Exploring the Connection Between Emoji Usage, User Identity and Context Using Statistical and Machine Learning Approaches

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Abstract: Due to the growing popularity in emojis on social media platforms, comprehensive researches regarding the relationship between emoji usage and factors such as user identity, platform and context are of great importance. Based on a dataset of typical emoji usage records, the research uses statistical analysis methods and machine learning techniques to reach the target. In particular, chi-squared test, K-means and t-Distributed Stochastic Neighbour Embedding (t-SNE) are used in the research. In the statistical analysis phase, the research classifies the dataset based on different factors and compares the distributions of the subsets of data with p-values generated by chi-squared results to determine the importance of the factors' influences on emoji usage. In machine learning phase, the research uses K-means to classify the users and emoji usage, to explore the hidden user classification and emoji usage types. The research yields multiple results. In the analysis of individual factors, context and user gender are the more important factors, while user age and platform are less important. However, the classification concerning user gender and age combined has the greatest impact on users' emoji usage, showing different emoji usage distribution under the same context. The research finds that classifying the users into 4 groups will best distinguish the users' trends in using emojis. Finally, the research categorizes the emoji usage behaviours into 3 classes, with 1 major usage and 2 exceptional or sarcastic usages.

1 INTRODUCTION

Nowadays, emojis have become an indispensable part of online communication, both delivering precise messages that pure texts fail to express and showcasing strong emotions that pure texts may lack the strength (Boutet, LeBlanc, Chamberland and Collin, 2021). The precursor to emojis originated in Japan, where the first set of emojis with only 12x12 pixels was created in the late 1990s. In 2007, Unicode, the international standard for text encoding, included emojis in its character set. This rendered emojis an opportunity to make their debut on any online platform and operation system. By the early 2010s, emojis became a mainstream tool for online communication, used in almost all online social platforms (Stark and Crawford, 2015). Due to their significance, they not only have unique semantic and emotional features, but are also closely related to marketing, law, health care and many other areas.

The research on emojis has become a hot topic in the academic field, and an increasing number of scholars from the fields of data science and communication etc. are studying them. In the field of data analysis and computer science, the research topics mainly focus on these certain aspects (Bai, Dan, Mu and Yang, 2019): 1) Analyzing emotional and semantic meaning of emojis using big data. 2) Switching between emojis and other expression modalities 3) Using emojis for emotional analysis of online data. 4) Using emojis for optimizing computer systems. The researches mainly focus on the expression and emotional meaning of emojis, using deep learning and system optimization methods to explore the usage of emojis.

In the field of communication modality, the visual features and Unicode basis of emojis make them an independent expressive language that is different from text and pictures. A lot of research focuses on connection between emoji and other modalities such

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as text, picture and video. In-depth researches on the interconnection between emojis and texts often focus on emoji prediction model, which predicts the emoji used in text such as tweets and comments. For example, a project using the BERT model was successful in predicting most of the emojis in related text (Ma, Liu, Wang and Vosoughi, 2020).

Apart from the academic field, the social network applications have been using deep learning models to recommend emojis for users based on the data they produce, including their reading history and published text. For example, a type of model CAPER is able to recommend emojis based on the context using recommender system (Zhao, Liu, Chao and Qian, 2021).

Despite the previous researches, research gaps still exist as most researches focus on direct relationship between emojis and text and emoji recommendations for users. However, the diversity of users may have impact on the emoji preference. Furthermore, the inter-platform comparison of emoji is often neglected as well. Previous researches have found that users of certain groups may have higher frequency of using emojis (Benkhedda, Xiao and Magdy, 2024). The research exhibited that users' identities have impact on their choices of using emojis. Therefore, comprehensive analysis on the association between the users' information such as gender, age and the platform where they are posting, and their emoji choices has become a research gap that needs to be filled.

In this regard, this research aims to fill the gap through implementation of data analysis, visualization and machine learning methods such as clustering and dimension reduction on a dataset containing records of emoji posted and the users' basic information. Specifically, the dataset is gained from the platform Kaggle (Kaggle, 2024). This research implements K-means clustering and t-Distributed Stochastic Neighbour Embedding(t-SNE) analysis to study the user groups' emoji preference and uses one-hot embedding to vectorize the set of user-emoji information for further research.

