Emojis Decoded: Leveraging ChatGPT for Enhanced Understanding in Social Media Communications

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Abstract

Emojis, which encapsulate semantics beyond mere words or phrases, have become prevalent in social network communications. This has spurred increasing scholarly interest in exploring their attributes and functionalities. However, emoji-related research and application face two primary challenges. First, researchers typically rely on crowd-sourcing to annotate emojis in order to understand their sentiments, usage intentions, and semantic meanings. Second, subjective interpretations by users can often lead to misunderstandings of emojis and cause the communication barrier. Large Language Models (LLMs) have achieved significant success in various annotation tasks, with ChatGPT demonstrating expertise across multiple domains. In our study, we assess ChatGPT's effectiveness in handling previously annotated and downstream tasks. Our objective is to validate the hypothesis that ChatGPT can serve as a viable alternative to human annotators in emoji research and that its ability to explain emoji meanings can enhance clarity and transparency in online communications. Our findings indicate that ChatGPT has extensive knowledge of emojis. It is adept at elucidating the meaning of emojis across various application scenarios and demonstrates the potential to replace human annotators in a range of tasks.

1 Introduction

Emojis, as prevalent non-verbal tokens in social networks, are crucial in developing an effective discussion in online communication. These language units encode rich semantic meanings that range from emotions, objects, to actions. The crucial role of emojis has attracted a number of researchers to study various emoji-related topics, from emoji functionality, emoji usage patterns, to the emoji application on downstream tasks. However, there are two challenges for emoji research and emoji applications for social users. For emoji research, to determine the meaning, sentiments, or intentions of emojis in different scenarios, researchers usually hire human annotators to carry out annotation jobs (Lu et al. 2018; Hu et al. 2017), which is not scalable and time consuming. For social users, their differences in demographics, cultural background, or personal experience could lead to misunderstanding of emoji, such as 🙃 (upside-down face) to express irony, and incorrect interpretation may cause miscommunication and block emoji diffusion.

Large language models (LLMs), pre-training on large corpuses, have demonstrated the remarkable achievements in multiple natural language processing tasks. Among various LLMs, ChatGPT (GPT3.5 and GPT4) (Ouyang et al. 2022; OpenAI 2023), has been utilized on downstream application tasks in different domains due to its inexpensive costs and human-aligned response (Ouyang et al. 2022). There is an increasing interest in the use of ChatGPT on social science research questions, especially questions about social networks (Ziems et al. 2023; Zhu et al. 2023). ChatGPT could be the potential solution to these two challenges. First, motivated by the superiority of ChatGPT over human annotators in various text annotation tasks (Kocoń et al. 2023), we hypothesize that ChatGPT has a deep understanding of emoji applications and can replace human workers to label emoji attributes. Second, if ChatGPT has a similar understanding of emojis to humans, when users encounter unfamiliar emojis, they can ask ChatGPT to explain the meaning of the emoji to increase information transparency. On the other hand, previous work suggests that there exist hallucinations in LLMs' generations (Zhang et al. 2023), inconsistencies between the model's output and the real-world facts or user inputs. Whether ChatGPT can produce generations similar to humans for the meaning of emojis is still questionable.

To verify ChatGPT's potential on emoji research and application, our paper conducts a qualitative and quantitative study about ChatGPT's understanding on emoji usage in multiple tasks. Based on the current work on emoji studies, we propose three research questions to probe the ChatGPT's capability on emoji-related tasks.

RQ1 Does ChatGPT generate similar explanations on emoji semantics, sentiments, and usage intentions as humans?

RQ2 Does ChatGPT encode knowledge about emoji usage patterns associated with different communities?

RQ3 What is the performance of ChatGPT in emoji-related downstream tasks?

To answer these research questions, we first ask ChatGPT to explain the semantics, sentiments, and intentions of emojis with or without text context, across different platforms or cultures (Section 3, 4, 5). We find that the interpretation of ChatGPT on emojis is consistent with the human answers in the existing literature in most cases. Next, we ask ChatGPT to generate the associated emoji patterns with multiple communities (gender, platform, hashtag, and culture) to probe ChatGPT's knowledge about emoji usage in different communities (Section 6). Finally, we test ChatGPT on emoji-related downstream tasks, i.e. irony annotation and emoji prediction (Section 7, 8), and the results reveal that ChatGPT is capable of using the emoji information for irony annotation and making emoji recommendations based on user identity.

2 Related Work

Our work can be related to two streams of previous research studies: emoji functionalities and ChatGPT applications on the computational social science domain.

2.1 Emoji Interpretation

With the prevalence of emojis on social networks and other platforms, there has been increasing interest in studying the emoji functionality. Researchers have explored emojis with the functions to express the sentiment, highlight topics, decorate texts, adjust tones, indicate identities, and engage the audience (Ai et al. 2017; Lu et al. 2016; Ge 2019; Hu et al. 2017; Cramer, de Juan, and Tetreault 2016), and with these emoji functions, the researchers summarized the intentions to use emojis on different platforms (Hu et al. 2017; Lu et al. 2018). In addition to these functions and intentions, the researchers also noticed differences in the use of emojis in different application scenarios, such as apps, cultures, genders, hashtags, and platforms (Tauch and Kanjo 2016; Lu et al. 2016; Chen et al. 2018; Barbieri et al. 2016; Zhou and Ai 2022; Wood-Doughty et al. 2021). However, many works on emoji functionality choose to perform crowdsourcing work to conduct the emoji interpretation, but with rich and diverse source of emoji applications, it is essential to have an automatic tool to interpret the emoji usage. In addition to emoji functionality, several researchers have applied emoji information to downstream tasks, such as emoji prediction(Barbieri et al. 2020, 2018), improving sentiment analysis (Chen et al. 2021, 2019; Felbo et al. 2017), predicting developer's dropout (Lu et al. 2022).

2.2 LLMs in Computational Social Science

With the prevalence of LLMs, there are emerging researches evaluating their performances on various tasks (Chang et al. 2023), including Computational Social Science (CSS) tasks (Ziems et al. 2023; Zhu et al. 2023). Researchers have examined ChatGPT's capacities in the zero-shot or few-shot (with in-context learning) settings, in various text annotation tasks such as political affiliation classification of tweets (Törnberg 2023); hate speech detection (Huang, Kwak, and An 2023; Li et al. 2023b; Zhu et al. 2023); discourse acts (Ostyakova et al. 2023); sentiment analysis and bot detection(Zhu et al. 2023; Zhou et al. 2023b). A comprehensive evaluation (Ziems et al. 2023) shows ChatGPT exhibits unsatisfactory results on tasks that have complex structure or have subjective taxonomies whose semantics differ from definitions learned in pretraining, while achieving better results on tasks that have objective ground truth (e.g., misinformation and fact checking) or have labels with explicit colloquial definitions in the pretraining data (e.g., emotion and political stance). Nevertheless, the results demonstrate the potential of using LLMs to help researchers with CSS tasks and general users with social-related daily activities.

