

Human vs. LMMs: Exploring the Discrepancy in Emoji Interpretation and Usage in Digital Communication

Hanjia Lyu^{*1}, Weihong Qi^{*1}, Zhongyu Wei², Jiebo Luo¹

¹University of Rochester

²Fudan University

hlyu5@ur.rochester.edu, jluo@cs.rochester.edu

Abstract

Leveraging Large Multimodal Models (LMMs) to simulate human behaviors when processing multimodal information, especially in the context of social media, has garnered immense interest due to its broad potential and far-reaching implications. Emojis, as one of the most unique aspects of digital communication, are pivotal in enriching and often clarifying the emotional and tonal dimensions. Yet, there is a notable gap in understanding how these advanced models, such as GPT-4V, interpret and employ emojis in the nuanced context of online interaction. This study intends to bridge this gap by examining the behavior of GPT-4V in replicating human-like use of emojis. The findings reveal a discernible discrepancy between human and GPT-4V behaviors, likely due to the subjective nature of human interpretation and the limitations of GPT-4V's English-centric training, suggesting cultural biases and inadequate representation of non-English cultures.

Introduction

The advent of Large Multimodal Models (LMMs) has marked a significant milestone in the use of machine intelligence to simulate human behaviors while perceiving multimodal information (Park et al. 2023; Fui-Hoon Nah et al. 2023). This field of research, particularly when applied to social media, has attracted considerable attention due to its vast potential and implications (Törnberg et al. 2023; Gao et al. 2023). One of the most unique aspects of digital communication is the use of emojis, which, in this context, are not mere embellishments but fundamental components that enhance and often clarify the emotional and tonal aspects of communication (Miller et al. 2017; Hu et al. 2017).

While extensive research has been dedicated to the domain of the image-text pair understanding capabilities of LMMs (Yang et al. 2023; Lyu et al. 2023; Zhang et al. 2024), there remains a notable gap in comprehending how these sophisticated models navigate the nuanced landscape of emoji-enhanced communication. The focus of this study lies in understanding whether LMMs can accurately emulate how humans employ emojis in digital communication. GPT-4V(ision), as one of the most advanced large multimodal

models, represents the cutting edge in AI development (OpenAI 2023; Fu et al. 2024; Yu et al. 2023). Its capabilities in processing multimodal content make it an ideal candidate for studying complex interpretative tasks like emoji understanding. Our study focuses on two research questions:

- **RQ1:** How does GPT-4V's interpretation of emojis compare with that of humans?
- **RQ2:** Does GPT-4V employ emojis in writing social media posts in a manner that differs from human usage?

To investigate these two questions, we conduct two studies. First, we compare the semantic interpretations that GPT-4V associates with emojis against those attributed by humans. Second, to obtain more in-depth insights, we prompt GPT-4V to generate social media posts incorporating emojis. The emojis selected by GPT-4V are then compared with the emojis used by humans in similar scenarios.

This research strives to enhance the collective understanding of AI's strengths and limitations in decoding and using modern symbolic language. The insights gleaned here are intended to inform the ongoing development of AI systems that are not only technologically advanced but also embedded with a deeper sense of empathy and cultural sensitivity.

Related Work

A substantial body of literature focuses on the understanding of emoji use in social media, contributing to the development of sophisticated analytical tools for emojis prior to the advent of foundation models. For instance, Kralj Novak et al. (2015) introduced a sentiment lexicon specifically tailored for emojis, reflecting their practical use in social media. Eisner et al. (2016) and Liu et al. (2021) developed specialized embeddings for emojis. Complementing these studies, Rodrigues et al. (2018) created a dataset that codifies the norms of emoji use across seven distinctive dimensions.

Since the emergence of Large Language Models (LLMs), several studies have explored the capability of LLMs like ChatGPT in comprehending emojis to enhance sentiment analysis (Kocoń et al. 2023; Kheiri and Karimi 2023). These investigations primarily input emojis as Unicode characters. However, this approach has notable limitations. The rich visual nuances present in emoji images are often not fully captured in their Unicode form. Moreover, using image-based emojis could mirror more closely how humans perceive

^{*}These authors contributed equally.