2 METHOD

2.1 Dataset Preparation

This research uses the open dataset for emoji trends to implement analysis (Kaggle, 2024). The dataset features over 4, 000 typical records of emoji usage on social media platforms including Twitter, Snapchat and Facebook etc. Each record of emoji usage includes the gender, age of the user and the context in which the emoji is used. The context includes happiness, sadness, support etc. The feature names are: User Gender, User Age, Context and Platform. The dataset contains data with 30 types of emojis, 10 types of contexts, and 6 types of platforms. The type information is described using string. The emojis are stored using Unicode. Figure 1 is an example of the emojis in the dataset.

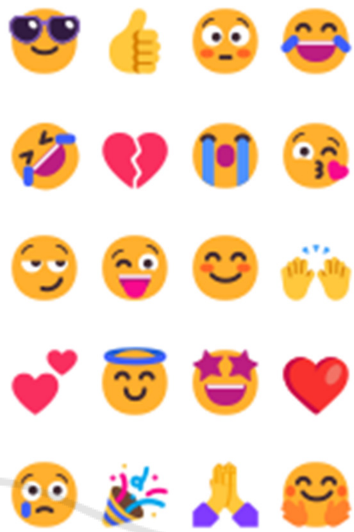


Figure 1: The visualization of various Emojis (Kaggle, 2024).

2.2 Statistical Analysis

A method used in the statistical analysis of the research is chi-squared test and the corresponding p-value analysis. To determine whether the association between two or more variables is statistically significant, a test of significance called the Chi-Square Test (Mindrila, Balentyne and Tables, 2013) is often conducted. The chi-square test method mainly compares the observed values to the expected values through an equation called the chi-square statistics. Then the p-value calculated is compared to the alpha level to determine the reliability of the association. In this particular research, the chi-square test is used to determine the difference and association between the emoji usage of different types.

The research uses a comprehensive analytical method to study the pattern of emoji usage. First, the research intends to study the influence of an individual feature on the usage of emojis. The research studies the relationship between the user gender and the emoji usage by counting the usage of each emoji of male and female users separately and drawing bar plot to visualize the times of usage and the difference by gender. The research studies the relationship between the user age and the emoji usage by calculating the average user age of each emoji. The research studies the relationship between platform and emoji usage by two means: analyzing the top emojis and counting the overall pattern of emoji usage.

The research analyses and compares the top 5 emojis used in each platform and counts the pattern of emoji usage, implementing chi-squared test and calculating p-value to compare the difference in distribution (Mindrila et al., 2013). Assuming the distribution pattern of emoji usage on different social media platforms is the same, the chi-squared test is then used on the set of individual distribution patterns and calculated the p-square accordingly. Similar to the analysis method of platforms, the research finds the top 5 emojis used in different contexts and counts the distribution patterns. The chi-squared tests are applied accordingly.

In addition to single-factor analysis, the research studies the interconnection of different factors and their impact on emoji usage. The research first classifies all the users by their age and gender into 6 user groups: Male, Young (age 0-30); Male, Mid (age 30-60); Male, Old (age more than 60); Female, Young; Female, Mid; Female, Old. Then the research counts the emoji usage pattern of the 6 user groups and uses the chi-squared test to generate the corresponding p-value to study the difference of the distributions. The research also considers the usage of emojis among different user groups under different contexts, studying the preference of users to use emojis when expressing the same emotion. To make the study more concentrated, the research analyzes the count of the top 5 emojis usage under each context. The bar plot is drawn for each context to visualize the different usage of the top 5 emojis by user group. Then, chi-squared test is used for the distribution of 6 user groups under each context and p-values are gathered. Analyzing the p-values, the research can find out under which context the different groups of users diverge in their choice of emojis.

With all the statistical analysis, the research intends to figure out the direct single-factor influence on emoji usage as well as the combined influence of multiple factors. Specifically, the research aims to find and analyze the pattern of emoji usage among different users.