Not too many studies focus on emojis and ChatGPT at the same time, and emoji as an emerging "language" has not received enough attention in LLM studies. Only a few works in the literature suggest the ability of ChatGPT in emoji understanding, but do not provide detailed evidence and discussion. de Janeiro (2023) asks ChatGPT to generate different facial emojis to represent the valence of the words and Peng et al. (2023) translates natural language to emoji sequence. The most similar works on the use of ChatGPT in emoji-related tasks are Belal, She, and Wong (2023) and Kocoń et al. (2023). Belal, She, and Wong (2023) finds that ChatGPT performs better than lexicon-based approaches for the sentiment prediction task on a soccer tweet dataset with emojis, and they imply the emoji understanding ability of ChatGPT. In Kocoń et al. (2023), the emoji prediction task, as one of the evaluation tasks in their work, reveals the ChatGPT's performance on emoji recommendation.

In comparison, we thoroughly examine the consistency of ChatGPT's annotations on emoji semantics, sentiment, and intentions with humans and probe ChatGPT's knowledge about the emoji usage patterns linked to various communities. We evaluate ChatGPT's performance on emoji-related tasks and explore the importance of emojis to ChatGPT in downstream tasks. Our evaluation task is performed across multiple languages and multiple platforms, which qualitatively and quantitatively demonstrate the ChatGPT's ability on emoji understandings in broader contexts.

3 Emoji Semantics

We start evaluating ChatGPT's understanding on emojis by asking ChatGPT to explain the semantic meanings of the emoji. Emojis, as universal language tokens, are applied by users with different language and cultural backgrounds. In this section, we conduct a qualitative study on the LLM explanation of emoji universal semantics without any given context, and then we probe the ChatGPT understandings in two different language and culture settings: the English context and the Chinese context.

3.1 Emoji Semantics without Context

We first collect the 50 emojis most frequently used from 2019 to 2022 provided by the Unicode organization,[1] and investigate how ChatGPT explains these emoji semantics without any context. The probing prompt for GPT4 is designed as follows:

Could you please describe this emoji `[Emoji]` *and explain its meaning?*

where `[Emoji]` is the Unicode of selected emojis. To compare the understandings between ChatGPT and humans, we also collect the meaning of emojis on the Emojipedia

[1] https://home.unicode.org/emoji/emoji-frequency/

Prompt: Could you please describe this emoji 🤷 and explain its meaning?

GPT4V: The emoji "🤷" is known as the "Person Shrugging." It depicts a person lifting both shoulders, a gesture commonly used to express a lack of knowledge, indifference, or a sense of 'I don't know' or 'I don't care.' This emoji can be presented with various gender options, such as "🤷‍♂️" (man shrugging) and "🤷‍♀️" (woman shrugging).

EmojiPedia: A person shrugging their shoulders to indicate a lack of knowledge about a particular topic, or a lack of care about the result of a situation. ¯_(ツ)_/¯
Displays as raised shoulders, sometimes in conjunction with raised arms and flat hands. The shrug gesture in text (emoticon / kaomoji) form is known as a shruggie and typed as: ¯_(ツ)_/¯. The Unicode character Shrug ("Person Shrugging") does not specify a gender. See also Woman Shrugging or Man Shrugging.

Prompt: Could you please describe this emoji 💜 and explain its meaning?

GPT4V: The emoji "💜" is the "Purple Heart" emoji. It depicts a classic heart shape colored in various shades of purple. This emoji is often used to express affection, love, or admiration, similar to the traditional red heart emoji, but it can also carry additional meanings specific to its color. The "Purple Heart" can represent a form of love that is compassionate, understanding, and supportive, often associated with close friendship, familial love, or platonic relationships. The color purple itself is sometimes associated with meanings of luxury, power, and ambition, but in the context of the heart emoji, it often leans more towards conveying a sense of nurturing and care.

EmojiPedia: A purple heart emoji, often used alongside other colored hearts. Frequently used on Twitter in reference to Korean boy band Bangtan Sonyeondan, more commonly known as BTS. Previously shown as a pink heart in Android 4.4.

Prompt: Could you please describe this emoji💙 and explain its meaning?

GPT4V: The emoji "💙" is known as the "Blue Heart" emoji. It depicts a blue heart, often used to convey feelings of love, affection, or care. However, the blue color of the heart can also carry specific meanings related to emotions and personality traits. The "Blue Heart" emoji is commonly employed to express deep feelings of love, affection, and trust. It can represent a sense of calm, tranquility, and stability in a relationship. Blue is often associated with sincerity and loyalty, so this emoji can convey a deep and genuine form of love. In digital communication, the "Blue Heart" emoji is used to express love or affection in a way that emphasizes qualities such as loyalty, trustworthiness, and sincerity. It's often used in messages to convey profound emotional connections or to reassure someone of the sender's deep feelings. The blue color adds a sense of calm and reliability to the expression of love.

EmojiPedia: A blue heart emoji, commonly used by brands as a neutral heart color. An early Google design of this emoji depicted the heart as if it were made out of gemstone.

Figure 1: Meaning and explanation of emoji usage from ChatGPT and Emojipedia. Different interpretations are highlighted in red and similar interpretations from both ChatGPT and Emojipedia are highlighted in green.

website,[2] which is researched and written by Emojipedia editors and lexicographers, as human annotations of emoji meanings. We present three representative examples for the emoji 🤷 (person shrugging), 💜 (purple heart), 💙 (blue heart) in Figure 1, highlighting the same contents mentioned by humans and ChatGPT by green and different contents by red color.

From Figure 1, for the emoji 🤷 (person shrugging), it is consistently observed, both in ChatGPT's responses and human annotations, that this emoji primarily conveys a lack of knowledge without implying any specific gender. Regarding the emoji 💜 (purple heart), ChatGPT provides an explanation on the significance of the color purple, while human annotations predominantly discuss its usage in tweets related to a Korean boy band. For the emoji 💙 (blue heart), ChatGPT exclusively addresses the particular meaning associated with the color blue. However, both ChatGPT and human sources agree that 💙 typically expresses sentiments of calmness and neutrality.

The findings suggest that the explanation from ChatGPT on semantics of most emojis overlaps with the meaning in Emojipedia. Moreover, the content of ChatGPT and human annotations can be supplementary to each other.

