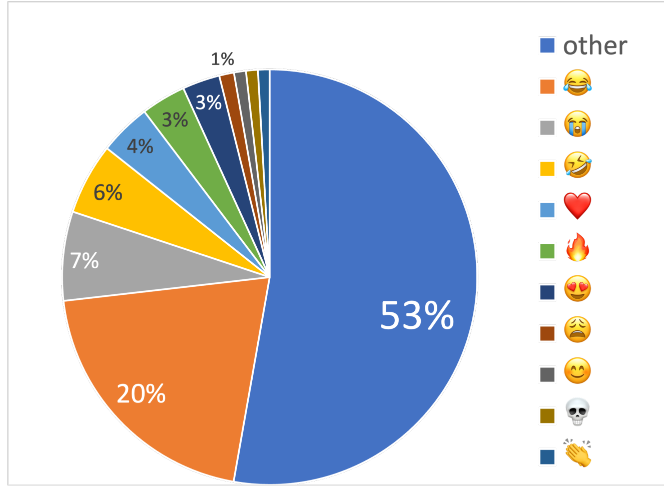


Fig. 1: Top used emoji in our collection

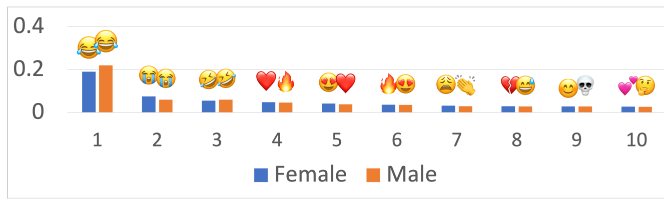


Fig. 2: Top used emoji by gender

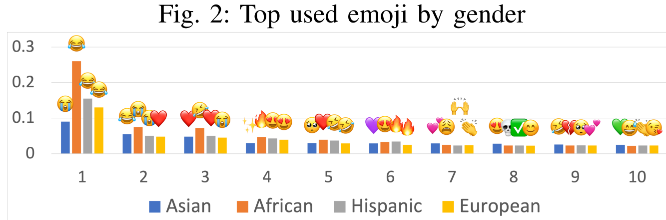


Fig. 3: Top used emoji by ethnicity

After analyzing the top used emoji within each demographic group based on gender (Figure 2) and ethnicity (Figure 3), we observe that the most popular emoji are largely similar with minor variations. These findings are consistent with previous studies [6], [16], [44], [45]. The consistency of our findings suggests a pattern in emoji usage across different demographic groups. This suggests that emoji have attained a level of cultural and communicative significance that goes beyond specific demographic.

Group	Male	Female	Asian	African	Hispanic	European
Mean	0.180	0.229	0.210	0.295	0.197	0.131
Std	0.172	0.188	0.170	0.183	0.174	0.145

TABLE II: Mean and standard deviation of the proportion of tweets that contains emoji

C. Distinctive Emoji

In this section, we examine the most distinctive emoji used by each demographic group. Using frequency of emoji for comparison among groups did not show much differences. In this part, we apply Chi-square[2] for detecting the most distinctive emoji with each demographic group compared to the rest. For each group, we compare the distribution of emoji by probability of use within the group. For gender groups, males are compared to females; while for ethnicity groups, each group is compared to the rest.

Rank	p-value	Emoji
1	0.001855	⚽
2	0.002020	🤷‍♂️
3	0.005314	🤦🏽‍♂️
4	0.007604	👍
5	0.008712	🐐
6	0.009241	🔴
7	0.019617	🏆
8	0.027838	🔵
9	0.033813	🤦🏻‍♂️
10	0.035098	🚀

(a) Distinctive emoji for male

Rank	p-value	Emoji
1	1.79e-11	💕
2	9.78e-06	😘
3	8.34e-05	❤️
4	1.81e-04	💗
5	1.84e-04	💜
6	1.93e-04	✨
7	2.71e-04	😍
8	3.26e-04	🌸
9	6.92e-04	💖
10	3.61e-03	💋

(b) Distinctive emoji for female

TABLE III: Distinctive emoji by gender ranked by p-value of Chi-square test

Table III illustrates the top 10 distinctive emoji used for male and female groups, based on the p-value of the Chi-square test. As shown, there is significant difference between the distinctive emoji for male and female genders. Notably the most distinctive emojis reflect some stereotypical notions. Men tend to use emojis that are related to sports and gestures, while women prefer emojis that concern the emotional and affective sphere. In addition, there are three emoji that are used to represent the body gesture for male (🤷‍♂️, 🤦🏽‍♂️, and 🤦🏻‍♂️). For female gender, it is interesting to notice the most of the distinctive emoji are related to hearts (💕, ❤️, 💗, 💜 and 💖), flowers, and kisses. This again aligns with some stereotypes about females.