2.3 Dimensional reduction and clustering analysis

To further analyze the pattern of emoji usage, the research uses K-means algorithm to perform clustering and uses t-SNE after One-hot encoding to reduce the dimension and visualize the data. K-means is an unsupervised machine learning algorithm used for clustering tasks (Ahmed, Seraj and Islam, 2020). It classifies a dataset into K distinct clusters based on minimizing the largest Euclidean distance within each cluster. The algorithm works by initializing K cluster centroids randomly, assigning each data point to the nearest centroid, and then updating the centroids based on the mean of the points in each cluster. This process repeats until convergence, generating the final result. t-SNE is a nonlinear dimension reduction technique (Van and Hinton, 2008). It works by converting the high-dimensional Euclidean distances between data points into probabilities that represent the extent to which the data pairs are similar. t-SNE then minimizes the divergence between these probabilities in the lower-dimensional space, while preserving the local structure of the data.

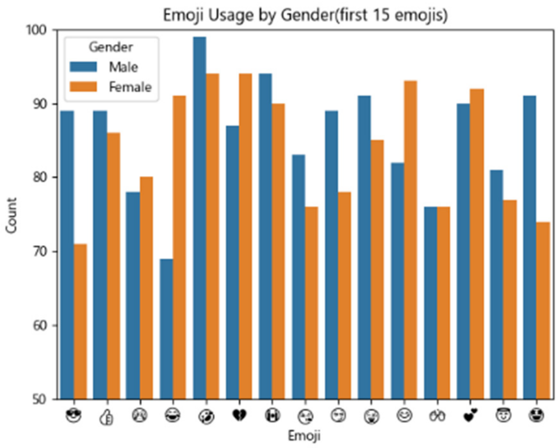
In this research, the K-means algorithm is mainly used for classifying the records of emoji usage and users. Classification of the users with K-means can establish categories for emoji users for further research and study. Classification of the emoji usage with K-means can study the different usage patterns, for example, the normal usage or ironic usage, and spot the special and rare usage of emojis. The t-SNE technique is used for visualizing and validating the result of K-means and reduce the dimension of the data. The research first uses the K-means clustering result of the users to regroup the users and perform chi-squared test to generate p-value. The research then analyzes the K-means clustering result of the emoji usage record to distinguish different ways of using emojis to express feelings.

3 RESULTS AND DISCUSSION

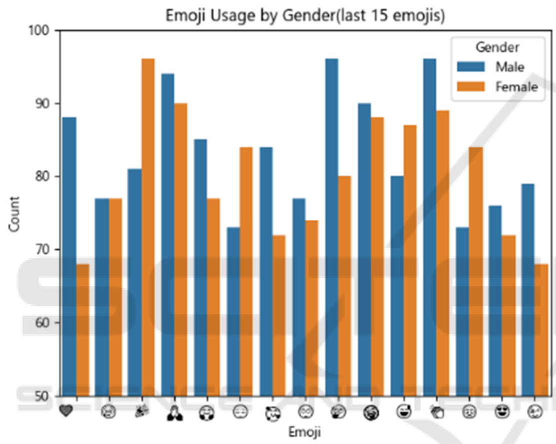
3.1 Statistical Findings

3.1.1 The Relationship Between User Gender and Emoji Usage

As is shown in Figure 2, the difference in user gender will lead to notable differences in the usage of emojis. The Figure 3 visualizes the difference and shows that some particular emojis have more significant usage differences caused by genders. For example, the emojis “face with tears of joy” and “red heart” have the biggest difference in used times by male and female users respectively. The chi-squared test of the emoji usage distribution of male and female users generates a p-value of 0.941, suggesting the gender factor is an important factor in the emoji usage pattern.



(a)



(b)

Figure 2: Emoji usage by gender (Picture credit : Original).

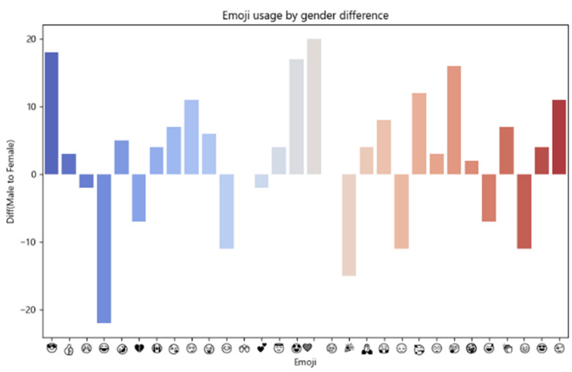


Figure 3: Emoji usage by gender difference (Picture credit : Original).