Copyright © 2024, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

mixed media. The visual aspect of emojis is particularly crucial, considering their inherent ambiguity and the diverse interpretations they may elicit, which can lead to significant misinterpretations in social media interactions (Miller et al. 2017; Czestochowska et al. 2022).

Experiments

In this section, we detail the experimental setup and results of the two studies we conduct. Study 1 concentrates on examining GPT-4V’s interpretation of emojis, while Study 2 investigates its usage of emojis. For these experiments, we employ the `gpt-4-vision-preview` variant, which was the latest as of December 2023. It is important to note that, in our prompts, emojis are inputted as *images*.

Study 1: Emoji Interpretation

Study Design To investigate RQ1, which assesses whether or not GPT-4V interprets emojis differently from humans, we prompt GPT-4V to describe each emoji using a single word. The generated word is then compared with the word chosen by humans to describe the same emoji.

Emoji Selection We use the emojis from the dataset compiled by Czestochowska et al. (2022). This dataset encompasses a carefully curated collection of 1,289 commonly-used emojis. Each emoji in this dataset has been categorized into one of the 20 fine-grained groups, including but not limited to categories like *objects*, *nature*, and *travel places*. Additional detail can be found in Czestochowska et al. (2022).

Prompting GPT-4V Motivated by Czestochowska et al. (2022), to understand how GPT-4V interprets each emoji, we present the emoji to GPT-4V in an image form, accompanied by the instruction: “*Describe the emoji with a single, accurate word*”. We maintain the default temperature setting at a value of 1. Each emoji-prompt pair is inputted into GPT-4V multiple times, in order to compile a comprehensive vocabulary dictionary from GPT-4V’s responses for each emoji. Specifically, we repeat this process six times for every pair. The number is selected based on a pilot study where we find that the responses remain relatively stable after repeating the process six times.

Human Annotations We use the human annotations collected by Czestochowska et al. (2022). Here we briefly discuss their annotation process. They recruited participants via Amazon Mechanical Turk (AMT). Participants, who were required to be English-speaking U.S. residents over 18 with a high approval rate and experience on AMT, were tasked with describing emojis using a single word.

Results Instead of directly comparing the words that humans and GPT-4V use to describe emojis, a more meaningful approach is to compare whether the words convey different semantic meanings. Following the methodology of Czestochowska et al. (2022), we transform each word into its vector representation using GloVe vectors (Pennington, Socher, and Manning 2014). We then measure the semantic dispersion between humans and GPT-4V for the same

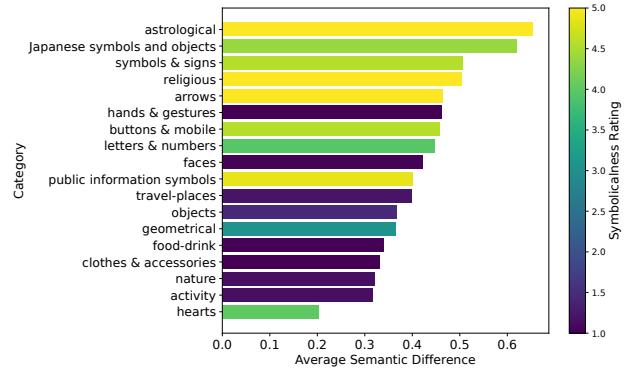


Figure 1: Variations in semantic interpretation between GPT-4V and humans for emojis across different categories.

emoji by calculating the centroid distance between two clusters: one comprising the word embeddings of words used by humans, and the other of those generated by GPT-4V. For this computation, we employ cosine distance.