3.2 Emoji Semantics with Text Context

The accurate explanation of ChatGPT in emoji semantics without text context follows our expectation due to the notable performance of ChatGPT in sentiment analysis and tweet related tasks (Zhu et al. 2023; Törnberg 2023). But it is well known that emojis will evolve extensive semantics according to the applied text context. For example, 🐐 (goat) can mean the greatest person, and 🐍 (snake) can mean Python language. We thus explore whether ChatGPT can interpret an emoji's meaning when giving tweets containing emojis with extensive semantics. We choose a few emojis (🐐 goat, 🐝 honey bee, and 🐍 snake) with widely accepted special meanings [3] and randomly extract tweets in 2022 that contain these emojis via Twitter API. We feed these tweets to ChatGPT and ask ChatGPT to give the semantic explanation based on the context of the tweet. We present the prompt and the GPT4 response in Figure 2.

Figure 2 illustrates that ChatGPT's interpretations of emoji semantics align closely with human understanding in most instances. ChatGPT accurately interprets the emoji 🐐 (goat) as "the greatest of all time." Additionally, it interprets 🐝 in a Valentine's context as "be mine." In the third example featuring the 🐍 emoji, ChatGPT recognizes its use in symbolizing the Python programming language. However, in the last example with the tweet context "Whole lotta snakes in my grass 🐍🐍," we argue that the emoji should symbolize the animal snake rather than untrustworthy people. The frequent use of the snake emoji to represent betrayal might have led to this misinterpretation. In conclusion, ChatGPT generally demonstrates a precise understanding of emoji semantics in textual contexts. However, when an emoji represents a less commonly used object, ChatGPT may provide erroneous interpretations.

3.3 Emoji Semantics with Language/Cultural Context

In addition to the application in the English context, emojis also show prevalence in other specific language and culture contexts (Chen et al. 2019), and explaining emoji semantics in the Chinese context is more challenging. With the similar experiment setup in Section 3.2, we first choose emojis that

[2]https://emojipedia.org/meanings

[3]selected from this website https://bestlifeonline.com/emoji-meanings/

Prompt: Based on the tweet contents, could you explain the semantics and intentions of the emoji 🐐 ? Tweet: Cristiano Ronaldo's goalscoring consistency will never be matched 🐐 .

GPT4V: The emoji 🐐 in this context represents the acronym "G.O.A.T.," which stands for "Greatest Of All Time." It's often used in sports and pop culture to denote a person who is considered the best in their field or area of expertise. In the tweet about Cristiano Ronaldo, the use of the 🐐 emoji implies that the speaker believes Ronaldo is the greatest football player of all time, especially in terms of his goalscoring consistency. This is a form of high praise and recognition of his exceptional skill and achievements in football.

Prompt: Based on the tweet contents, could you explain the semantics and intentions of the emoji 🐝 ? Tweet: RT @user: ✨ Shop is now live with bee 🐝 mine plushies, and valentines themed bucket hats 💕

GPT4V: The emoji 🐝 in the tweet is used to symbolize bees, linking directly to the "bee mine plushies" mentioned in the message. Its use here is a clever play on words, combining the sound of the word "bee" with the phrase "be mine," a common expression of affection, especially relevant around Valentine's Day. The emoji not only visually represents the bee-themed products being sold but also adds a cute, thematic touch to the message, enhancing the playful and affectionate tone associated with Valentine's Day merchandise. By using the bee emoji, the tweeter effectively communicates the nature of the products (plushies shaped like bees) and aligns the message with the love-themed holiday, likely aiming to attract customers interested in unique and thematic gifts.

Prompt: Based on the tweet contents, could you explain the semantics and intentions of the emoji 🐍 ? Tweet: RT @user: 🐍 Learning Python 📰 — The Hitchhiker's Guide to #Python

GPT4V: In this tweet, the 🐍 emoji is used to symbolize Python, which in this context refers to the Python programming language, not the animal. The tweet promotes a learning resource for Python, titled "The Hitchhiker's Guide to Python." The use of the snake emoji is a common and playful way to represent Python in digital communications, as the language is named after the British comedy series "Monty Python," but the snake image provides a convenient and recognizable visual symbol. By using the 🐍 emoji, the tweet efficiently communicates that the content is related to Python programming. It serves as a visual cue to attract the attention of those interested in learning or improving their Python skills, fitting well with the theme of programming and coding.

Prompt: Based on the tweet contents, could you explain the semantics and intentions of the emoji🐍 ? Tweet: Whole lotta snakes in my grass 🐍 🐍

GPT4V: The 🐍 emoji in this tweet is used to convey the presence of multiple deceitful or untrustworthy people in the tweeter's life, emphasizing the abundance and potential threat they represent. The use of multiple snake emojis emphasizes the abundance or prevalence of such individuals in the tweeter's life. This expression and the accompanying emojis convey a sense of wariness or distrust, possibly indicating that the tweeter has experienced or is aware of disloyalty or betrayal from people around them. The emoji here is used to visually reinforce the metaphor and add emphasis to the message's overall tone of caution and awareness of hidden negative intentions in others.

Figure 2: Semantic explanation from ChatGPT of emojis with special meaning. The green color highlights the semantic explanation consistent with human understanding, and the red color highlights the hallucinations. From the case study, ChatGPT can precisely understand the semantics of emojis with special usage when given the specific context in most cases.

have unique meanings on Chinese social networks and test if ChatGPT can properly explain their semantics, that is, 🙂 (slightly smiling face), 💊 (pill), and 🐶 (doge). Additionally, we include an emoji combo, 🐮 🍺, that consists of a cow face and a beer mug. We prompt ChatGPT to explain the usage of these emojis. The prompts are written in English or Chinese, with or without specification of usage in Chinese pop culture.

We find that GPT models can generate desired interpretations in all cases, but only with appropriate prompts. The prompts need to include very specific information sometimes. For instance, when prompted with "Explain `[Emoji]`", GPT models failed to generate desired explanations and answered with literal interpretations from their Unicode names or visual cues (e.g., 🙂 as friendly instead of its common ironical use in Chinese pop culture (Wang 2022)). When prompted in Chinese, only 🐮 🍺 got the correct explanation. However, 🙂 and 🐶 get desired explanations when prompted with "Explain the `[Emoji]` in the context of Chinese pop culture", no matter whether prompted in English or Chinese. For 💊, we had to specifically mention its homophonic usage with yào wán through a multi-turn interaction with ChatGPT.

We also observe that the Chinese answers generated by prompts written in Chinese contained more specific and useful information in general, compared to the counterparts in English. For example, the English answer for 🙂 mostly conveys that its usage can be context-dependent and culturally specific and only briefly mentions "it might be used ironically", while the Chinese version details the several specific contexts when it can be used ironically.

Meanwhile, answers in both languages are prone to hallucinations even when a large proportion of answers are desired. The model links 💊 to the red pill and blue pill metaphor from the Matrix movie and incorrectly states that this is a common usage in Chinese social media.