3.1.2 The Relationship Between Average User Age and Emoji Usage

The research finds that the average user age of each emoji does not have notable differences as is shown in the Figure 4. The average user age of each emoji is from 35 to 40 with less than a difference of 5, suggesting the average user age using emoji is around 35. The research concludes that the different emojis do not have particular user age preferences, yet the distributions of the user age of different emojis have differences and will be featured in the following sections.

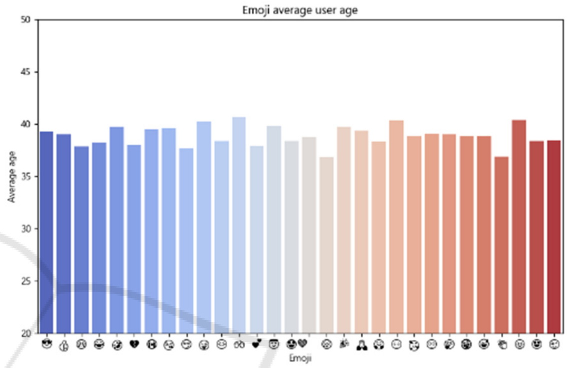


Figure 4: Emoji average user age (Picture credit : Original).

3.1.3 The Relationship Between Platform and Emoji Usage

The research counts the record of emoji on particular platforms and performs chi-squared test on the statistics. The corresponding p-value is 0.060, which is smaller than the common alpha level, suggesting the relationship between platform and emoji usage is unreliable. The platform on which the emoji is posted has little impact on the actual content of the emoji given that other factors are kept the same.

3.1.4 The Relationship Between Context and Emoji Usage

On the basis of the conclusion that context is related to the usage of emojis, the research finds the 5 most used emoji under each context. The result is shown in Figure 5. Some emojis appear in different contexts, suggesting certain flexibility in the usage of emojis even in opposite emotions. For example, the emoji "Rolling on Floor Laughing" can be used under confusion and celebration contexts.

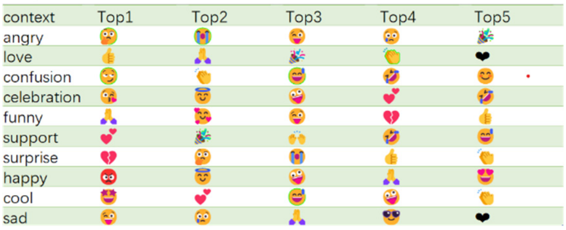


Figure 5: Most used emojis under different contexts (Picture credit : Original).

3.1.5 The Relationship Between User Group and Emoji Usage

The research classified the users into 6 groups, based on their age (divided into the young, the middle-aged and the old) and gender. The result of chi-squared tests on the overall distribution of emoji usage of the 6 groups shows a p-value of 0.640, indicating the significance of the user group on emoji usage. The research finds the 5 most used emoji under each context and within each user group. The corresponding results mainly kept the same with the most used emojis of all users. The research performs chi-squared tests on all the counts of the top 5 most used emojis under each context and within each user group. The corresponding p-values are shown in the Table 1. The result shows that all the p-values are above 0.1, indicating the distribution of different user groups' emoji usages are different under all the contexts. Certain contexts including love, sadness and happiness will strengthen the difference and make the choices of emojis of users from different groups diverge more significantly. The p-values also show that the effect of gender and age combined will exceed the effect of each factor considered alone, suggesting related researches and businesses take both age and gender factors into consideration.

Table 1: The p-value of user-group related emoji distributions under contexts.

Context	p-value
Angry	0.366
Love	0.896
Confusion	0.294
Celebration	0.354
Funny	0.359
Support	0.650
Surprise	0.725
Happy	0.962
Cool	0.527
Sad	0.777

3.2 Machine Learning-based Analysis

3.2.1 The Clustering of Users

The research implements K-means method on the features concerning user information. To identify the most suitable hyperparameter K, the elbow graph is drawn, as shown in Figure 6. The elbow graph shows the best K is 4. The research performs one-hot encoding and t-SNE on the data and the corresponding results are shown in the visualization (Figure 7).