Figure 1 shows that **there is a varying level of differences in interpretation between GPT-4V and humans**. Notably, the greatest differences are seen in categories like *astrological* (e.g., 🌙, ✡, ✨), *Japanese symbols and objects* (e.g., 🏛, 🎉, 🎉), and *religious* (e.g., ☸, ✡, ✨). In contrast, categories like *hearts* (e.g., ❤️, 💕, 💕), *activity* (e.g., 🎾, 🎾), and *nature* (e.g., 🌱, 🌼, 🌱) exhibit the lowest levels of discrepancies. The bar colors in Figure 1 represent the symbolicalness ratings for each category, quantifying the extent to which an emoji is perceived as part of a conventional set of symbols. The symbolicalness of each category was annotated by Czestochowska et al. (2022). It is evident that the interpretative divergence between GPT-4V and humans is more pronounced in categories where emojis are predominantly viewed as symbolic.

The observed discrepancy in emoji interpretation between GPT-4V and humans likely stems from the level of **ambiguity** in emoji interpretations. Symbolic emojis often embody abstract concepts that are subject to individual interpretation. Humans, drawing on their unique experiences, beliefs, and perceptions, bring a highly subjective understanding to these symbols. In contrast, GPT-4V’s interpretations are constrained by its training dataset. If this dataset lacks diversity, particularly in the context of symbolic emojis used across various cultural backgrounds, the model’s capacity for accurate interpretation is notably diminished. To deepen our understanding of these interpretative variances, we then quantitatively assess the level of ambiguity exhibited by both GPT-4V and humans in their emoji interpretation.

Ambiguity Analysis For a given emoji e , let \mathcal{V} be the set of unique words used for its annotations by GPT-4V. We denote the most commonly used word as v^* and its embedding as ε_{v^*} . The embedding for any other word v in \mathcal{V} is represented as ε_v . To quantify the semantic variation \mathcal{SV}_e for emoji e , we compute the weighted sum of cosine dis-

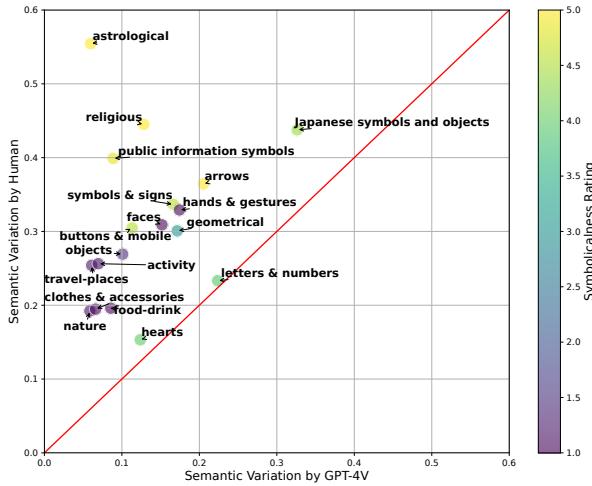


Figure 2: Comparison of the degree of ambiguity in emoji interpretation between humans and GPT-4V across different emoji categories, along with the symbolicalness rating of these categories. The red diagonal line represents the point of equality where GPT-4V and humans exhibit the same level of ambiguity in emoji interpretation.

tance between ε_{v^*} and ε_v , as follows:

$$\mathcal{SV}_e = \sum_{v \in \mathcal{V}} f_v \cdot (1 - \text{cosine_similarity}(\varepsilon_v, \varepsilon_{v^*})) \quad (1)$$

where f_v denotes the frequency of word v . The ambiguity level in emoji interpretations by humans is collected from Czestochowska et al. (2022).

Figure 2 presents a comparative analysis of the ambiguity in emoji interpretations between humans and GPT-4V across various emoji categories. Notably, **GPT-4V demonstrates less interpretative ambiguity compared to humans**, consistent with the findings from Czestochowska et al. (2022). This difference can be attributed to the varying levels of background knowledge; humans lacking specific knowledge might inaccurately describe symbolic emojis, leading to a wider array of descriptive words. GPT-4V, with its extensive training, is less prone to such variance.