Observation 1 *ChatGPT can output consistent explanations on emoji semantics when giving no context or specific English context. However, when probing the special meaning of an emoji in Chinese context, ChatGPT are prone to hallucinations with English prompts and more accurate explanation when prompting in Chinese.*

4 Emoji Sentiment

Expressing sentiment is one of the main functionalities of using emojis (Ai et al. 2017), and for most emojis, especially face emojis. Previous work has performed human annotation of emoji sentiment (Hu et al. 2017) and incorporated emoji information to improve the downstream sentiment (Felbo et al. 2017; Chen et al. 2019). In this section, we ask ChatGPT to annotate the emoji sentiment and evaluate ChatGPT performance on the sentiment of tweets with emojis.

4.1 Emoji Sentiment Annotation

We first ask ChatGPT to label the 50 most frequently used emojis in Section 3.1 with positive, neutral, and negative sentiment and compare the differences between human and ChatGPT annotations. We present the prompt details in Table 9a in Appendix.

We compare the GPT4 annotation with the human annotation in Hu et al. (2017), and the only difference is the sentiment annotation of emoji 😳 flushed face. The human annotation is neutral and the response of ChatGPT is negative, considering feelings of embarrassment or a sense of being overwhelmed in 😳. The same sentiment annotation indicates that ChatGPT can fully understand the sentiment in the emojis. From the response from ChatGPT, it often mentions that it requires the text context to determine the emoji sentiment, so we discuss the influence of emojis for ChatGPT on the downstream sentiment analysis task.

4.2 Sentiment Prediction with Emojis

Previous researchers have developed multiple methods to involve emoji information to enhance sentiment classification (Chen et al. 2019; Felbo et al. 2017). We also ask: When ChatGPT performs the sentiment classification task, does it consider the emoji in the texts in its predictions? For the experiment setup, we choose the sentiment analysis dataset from the TweetEval benchmark (Barbieri et al. 2020) with three labels: negative, neutral, and positive. We extract tweets with emojis from the data and obtain 805 tweets. We perform sentiment prediction by in-context learning (ICL) with GPT4 and GPT3.5 with 5 demonstrations on these tweets and obtain 70.31% and 71.67% accuracy for GPT4 and GPT3.5, respectively. The fine-tuning Roberta model with pretraining on the tweet corpus can achieve 69.3% accuracy (Barbieri et al. 2020), which indicates a reliable sentiment prediction from ChatGPT.

Next, we remove the emojis from the input text and ask ChatGPT to assign a sentiment label again, and the performance accuracy decreases to 69.56% and 70.19% for GPT4 and GPT3.5, respectively. However, the accuracy decrease cannot demonstrate that ChatGPT utilizes emoji information for emoji prediction, since the accuracy change is not significant and the emoji removal may also change the ground truth sentiment for the text. We compare the sentences in which ChatGPT changes the sentiment prediction after removing the emojis and find that 19.50% / 18.13% tweets flip the prediction labels for GPT3.5 / GPT4 annotations. We present three randomly selected tweets with flipped predictions for GPT4 in Table 1.

Tweet	Label	p_{emoji}	$p_{noemoji}$
How many more days until opening day? 😩	neutral	negative	neutral
@user Everyone knows that vegetarianism is synonymous with wellness! 🙄	positive	neutral	positive
#MPN #OneDirection#MtvStarsNiallHoran JESUS 😍😍😍😍😍	positive	positive	neutral

Table 1: Tweets with flipped sentiment predictions from ChatGPT, where p_{emoji} and $p_{noemoji}$ represents the ChatGPT predictions with and without emojis.

The analysis of examples in Table 1 reveals that ChatGPT's sentiment predictions are influenced by the presence of emojis within the text. Incorporating emojis like 😩 (weary face) and 🙄 (face with rolling eyes), which carry negative sentiment, results in a shift in sentiment prediction from neutral to negative and from positive to neutral, respectively. Similarly, the addition of multiple 😍 (smiling face with heart eyes) emojis leads to an elevation in sentiment prediction from neutral to positive. This case study suggests that ChatGPT considers emoji tokens in text as significant indicators when assessing overall sentiment.

Observation 2 *GPT4v and GPT4 annotate the similar emoji sentiment labels with humans, and when performing the sentiment classification task, ChatGPT considers emoji sentiment to enhance the prediction.*

5 Emoji Usage Intention

In addition to sentiment and meaning, previous researchers are also interested in the intention of using emojis, and ask human annotators to label emoji intentions with or without context (Hu et al. 2017; Lu et al. 2018). In this section, we follow the approaches and intention definition in the previous work (Hu et al. 2017) and ask ChatGPT to reannotate the emojis with or without any context to observe whether human and ChatGPT have similar understandings for the intention of using emojis.

5.1 Emoji Intention Annotation without Context

We first annotate emojis without any context to probe the understanding of ChatGPT on the universal intention. We select the same seven types of candidate intentions: expressing sentiment, strengthening expression, adjusting tone, expressing humor, expressing irony, expressing intimacy, and describing content, with previous work, and detailed definitions can be found in Hu et al. (2017). We select 15 emojis (5 positive, 5 neutral, and 5 negative emojis) in Hu et al. (2017) and ask ChatGPT to rate the willingness to use the emoji for each intention on a 7-point scale (7 = totally willing, 1 = not willing at all), same as the annotation method in Hu et al. (2017) and the complete prompt in Table 10.

We calculate that the average difference values between ChatGPT-rated scores and humans are -0.13 (expressing sentiment), -0.29 (strengthening expression), -0.07 (adjusting tone), -0.54 (expressing humor), -1.49 (expressing irony), -0.05 (expressing intimacy), and 1.11 (describing content), respectively. The average standard deviation (SD) of human-rated scores of seven intentions from Hu et al. (2017) is 1.643. ChatGPT and human annotators reach a high consensus on emojis in the intention of expressing sentiment, strengthening expressing, and adjusting tones. On other intentions, such as describing content, ChatGPT vary from human annotated scores but the score discrepancy is still smaller than the average human SD. Hence, we claim that the understanding of ChatGPT on the universal usage intention of emojis is generally similar to human users.

5.2 Intention of Emoji Usage in GitHub Posts

The similar intention annotation without context between ChatGPT and humans is consistent with the accurate explanation of emoji semantics and the precise annotation of emoji sentiment. When using emojis on different platforms, the intention could also vary. For example, users from GitHub may apply emojis to organize the content in the post, but seldom apply emojis to express irony. It is more challenging for ChatGPT to understand the emoji intention when given GitHub post context. In this part, we collect the same 2,000 emoji posts on GitHub with human annotations in Lu et al. (2018) and compare the annotation of emoji intention from ChatGPT and human ground truth labels. The candidate intention of emojis in GitHub posts is shown in Table 2, and the details of the definitions are shown in Lu et al. (2018).