Furthermore, we analyzed the most distinctive emojis for ethinc groups and found notable discrepancies. Firstly, when we set the p-value to 0.05, the number of distinct emoji increased significantly for all ethnicities. Specifically, Asians had 92 distinctive emoji, African had 29, Hispanics had 67, and Europeans had 72. Secondly, we observed that the most distinctive emoji for Asians was the ”Loudly Crying Face” (😭), while for Africans, it was the ”Face with Tears of Joy” (😂). This aligns with the ranking of the most frequently used emoji for these two ethnic groups, as shown in Figure 3. Lastly, within the top 10 distinctive emoji for Africans, Hispanics, and Europeans, we found some tone-modified emoji. These included 🙏🏾, 🙌🏾, 👏🏾, 🙏🏿 (for Africans), 🙏🏽, 🤦🏻‍♂️ (for Hispanics), 👏🏻, 👏🏼, 🙌🏻 (for Europeans). These results support the findings of Robertson et al. (2018), who reported a strong relationship between tone-modified emoji and the tone expressed by Twitter users.

[2]We also examined using Mutual Information (MI) and obtained results were similar

V. Demographic Prediction

In the preceding section, we observed variations in emoji usage across different demographic groups, which corroborate previous research studies. Building upon these findings, we now delve into investigating whether these differences in emoji usage can be utilized to infer users' demographic identity, addressing our main research question (RQ2).

To accomplish this, we employ a range of machine learning models in conjunction with various feature extraction techniques. We thoroughly examine the predictive capabilities of each combination and assess their effectiveness in inferring users' demographic information.

A. Ethical Consideration

The work in this section investigates how minor signals in user's profile, such as emoji, might be an indicator to their demographic information. It is important to be noted that the objective here is not to build a demographic classifier, but rather we are interested to investigate how user's privacy might be violated with such minor signals.

An ethical approval has been obtained from the home institute of the authors to perform this study.

B. Feature Extraction

We use four feature extraction techniques as follows:

Bag of emoji (BOE): Users are represented as a frequency distribution over all emoji dictionary. Each user is represented by a vector of 2,600 cells, where each cell represent the frequency of emoji in this user's timeline.

Word2Vec embedding: This method implements the existing baselines in literature, where all the words in a users' timeline are embedded into a Word2Vec vector. A tweet vector is represented as the average of the word vectors in the timeline. Each user will be represented by taking the average of their tweets timeline vectors.

Emoji2Vec embedding: All the emoji in a tweet will be embedded into a vector. And similarly, tweets will be represented as the average of all the emoji vectors, and users will be represented as the average of the corresponding tweet vectors.

Word2Vec + Emoji2Vec: A combination of the Word2Vec embedding and Emoji2Vec embedding described above. Here both words and emoji will be taken into consideration when creating a tweet vector.

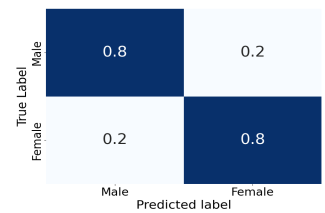
For the features based on Word2Vec embedding, we use the pre-trained 300-dimension Word2Vec model provided by mikolov2013distributed. For the Emoji2Vec embedding, we use the pre-trained Emoji2Vec model released by its original authors [46]. The pre-trained Emoji2Vec model is learned from the description of emoji. The description vector corresponding to an emoji is calculated by taking the sum of the word vectors in that description. In the pre-trained Emoji2Vec model, these word vectors are generated by using the 300-dimension Word2Vec model, which is the same space size for the Emoji2Vec model, and the combination of the two models (Word2Vec + Emoji2Vec). To perform the feature extraction, we use Phrase2Vec, a framework provided by eisner2016Emoji2Vec.

C. Prediction Setup

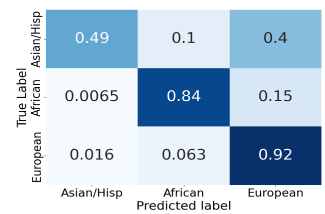
Our feature extraction rendered four different embeddings for each of the 18,689 users. The ratio between the training set and the test set is 4:1. Our prediction setups for gender and ethnicity are the nearly the same. However, When it comes to ethnicity, our dataset contain larger number of African and European users compared to Asian and Hispanic. Hence, we merged the two last groups (Asians and Hispanics) into one group when predicting ethnicity labeled as Asian/Hispanic. We use Three different classification algorithms : Support vector machines (SVM), Random Forest (RF), and Gradient Boosting Classifier (GBC). wood2018predicting explored character-level neural networks (CNN and RNN) to predict the gender and ethnicity of Twitter users. They exploited User Name and/or Screen Name. We choose their CNN approach as the baseline method for our demographic prediction. Both accuracy and (macro) f1-score are used to evaluate our prediction results