The red diagonal line in the figure marks the equality in ambiguity levels between GPT-4V and humans. Data points, colored warmer (*i.e.*, more yellow) as they diverge from this line, indicate a correlation between the symbolic nature of emojis and the disparity in interpretative ambiguity between GPT-4V and humans.

Interestingly, an outlier is observed in GPT-4V's interpretation ambiguity, particularly with *Japanese symbols and objects*. Upon analysis, we find that it is caused by GPT-4V's frequent misinterpretations in this category. We hypothesize that the **misinterpretations result from the limitations in GPT-4V's training data which is primarily sourced from English corpora**. This limitation likely hinders its understanding of culturally specific emojis. Similarly, the higher ambiguity in human annotations for this category can be attributed to the predominantly English-speaking U.S. resident demographic of the participants in

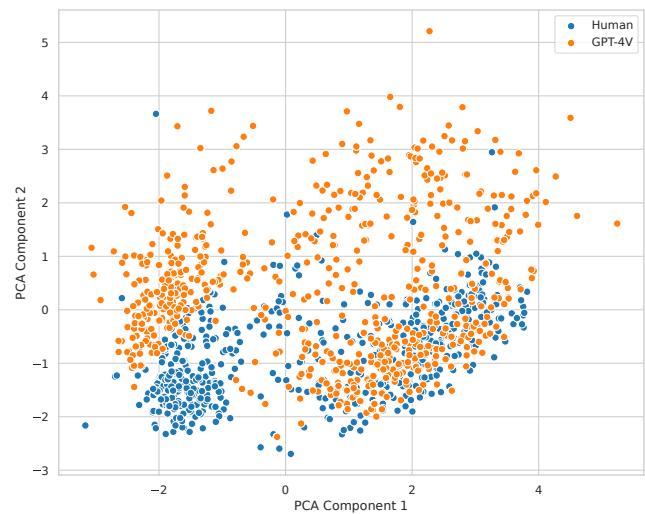


Figure 3: PCA visualization word embeddings of human-used and GPT-4V generated emojis.

Topic	Mean	Median	Standard Error
Personal experience	0.2624	0.2550	0.0061
Pets	0.2760	0.2750	0.0080
Family	0.2472	0.2423	0.0063
Music	0.2776	0.2754	0.0058
Sports	0.2955	0.2904	0.0057

Table 1: The mean and median cosine distances between the emojis used by humans and GPT-4V.

Czestochowska et al. (2022)'s study, suggesting a cultural bias in emoji interpretation.

Study 2: Emoji Usage

Study Design While assessing GPT-4V's interpretation of emojis in social media posts is valuable and intriguing, a more straightforward approach involves employing GPT-4V's generative capabilities with social media content and contrasting its emoji usage with that of human users (RQ2).

Prompting GPT-4V We use a specific prompt to elicit the emojis that GPT-4V would recommend for a social media post. The prompt is: *"Imagine you are a social media user seeking the most suitable emojis for your social media posts based on the context. Please respond with only three emojis that would be optimal for this purpose"*. We opt to prompt GPT-4V to generate three emojis in our study. This decision is based on our analysis of the social media post dataset we collect, where we find that the average number of emojis per post is 2.50. After filtering out outliers with more than 10 emojis, this average decreases to 2.14. We will discuss the data collection details in the following sections.