The annotated accuracy between GPT3.5 and GPT4 with human annotation is 38. 8% and 49. 0%, respectively. The

Intention	Sentiment expressed	Sentiment strengthened	Tone adjusted	Content described
Accuracy	67.43%	30.85%	48.64%	47.54%
Intention	Content organized	Content emphasized	Non communication use	Symbol
Accuracy	40.63%	55.49%	34.62%	14.58%

Table 2: Accuracy of ChatGPT annotation for each intention on emojis in GitHub posts with human annotation as the ground truth labels.

detailed accuracy of GPT4 for each intention is presented in Table 2. We observe that for emojis to express sentiment and emphasize content in GitHub posts, ChatGPT gives more similar judgement with the human annotators. However, for symbol (symbolize emojis) and non-communication use (unintentional use), which is rarely applied in other social platforms, ChatGPT cannot generate the same intention annotation with annotators. To analyze the discrepancy of understanding between humans and ChatGPT, we conduct a case study and present three randomly selected posts with different annotations in Table 3.

Post	Human label	ChatGPT label
Make awesome stuff with half the time OR make quadriply awesome creations with the same time ✨	sentiment strengthened	content emphasized
thanks 🙏	sentiment strengthened	sentiment expressed
📋 Example	content organized	content described

Table 3: GitHub posts with different annotation labels for emoji usage intention from ChatGPT and humans.

Furthermore, we analyze the ChatGPT annotations in Table 3 as well as the human labels. We feed the ChatGPT annotations back to the LLM and ask for the justification. In the first post, human annotators perceive the use of ✨ as an enhancement of the post's positive sentiment, whereas ChatGPT interprets its use as a means to attract attention. In the second post, which contains the word "thanks" accompanied by 🙏, human annotators believe that "thanks" alone conveys positive sentiment, and the emoji serves to reinforce this sentiment. In contrast, ChatGPT's interpretation does not align with this view. The final post features 📋, which human annotators suggest is used for organizing content to enhance readability, while ChatGPT views it as a symbol or emphasis of a document. This case study highlights that ChatGPT's interpretations of emoji usage in GitHub posts are not only plausible but also indicative of ChatGPT's nuanced understanding of emoji applications.

Observation 3 *ChatGPT precisely deduces the intention of emoji usage when giving no context, and when giving a specific GitHub post, ChatGPT reaches a consensus with human annotations on the intention of emojis.*

6 Emoji Usage Associated with Communities

Previous work has explored that emoji usage can be different when associated with different communities, such as platforms, languages, genders, and hashtags (Lu et al. 2018, 2016; Chen et al. 2018; Zhou and Ai 2022; Zhou et al. 2023a). In this part, we probe whether the knowledge of the associated emoji usage patterns is encoded in ChatGPT when given the prior information about the users, platform, or co-occurred hashtags. We compose the prompt by directly asking for the most used emojis given different community information, and ChatGPT outputs the most used emojis and its justification. The probing prompt for ChatGPT is designed as follows: *Could you output 10 emojis that are associated with the* {*specific community*}*?* where {*specific community*} is the associated community, such as female users, French users, hashtags, and the GitHub platform. We present the answer from ChatGPT and the findings from previous work in Tables 4, 5 and 6. In particular, emojis associated with French, female, and male users are explored in Lu et al. (2016); Chen et al. (2018) and emojis co-occurred with different hashtags and the GitHub platform are reflected in Zhou and Ai (2022); Zhou et al. (2023a).

User	Emoji from actual usage	Emoji from ChatGPT
French user (Lu et al. 2016)	❤️ 😂 💘 💖 😘 😍 💕 💞 💜 💗	🇫🇷 🍷 🥐 🗼 😘 🧀 🥖 🎨 🥂 💋
Female user (Chen et al. 2018)	👭 🎂 🎉 🎁 💋 🎈 🌸 💕 💜 💅	👩‍💼 👩‍🎓 💃 👰 👩‍👧‍👦 🛍️ 💅 👚 👛 🌸
Male user (Chen et al. 2018)	⚽ 🚬 ♂	😎 🕺 💪 👨 🎮 ⚽ 🍔 🏋️ 🎸 🏍️

Table 4: Outputs from ChatGPT and emojis from actual usage (Lu et al. 2016; Chen et al. 2018) associated with French users, female users, and male users.

Hashtag	Emoji from actual usage	Emoji from ChatGPT
#BlackOutBTS	✨ 😌 🥺 ❤️ 🖤	💜 🎵 🕺 🎤 😍
#MothersDay	❤️ 💕 💐 🤍 💫	❤️ 👩‍👧‍👦 💐 🎁 😘
#TheLastDance	🐐 😂 🍿 🐍 🔥	🏀 🏆 📺 👟 😲

Table 5: Outputs from ChatGPT and emojis from actual usage (Zhou and Ai 2022) associated with different hashtags.

Source	Emojis associated with GitHub
Actual usage	👍 🛑 😄 🚀 👋 🎉 ✅ 🐛 ⚠️ 🤔 ✨ 🙂 ❤️ 😅 🐞 😊 💰 🙏 📐 😃
ChatGPT	👍 👎 🐛 🚀 💻 🎉 🐧 ✨ 📚 🔨 🔄 🤔 🌎 🔥 🚧 ⚠️ 🐍 📈 🤖 📅

Table 6: Outputs from ChatGPT and emojis from actual usage (Zhou et al. 2023a) associated with the GitHub platform.

From Table 4, 5 and 6, we observe that ChatGPT depends on stereotypical associations with the attribute of the user or the platform to select the emojis and in most cases, stereotypical selection can extract the same emojis or emojis with semantics similar to the emojis shown in previous works. Both ChatGPT and existing literature identify certain emojis as indicative of gender preferences, such as ⚽ (soccer) for male users and 🌸 (cherry blossom) for female users. In the context of the GitHub platform, a comparison between prior findings and ChatGPT's responses reveals a significant overlap, with seven emojis common to both lists. Furthermore, additional emojis identified by ChatGPT align with the distinctive characteristics of the GitHub environment. For instance, 🐧 (penguin) is associated with Linux and 🐍 (snake) is linked to Python programming.

The reliance of ChatGPT on stereotypical associations to deduce emoji usage yields insights, yet also reveals certain limitations. For instance, despite the documented preference of French users for heart-related emojis (Lu et al. 2016), the responses of ChatGPT do not reflect this trend. Furthermore, while ChatGPT employs basketball emojis in reference to #TheLastDance and Michael Jordan, it notably omits the 🐐 (the greatest of all time) emoji, which frequently accompanies mentions of Michael Jordan. In summary, these observations suggest that although ChatGPT demonstrates an understanding of varied emoji applications across different contexts, it does not fully capture all the nuances and specificities within the domain of emoji use.