D. Prediction Results

Table IV illustrates the performance comparison of the gender's prediction using different classifier algorithms and feature embedding models. The table reports the general prediction accuracy and general F1-Macro score, along with the male F1 score (F1_M) and female F1 score (F1_F). As shown in the table, three feature models (BOE, Word2Vec, and Word2Vec + Emoji2Vec) achieve higher accuracy and (macro) F1 scores compared to the baseline method. On the other hand, the ML algorithms trained solely on Emoji2Vec features perform less better. This means that the character sequences of the User Name are more indicative of his gender than the user's emoji. The best performing combination (highest F1 score) for male gender is the GBC algorithm combined with BOE embedding, while the SVM combined with Word2Vec + Emoji2ve is the best combination for the female gender. SVM and GBC combined with Word2Vec+Emoji2Vec embedding obtained the highest general accuracy and f1-score at the same time, with a score of 0.806. Furthermore, by making a comparison between the classification algorithms trained



(a) Confusion matrix by gender



(b) Confusion matrix by ethnicity

Fig. 4: Confusion matrix by gender and ethnicity

using Word2Vec and the Word2Vec+Emoji2Vec models, it is noticeable that adding emoji vectors when constructing user representation increases the prediction performance.

We also achieve significant results for ethnicity prediction, which is demonstrated in table V. When using the baseline method, by feeding the user name and screen name into the CNN model, we obtained similar prediction results to the original author work [10]. However, we found that the CNN model has prediction performance to the ethnicity of Asian and Hispanic users. This might be related to the unequal distribution of classes in our dataset. Similar results were obtained when using BOE and Emoji2Vec prediction on Asian/Hispanic users. Word2Vec and Word2Vec+Emoji2Vect embeddings performed remarkably well. Both SVM combined with Word2Vec and Word2Vec+Emoji2Vec achieved the highest f1-score for African users(0.868), while the Gradient Boosting Classifier combined with Word2Vec+Emoji2Vec achieved the best score for European users(0.872). For gender prediction, the bag of emoji (BOE) feature model achieves similar results to the Word2Vec model.

We also provide the confusion matrix for gender and ethnicity in Figure 4. Notably, a significant majority of male and female samples have been correctly predicted. Similarly, the prediction accuracy is high for European and African users' ethnicity. On the other side, only half of the Asian/Hispanic users have been correctly predicted. Our predictions results indicate that the emoji is a good resource to make gender and ethnicity prediction. The reason behind this might be related to to the tone modified emoji. We think people use the emoji that express their biological and ethnical identity. For example, the use of national flags emoji can be used to predict the nationality of people. In the future, we expect that emoji will be more diversified and widely used, which implies that emoji can have more prediction power in the future to infer other demographic attributes. Both the gender prediction and ethnicity

Feature	Classifier	Acc.	F1	F1_M	F1_F
UserName	Baseline	0.74	0.74	0.74	0.74
BOE	SVM	0.77	0.77	0.79	0.75
	RF	0.79	0.79	0.79	0.79
	GBC	0.80	0.80	**0.81**	0.80
Emoji2Vec	SVM	0.67	0.67	0.71	0.62
	RF	0.71	0.71	0.72	0.71
	GBC	0.73	0.73	0.73	0.73
Word2Vec	SVM	0.80	0.80	0.80	0.81
	RF	0.77	0.77	0.78	0.78
	GBC	0.80	0.80	0.80	0.80
W2V + E2V	SVM	**0.81**	**0.81**	0.80	**0.81**
	RF	0.78	0.78	0.78	0.78
	GBC	**0.81**	**0.81**	0.80	0.81

TABLE IV: Gender Prediction Results. F1_M represents the F1-score for the male gender, and F1_F represents the F1-score for the female gender.

Feature	Classifier	Acc.	F1	F1_AH	F1_A	F1_E
UserName	Baseline	0.70	0.48	0.00	0.69	0.76
BOE	SVM	0.81	0.71	0.46	0.84	0.84
	RF	0.83	0.72	0.44	0.85	0.85
	GBC	0.84	0.75	0.51	0.87	0.86
Emoji2Vec	SVM	0.71	0.53	0.12	0.70	0.77
	RF	0.74	0.61	0.29	0.75	0.78
	GBC	0.77	0.67	0.42	0.77	0.81
Word2Vec	SVM	0.83	0.76	0.56	**0.87**	0.86
	RF	0.83	0.76	0.58	0.83	0.85
	GBC	0.85	**0.77**	**0.59**	0.86	0.87
W2V + E2V	SVM	0.84	0.77	0.57	0.86	0.86
	RF	0.83	0.76	0.59	0.83	0.85
	GBC	**0.85**	**0.77**	0.59	**0.87**	**0.87**

TABLE V: Ethnicity Prediction Results. F1_AH represents the F1-score for Asian or Hispanic, while F1_A and F1_E indicate the F1-scores for African and European ethnicities, respectively.