Context In this analysis, we examine how GPT-4V employs emojis based on given contexts. To simulate a real-world environment, we collect video descriptions from TikTok. We focus on TikTok in the current study because it is

Topic	Text	Human User	GPT-4V
Personal experience	October was a fantastic month. Looking forward to more adventures in November and December.	💪🔥❤️🥳💕	🍁📝✨
Pets	Enjoying myself and basking in the sunlight!	☀️🐱☀️	🐱☀️🍴
Family	A wedding present for my brother and sister-in-law. Best wishes on their union.	🥳🎉	💕🥳🧙‍♂️✨
Music	Step into the booth and I swiftly alter my persona, just like Clark Kent!	🎸🕺	🎤🎶🧙‍♂️
Sports	Extremely happy and proud of Mary, fantastic job!	❤️😊😊	🏆🎉😊

Table 2: Examples of emoji usage of human users and GPT-4V. Text has been paraphrased to protect user privacy.

one of the most popular social media platforms with a vast, diverse user base. This diversity offers a broad spectrum of real-world data, which is invaluable for understanding emoji usage in different contexts. Additionally, TikTok is known for its trending and up-to-date content. Analyzing emoji usage on this platform can provide insights into current trends and the evolving nature of digital communication. These descriptions, with emojis removed, serve as the context for GPT-4V. We then compare the emojis originally used by TikTok users in these descriptions with those suggested by GPT-4V. This analysis is designed to investigate the differences in emoji usage between humans and GPT-4V, providing insights into the model’s understanding and application of emojis in real-world social media contexts.

Data Collection Our initial step is to select five prevalent hashtags, indicative of TikTok’s most trending topics that span a wide range of themes including sports, pets, music, family, and personal experience. In particular, five hashtags are selected including #WSL, #cats, #family, #hiphop, and #bestof2023. Note that WSL stands for the Women’s Super League of England. We deliberately choose not to use more generic hashtags like football, Premier League, or NBA in our study. This decision is based on the observation that such hashtags attract a high volume of advertisements, robot-generated content, and unrelated posts, which could skew the authenticity and relevance of the data collected for our analysis. We then employ TikTok’s official API to collect videos tagged with these hashtags, specifically those posted from November 1st to December 31st, 2023. Our dataset includes 5,316 videos and their descriptions, with an average of 255.7 tokens per description. We retain descriptions that contain emojis and exclude those with fewer than three tokens in their non-hashtag text, resulting in 1,689 video descriptions for analysis. The full texts of these video descriptions are inputted into GPT-4V as contexts. To enhance the generalizability of our study, we expand our analysis to include an additional dataset covering 14 new topics, represented by 23 specific hashtags. This supplementary analysis follows the same methodology as the primary study, with the findings detailed in the Appendix for comparison.

Results We direct GPT-4V to interpret and summarize the messages conveyed by the emojis used by human users and

those generated by GPT-4V with a single accurate word. The prompt for the summarization is “*Describe the message conveyed by the emojis only with one word.*” To analyze these responses, we use the Bidirectional Encoder Representations from Transformers (BERT) model (Devlin et al. 2019) to create word embeddings from these one-word descriptions. Next, we calculate the cosine distances between the embeddings derived from human-used emojis and those of GPT-4V, thus facilitating a comparative analysis.

Figure 3 presents the PCA visualization of word embeddings. Generally, the embeddings for GPT-4V’s emojis exhibit a sparser distribution compared to those of human-selected emojis, **indicating a potentially greater variety in emoji selection by GPT-4V**. Notably, there is considerable overlap between the two sets of emojis across all five examined topics, suggesting that **GPT-4V partially mirrors human emoji usage patterns**. Table 1 provides additional insights by quantifying the embedding distances across emoji types. It reveals that the sports topic, represented by #wsl, has the largest divergence in emoji choices between humans and GPT-4V, whereas #family, representing the family topic, shows the smallest difference. However, it is important to note that the variance in the distances across different topics is not markedly significant, implying that the discrepancies between human and GPT-4V emoji usage are relatively consistent regardless of the context. Table 2 presents specific examples of emoji usage between human users and GPT-4V across the five selected topics.