Observation 4 *ChatGPT employs stereotypical associations to infer emoji usage patterns associated with distinct communities, accurately reflecting variations in emoji use across genders, hashtags, and platforms, but fails to capture the nuances of emoji usage specific to different countries.*

7 Irony Annotation with Emojis

In Section 5, ChatGPT has reached a consensus with humans about the functionality of emojis to express irony. To assess ChatGPT's proficiency in discerning ironic emoji usage within distinct linguistic contexts, we initiated an ICL experiment on two datasets. One dataset comprises Arabic texts and annotation labels on the irony of emojis. The other consists of English tweets with emojis and annotation labels on the irony of the overall tweet. For the English dataset, we collect 405 tweets with emojis from the training dataset SemEval2018 Task 3 Subtask A (Van Hee, Lefever, and Hoste 2018), with binary annotation to indicate whether this tweet is ironic or not. Among the 405 tweets collected, 175 of them are annotated by humans as ironic, and the others are not ironic. We first use ChatGPT to predict the irony on the original tweets with emojis via ICL inference and we ask ChatGPT to annotate again by excluding the emojis in each tweet. The prompt details are in Table 12 For tweets with emojis, the accuracy of the irony prediction with GPT4 is 81.2% and when emojis are excluded, the accuracy decreases to 77.0%. Note that the accuracy drop does not mean that ChatGPT considers emojis to make irony predictions, since the irony of a sentence may change when removing emojis. We conduct a case study to show the three randomly selected irony tweets with flipped predictions after removing emojis in Table 7.

Tweet	Label	p_{emoji}	$p_{noemoji}$
work should be fun today 😒	irony	irony	no irony
So this week is just getting better and better 😭	irony	irony	no irony
I have three test and a two dance performances tomorrow!! 📚📖💃💃👯 #EasyDay	irony	no irony	irony

Table 7: Tweets with flipped irony predictions from ChatGPT, where p_{emoji} and $p_{noemoji}$ represents the ChatGPT predictions with and without emojis.

In the analysis of the first two tweets from Table 7, we observe a shift in irony prediction from "ironic" to "non-ironic" when emojis are excluded. This shift is attributable to the irony inherent in the emojis 😒 and 😭. The textual content of these tweets conveys positive sentiment, but the juxtaposition with negative emojis creates an ironic tone. ChatGPT effectively recognizes the discordance between the sentiments expressed in the text and the emojis, assigning an irony label. However, once the emojis are removed, this contradiction vanishes, leading ChatGPT to revise its classification to "non-ironic". In the final tweet, the irony is embedded in the hashtag #EasyDay, contrasting with the ostensibly busy scenario described in the text. The presence of emojis like 📚, 💃, and 👯, which do not inherently convey irony, potentially obscures ChatGPT's ability to discern the ironic intent. Removing these emojis enables ChatGPT to accurately detect the irony in the tweet. Overall, this case study illustrates that ChatGPT considers emoji tokens as crucial elements in assessing irony in English tweets, demonstrating its nuanced understanding of emojis' role in conveying irony.

To evaluate ChatGPT's understanding of the irony in emojis for other languages, we utilize a recently published Arabic dataset with the ironic annotations: ArSarcasMoji from Hakami, Hendley, and Smith (2023). Instead of labeling the irony of sentences, ArSarcasMoji provides the ground truth irony label of emojis into three categories: sarcastic, humorous and not ironic, where the sarcastic label represents that ironic emojis play a negative sentiment role and the humorous label indicates a positive role (Hakami, Hendley, and Smith 2023). Since the label distribution in the original dataset is biased, we first downsample sentences with the label "not ironic" and "sarcastic" to make a balanced dataset for evaluation. We compose the prompt with instruction, the detailed definition of "humorous" and "saracastic", and the examples of Arabic sentences with labels (the complete prompt in Table 13). The prediction accuracy for GPT4 and GPT3.5 is 60.1% and 63.1%, respectively, indicating that ChatGPT can understand the functionality of emojis to express irony in the Arabic context.

Observation 5 *In the emoji irony classification task, ChatGPT has promising performance in distinguishing whether the emoji is ironic or not and in the tweet irony classification task, ChatGPT considers the existence of emoji to decide the overall irony of a tweet.*

8 Emoji Recommendation

After knowing that ChatGPT can precisely point out the sentiments, meanings, and intentions of emojis, our next question is whether ChatGPT relies on its knowledge to recommend suitable emojis.

8.1 Recommendation Based on Text Context

For the experiment, we choose the SemEval 2018 Task 2 with English and Spanish sets for emoji recommendation (Barbieri et al. 2018). We select the validation sets with 5,000 English and Spanish tweets for inference. The task pre-defines a list of 20 or 19 emojis for models to choose for English and Spanish tasks, respectively, and our prompt is composed of the English instruction including the predefined emoji candidates and five exemplars from the English or Spanish training set, depending on the prediction text. The prompt details are shown in Table 14.

For emoji recommendation on English tweets, GPT4 and GPT3.5 can achieve 22.12% and 21.52% accuracy and the finetuned FastText classifier can achieve 42.56% accuracy. On Spanish tweets, GPT4 and GPT3.5 can obtain 20.14% and 20.96% accuracy while the finetuned FastText can obtain 31.63% accuracy. These results suggest that, on a closed-set emoji recommendation, the ICL of ChatGPT cannot beat the traditional fine-tuned classifer, but ChatGPT's performance is consistent across the languages while the fine-tuned classifier meets a large performance drop. We can observe the hallucinations of ChatGPT when performing the emoji recommendation, and 6.1% and 3.7% of tweets are annotated with the emoji not in the pre-defined candidates for GPT3.5 and GPT4 on English tweets.

8.2 Recommendation with User Identity

Previous work suggests the different emoji preference depending on the user identity (Chen et al. 2018; Lu et al. 2016) so when performing the emoji recommendation, it is also important to consider the user demographic attributes to recommend the proper emoji choices. ChatGPT has been shown to have the potential to play as a communicative agent with different roles (Li et al. 2023a). Moreover, as shown in Section 6, the knowledge about the discrepancy in the emoji usage patterns of different communities is encoded in ChatGPT. In this part, we investigate whether ChatGPT has the ability to consider user identity when recommending the emoji to the tweet.

We ask ChatGPT to play as a female or male Twitter user to give the recommendation of the emojis, respectively, and add another sentence at the beginning of the prompt like the previous work (Li et al. 2023a): *I want you to act as a female/male Twitter user. Never forget your role.* We repeat the GPT4 ICL experiment on 5,000 English tweets. Acting as a male or female twitter user can obtain 21.04% and 20.94% accuracy, respectively, and 1,110 tweets have different predictions. We present the distribution of the top 10 predicted emojis for female or male users in the first two rows of Table 8.