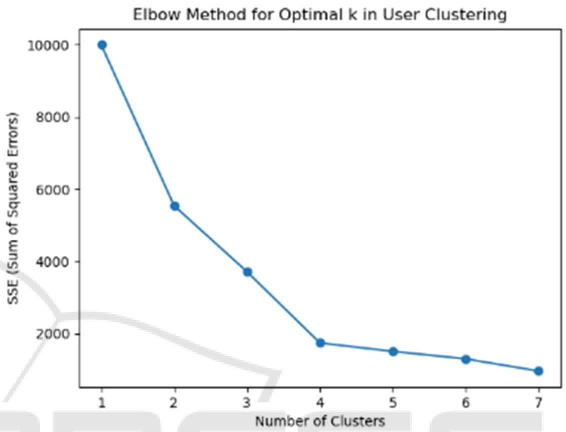


Figure 6: Optimal K determined by the Elbow method (Picture credit : Original).

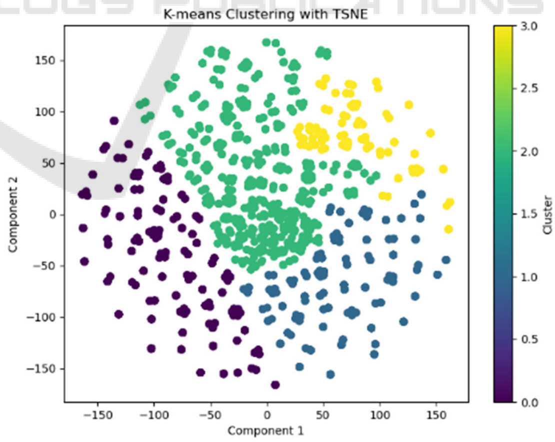


Figure 7: The visualization of K-means results (Picture credit : Original).

3.2.2 The Statistical Analysis of the User Clusters

The statistical analysis methods similar to that of user group patterns are implemented on the K-means generated clusters. The p-value of the chi-squared test on the emoji usage distribution of the 4 clusters reaches 0.957, significantly higher than that of the group classification considering user gender and age. The result shows that the users' K-means generated clusters have a higher impact on the emoji usage of users.

3.2.3 The Clustering of Emoji Usage Records

The result of the K-means clustering of the emoji usage is shown in Table 2. The platform factor is not included as previous results show that the relevance of platform and emoji usage is weak. The result suggests that different emoji usages can be classified into 3 clusters, with 1 cluster taking up most of the emoji usage record. Therefore, the assumption is that the 3 clusters represent 1 regular usage of emojis and 2 sarcastic usages of the emoji. To verify the assumption, the research calculated the p-value of the chi-squared tests on different clusters of emoji usage records under the featured contexts. Because the counts of Cluster 1 and Cluster 3 are scarce, the p-value of the test on Cluster 1 and 3 is greatly vulnerable to statistical mistakes. The results of the other two tests are shown in Table 2. From the table, the research concludes that the emoji usage discovered in Cluster 1,3 are significantly different from that of Cluster 2. Cluster 2 can be deemed as the normal usage of emojis and Cluster 1 and 3 are sarcastic or exceptional usage of emojis.

Table 2: The p-value of emoji-usage-cluster-related emoji distributions under contexts

Context	Cluster 1 & 2	Cluster 2 & 3
Angry	0.308	0.021
Love	0.023	0.711
Confusion	0.742	0.566
Celebration	0.677	0.513
Funny	0.558	0.567
Support	0.923	0.870
Surprise	0.451	0.150
Happy	0.562	0.613
Cool	0.425	0.525
Sad	0.823	0.155

4 CONCLUSIONS

In this work, a comprehensive analysis involving multiple features of emoji users and contexts has been implemented on a dataset of emoji usages to discover the pattern of emoji usage in a more systematic manner. Statistical analysis including single-feature and multi-feature analysis and machine learning methods are used in the research and the results are analyzed. The research concludes that user gender has a substantial influence on emoji usage while user age and platform alone have a slight influence. The research finds that user group, with age and gender considered together, has the greatest impact on choices of emojis under the same context. The research also regroups the users using K-means and the results of the new groups are more significant than the old group. The research categorizes emoji usages and identifies the normal usage and sarcastic or exceptional usage within the records. However, the result of the machine learning methods is yet to be explained better. The preprocessing phase of machine learning methods involves only one-hot encoding, which is also to be extended.

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