Features	Gender	Ethnicity
Text	0.800	0.850
Emoji	0.804	0.845
Text+Emoji	0.806	0.852

TABLE VI: Demographic Prediction Accuracy using Emoji in user's timeline vs whole tweets text in the timeline

prediction result showed that representing user features solely based on emoji frequency can achieve comparable results to the word embedding methods. Furthermore, the feature that uses both Word2Vec embedding and Emoji2Vec embedding can slightly improve the performance of the models that only use Word2Vec embedding, which finally achieves the best accuracy and macro f1-score for both gender and ethnicity.

Table VI shows the results of the best performing models for predicting Gender and Ethnicity of users when using: 1) only textual data from their timelines; 2) only emoji in their timelines; 3) Both emoji and textual data. As shown, Emoji are clearly an enough signal to effectively predict both the gender and ethnicity of users without the need to use any of the textual data in their timelines.

VI. Summary of Findings and Discussion

In this study, we investigated the usage of emoji on Twitter to uncover potential differences among various demographic groups. Our objective was to determine if emoji usage can reliably indicate a user's attributes, such as gender and ethnicity. Analyzing a substantial sample of Twitter data, we identified distinct patterns in emoji usage across demographic groups. Specifically, we found that females incorporate emoji more frequently in their tweets than males. Additionally, our findings indicated that African users make more extensive use of emoji compared to other racial or ethnic groups, while European users exhibit the lowest rates of emoji usage. Asian and Hispanic users fell between these two extremes. These outcomes align with prior research in the field and provide further insights into how different demographics engage with and express themselves through emoji usage.

To investigate the potential of emoji as signals for inferring user attributes, we explored in the second part of this paper the power of emoji in predicting user demographic attributes. For this, we employed state-of-the-art machine learning techniques. We leveraged various methods to extract user features, from single use of emoji to more advanced Emoji2Vec embedding. We explored the efficacy of such feature representations in predicting users' gender and ethnicity. Our findings revealed that the inclusion of emoji features significantly enhanced the accuracy of our predictive models. In particular, the integration of emoji features with binary classification algorithms yielded notable improvements in gender prediction accuracy. Similarly, when predicting ethnicity, our classification models achieved the best results.

Our findings address the research questions of this study: 1) yes, there are clear differences in emoji usage among different demographic groups, including different genders and ethnicities; 2) yes, these differences in emoji usage are sufficient signals to effectively predict users' demographic information. Our research highlights the fact that even minor signals on our social media profiles, such as emoji used in our posts, can reveal a lot of information about our identity without our awareness. This finding aligns with existing research on users' privacy online, where different signals, including text and network connections, can be exploited to infer personal information [9], [10], [32], [47]–[53].

The implications of our findings are significant in the field of computational social science. Understanding the nuances and variations in emoji usage among different demographic groups contributes to a more comprehensive understanding of digital communication and online behavior. Furthermore, the ability to predict user attributes, such as gender and ethnicity, based on emoji usage enhances our understanding of the social dynamics and cultural influences that shape online interactions. Our research provides deeper insights into the role of emoji in digital communication and their potential as signals for inferring user attributes. This knowledge can inform various domains, including marketing strategies, social sciences research, and computational linguistics, facilitating a deeper understanding of online communities and promoting more inclusive digital environments.

VII. Conclusion

This paper aimed to address a fundamental research question: Can the usage of emoji in social media accounts provide insights into users' demographic information? To investigate this, we conducted a comprehensive analysis of emoji found in the timelines of Twitter users. Our findings revealed notable variations in emoji usage patterns based on gender and ethnicity. Surprisingly, our prediction models achieved comparable performance using only emoji signals from users' timelines, without relying on textual content.

In future studies we intend to investigate the combination of a larger extent of demographic dimensions to uncover more insightful findings. Specifically, exploring the distinctions between African females and European descent females, as well as comparing African males and females, could provide a deeper understanding of how emoji usage relates to demographics. Additionally, employing a multitask learning classifier could offer an interesting approach to predict multiple demographic labels simultaneously. This would enhance our ability to make comprehensive predictions about user demographics, considering factors such as gender, ethnicity, and other attributes. By considering these avenues for future research, we can gain a better understanding of the intricate relationship between emoji usage and user demographics, contributing to our knowledge of digital communication and the socio-cultural dynamics that influence it.

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