An examination of the first two rows of Table 8 reveals a comparable emoji distribution with two notable exceptions: a higher frequency of 💕 (two hearts) when representing female users, and a higher usage of 😎 in representations of male users. This finding is consistent with ChatGPT's understanding of usage differences for female and male users in Section 6 and the findings from previous work (Chen et al. 2018). To further explore ChatGPT's comprehension of variations in emoji usage across different countries, an aspect not revealed by the results in Section 6, we conducted additional experiments. In these, we simulate interactions while portraying users from France and the United States, respectively. When asking ChatGPT to act as the French user, we translate the prompts and tweets to annotate in the French language. We also present the predicted emoji distribution

Role	Emoji distribution
Female	✨: 657, 😊: 582, 🥰: 573, 🔥: 418, 💕: 410, 😎: 367, 😂: 347, 😜: 224, 🎄: 194, ❤️: 186
Male	✨: 575, 😊: 560, 🥰: 527, 😎: 488, 🔥: 451, 😂: 341, ❤️: 237, 💙: 227, 💕: 219, 😜: 208
French	😊: 620, 🥰: 583, ✨: 530, 😎: 411, 😂: 396, 🔥: 381, 💕: 310 ❤️: 252, 😜: 236, 📸: 192
American	😊: 605, 🥰: 576, ✨: 566, 🔥: 448, 😎: 408, 😂: 361, 💕: 270, 😜: 233, ❤️: 216, 🎄: 207

Table 8: Distributions of top 10 predicted emojis when asking ChatGPT to play different roles. The yellow color highlights the emojis 💕 and 😎, which are two emojis with the largest change in the number of recommendations for acting as male or female users.

in the last two rows of Table 8.

From the last two rows, we can observe a similar emoji distribution for ChatGPT to portray users from France or the USA. In conjunction with the findings presented in Section 6 regarding ChatGPT's interpretation of emoji usage by French users, it can be concluded that ChatGPT lacks awareness of the variations in emoji usage across different countries.

Observation 6 *ChatGPT does not outperform the fine-tuned traditional classifier on the closed-set emoji recommendation task, but ChatGPT can depend on user's identity to make more personalized emoji recommendations.*

9 Implications and Limitations

Our paper reveals ChatGPT's precise understanding of emoji functionality and intention. The capability of ChatGPT on emojis could benefit further researchers and social media users. For researchers engaged in future emoji studies, leveraging human-aligned explanations of emoji semantics and intentions could significantly reduce the need for extensive crowd-sourcing efforts, particularly in multilingual contexts. This approach would enable more effective and efficient research into emoji usage and interpretation. As for social media users, they could utilize ChatGPT to decipher the semantics of unfamiliar emojis, thereby enhancing the clarity and transparency of online communication.

All the experiments in our paper treat emojis as text tokens in the Unicode form. But some emojis due to its application in the specific cultural context or new appearance are not included in the Unicode organization, such as (broken) and (onlooker) in Chinese social media. For these emojis without standard Unicode, we can utilize the vision language model (VLM) from ChatGPT: GPT4V, which has been demonstrated with significant progress in image understanding (Yang et al. 2023; Wang et al. 2024), to help us understand the emoji functions. We prompt the images of and to GPT4V for semantic explanations. An example is shown in Figure 3. We observe similar patterns as in Section 3.3. GPT4V generates hallucinations with Chinese prompts

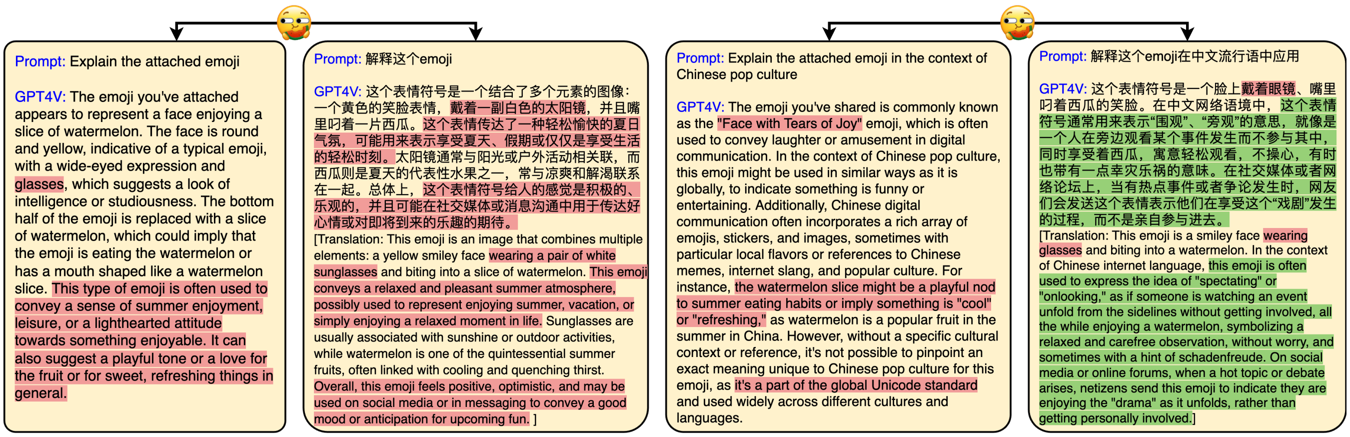

Figure 3: Qualitative Study of Emoji Semantics with Language/Cultural Context. Hallucinations are highlighted in red and desired interpretations are highlighted in green.

but outputs the correct explanation when supplementing the prompt with the context of Chinese pop culture.

We also repeat the annotation of the sentiment of emojis in Section 3.1 on GPT4V. For the 50 selected emojis, only 🥺 (pleading face) and 👀 (eyes) have different annotations for GPT4 and GPT4v. For the 🥺 emoji, VLM attributes a negative sentiment based on its visual features: frown, wide eyes, and raised eyebrows. In contrast, GPT4 associates the 🥺 emoji with positive sentiment, perceiving it as an expression of vulnerability, empathy, and affection. Regarding the 👀 emoji, GPT4 assigns a neutral sentiment, indicative of observation, while GPT4v leans towards a neutral, yet slightly positive, reflecting an underlying connotation of interest.

These findings suggest that, while the GPT4v and GPT4 sentiment annotations are generally the same, divergent interpretations of the 🥺 emoji can highlight the evolution of the emoji sentiment derived from the user application setting. The results in GPT4V imply that, when encountering specific emojis without the standard Unicode, the notable capability in emoji understanding of GPT4V can also help researchers and users.

There are several limitations in our exploration work. First, previous work has shown that the responses of LLMs are sensitive to temperature and the prompt (Yoo et al. 2021; Schick and Schütze 2020; Gilardi, Alizadeh, and Kubli 2023; Zhou, Maharjan, and Liu 2023), but in our work, for each task, we only explore one type of prompt presented in Appendix. For qualitative and quantitative studies (irony prediction, sentiment classification, and emoji recommendation) in our paper, we set the temperature to 0.7 and 0, respectively.

Second, emoji semantics or sentiment can evolve during the 5-year period and, for example, 🙂 (slightly smiling face) has evolved the sense of irony and negative sentiment in Chinese social networks. The human annotations utilized in this paper are almost before 2018, so the 5-year time period may lead to the different annotation results.

Lastly, our paper focuses on the ICL of GPT3.5, GPT4 and GPT4V for ChatGPT and does not involve the fine-tuning experiment with OpenAI API. Moreover, with the release of GPTs (the tailored version of ChatGPT for a specific task [4]), we can find there is a version of ChatGPT from OpenAI, called *genz 4 meme*, to help understand the latest memes, which may have better understanding for emojis. We leave further exploration of the different versions of ChatGPT in the future work.

10 Conclusion

In this study, we conduct a comprehensive evaluation of ChatGPT's proficiency in interpreting emojis, focusing on various aspects including meaning, sentiment, and intention. Our analysis reveals that ChatGPT's annotations closely align with human labels. We discover that ChatGPT has embedded knowledge of emoji usage patterns prevalent in different communities. Furthermore, ChatGPT exhibits strong performance in several downstream tasks that involve emojis, indicating its capability to leverage its emoji understanding in making predictions. The encouraging results in annotation tasks suggest that ChatGPT could significantly contribute to emoji research by serving as a substitute for human annotators, thus conserving human resources.

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Appendix

.1 Prompt Details

Could you assign a sentiment to this emoji: emoji? Please select the sentiment from positive, negative, or neutral.

(a) Prompt for probing emoji sentiment without text context.

I will provide you 5 tweets. Please assign a sentiment to each tweet. You can only select the sentiment from positive, negative, or neutral. Please only output the sentiment answer without justification. Here are some examples: 1. user user what do these '1/2 naked pics' have to do with anything? They're not even like that. 2. I think I may be finally in with the in crowd #mannequinchallenge #grads2014 user 3. user Wow,first Hugo Chavez and now Fidel Castro. Danny Glover, Michael Moore, Oliver Stone, and Sean Penn are running out of heroes. 4. An interesting security vulnerability - albeit not for the everyday car thief 5. Can't wait to try this - Google Earth VR - this stuff really is the future of exploration.... The sentiment output is: 1. neutral 2. positive 3. negative 4. neutral 5. positive Here is the tweet list: {tweet}

(b) Prompt for applying ChatGPT to label the sentiment of tweets, and {tweet} is the tweet to label the sentiment.

Table 9: Prompts of sentiment-related tasks for emojis.

Please rate the willingness to use the emoji {emoji} for the following 7 intentions: expressing sentiment, strengthening expression, adjusting tone, expressing humor, expressing irony, expressing intimacy, describing content, on a 7-point scale (7 = totally willing, 1 = not willing at all). The details of the intentions are suggested as below: {definition details}

Table 10: Prompt for probing the intention of emojis without given the text context. definition details can be found in Hu et al. (2017).

Please assign an intention of emoji usage from the following 8 intentions: sentiment expressed, sentiment strengthened, tone adjusted, content described, content organized, content emphasized, non-communication use, symbol. Please only output the intention answer without justification.
The details of the intentions are suggested as below:
{definition details}
Here are some examples:
1. Even the Guardian has TLS now.... 👍
2. merge when we receive 👍, shipit
3. Thanks for your effort 👍
4. ✔️ Creating directory
5. Remote Get: ✔️
The intention output is: 1. sentiment expressed 2. symbol 3. sentiment strengthened 4. non-communication use 5. content described
Here is the Github post list: {post}

Table 11: Prompt for applying ChatGPT to label the intention of emojis in GitHub posts. {post} is the GitHub to label the emoji intention. definition details can be found in Lu et al. (2018).

I will provide you 5 tweets. Please tell me whether the tweets are ironic or not. Please only output the irony label without justification. Here are some examples:
1. Such . You still have to #praisehim ;)
2. Hey heyy!!!I....wanna be a rockstar #vscocam hero #vsocam #hero #spiderman
3. user nice to see the ambulance service is so important to OUR mps
4. I love finals week! #justkidding #stressed
5. Literally cried when I woke up because I know what this day has in store for me #TheStartOfTechWeek Ready #JustShootMeKnow
The irony output is: 1. ironic 2. not ironic 3. ironic 4. ironic 5. not ironic
Here is the tweet list: {tweet}

Table 12: Prompt for applying ChatGPT to label the irony or not of a tweet. {tweet} is the tweet to label the irony.

I will provide you 5 tweets with emojis in Arabic language. Please tell me which type of irony the emojis in tweets convey. You can only select the irony type from humour, sarcasm, and no irony. Here is the definition of sarcasm and humour: Sarcasm, a specific facet of irony, employs language with a sharp, often bitter tone to mock or critique, often with exaggerated emphasis. Humour, while encompassing elements of irony, specifically denotes the ability to evoke amusement or laughter. Please only output the irony label without justification. Here are some examples:
1. {Arabic tweet example 1}
2. {Arabic tweet example 2}
3. {Arabic tweet example 3}
4. {Arabic tweet example 4}
5. {Arabic tweet example 5}
The irony output is: 1. no irony 2. no irony 3. sarcasm 4. sarcasm 5. humour
Here is the tweet list: {tweet}

Table 13: Prompt for applying ChatGPT to label the irony of emojis in Arabic tweets. {Arabic tweet example n} is the n-th example of an Arabic tweet that contains emojis with the ground-truth irony label for the emoji. {tweet} is the tweet that contains emojis to label the irony.

I will provide you 5 tweets. Please recommend only one emoji for each tweet. You can only select emojis from these emoji candidates: {emoji candidates}. Please only output the emoji answer without justification. Here are some examples:
1. Sunday afternoon walking through Venice in the sun with @user
2. Time for some BBQ and whiskey libations. Chomp, belch, chomp! (@user)
3. Man these are the funniest kids ever!! That face! #HappyBirthdayBubb @user Xtreme
4. #sandiego @San Diego, California
5. My little #ObsessedWithMyDog @user Capitol Hill
The emoji recommendation is: 1. ☀️ 2. 😏 3. 🥲 4. 🇺🇸 5. ❤️
Here is the tweet list: {tweet}

Table 14: Prompt for applying ChatGPT to predict the emoji in tweets. {tweet} is the tweet to predict the emojis. {emoji candidates} represents the candidate emojis that ChatGPT should select from and the details of candidate emojis can be found in Barbieri et al. (2018).