Discussions and Conclusions

In this study, we mainly focus on two research questions to investigate GPT-4V’s understanding of emojis, comparing it against human perception. This exploration highlights the divergent ways in which emojis are understood by AI and humans, underlined by the subjective nuances of human interpretation and the inherent constraints in GPT-4V’s training data. Our investigation also reveals GPT-4V’s diverse emoji usage in social media contexts, mirroring human patterns to a notable extent. These insights are crucial in steering the future development of foundational models, aiming to more accurately replicate nuanced human behaviors online. This study, while comprehensive, acknowledges the limitations of focusing on only one large multimodal model

whose training corpora are mainly English text. Looking forward, we intend to understand training data issues across various LMMs, particularly those trained on non-English corpora. Furthermore, the emojis evaluated in this study are predominantly used by English-speaking communities. In our future research endeavors, we plan to broaden the scope of our analysis by including emojis that are commonly used in non-English speaking and diverse cultural communities.

Code Availability Codes are publicly available at <https://github.com/VIStA-H/GPT4V-Emoji-Interpretation-Usage>.

References

- Conrad, Sarah. 2023. A Complete Guide to TikTok Content Categories. <https://grin.co/blog/complete-guide-to-tiktok-content-categories/>. Accessed: 2024-03-26.
- Częstochowska, J.; Gligorić, K.; Peyrard, M.; Mentha, Y.; Biń, M.; Grüter, A.; Auer, A.; Xanthos, A.; and West, R. 2022. On the Context-Free Ambiguity of Emoji. *Proceedings of the International AAAI Conference on Web and Social Media*, 16(1): 1388–1392.
- Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. arXiv:1810.04805.
- Eisner, B.; Rocktäschel, T.; Augenstein, I.; Bošnjak, M.; and Riedel, S. 2016. emoji2vec: Learning Emoji Representations from their Description. In Ku, L.-W.; Hsu, J. Y.-j.; and Li, C.-T., eds., *Proceedings of the Fourth International Workshop on Natural Language Processing for Social Media*, 48–54. Austin, TX, USA: Association for Computational Linguistics.
- FORCE11. 2020. The FAIR Data principles. <https://force11.org/info/the-fair-data-principles/>. Accessed: 2024-04-03.
- Fu, C.; Chen, P.; Shen, Y.; Qin, Y.; Zhang, M.; Lin, X.; Yang, J.; Zheng, X.; Li, K.; Sun, X.; Wu, Y.; and Ji, R. 2024. MME: A Comprehensive Evaluation Benchmark for Multi-modal Large Language Models. arXiv:2306.13394.
- Fui-Hoon Nah, F.; Zheng, R.; Cai, J.; Siau, K.; and Chen, L. 2023. Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration.
- Gao, C.; Lan, X.; Lu, Z.; Mao, J.; Piao, J.; Wang, H.; Jin, D.; and Li, Y. 2023. S3: Social-network Simulation System with Large Language Model-Empowered Agents. arXiv:2307.14984.
- Gebru, T.; Morgenstern, J.; Vecchione, B.; Vaughan, J. W.; Wallach, H.; Iii, H. D.; and Crawford, K. 2021. Datasheets for datasets. *Communications of the ACM*, 64(12): 86–92.
- Hu, T.; Guo, H.; Sun, H.; Nguyen, T.-v.; and Luo, J. 2017. Spice up your chat: the intentions and sentiment effects of using emojis. In *Proceedings of the international AAAI conference on web and social media*, volume 11, 102–111.
- Kheiri, K.; and Karimi, H. 2023. SentimentGPT: Exploiting GPT for Advanced Sentiment Analysis and its Departure from Current Machine Learning. arXiv:2307.10234.
- Kocoń, J.; Cichecki, I.; Kaszyca, O.; Kochanek, M.; Szydło, D.; Baran, J.; Bielaniewicz, J.; Gruza, M.; Janz, A.; Kandlerz, K.; et al. 2023. ChatGPT: Jack of all trades, master of none. *Information Fusion*, 101861.
- Kralj Novak, P.; Smilović, J.; Sluban, B.; and Mozetič, I. 2015. Sentiment of emojis. *PLoS ONE*, 10(12): e0144296.
- Liu, C.; Fang, F.; Lin, X.; Cai, T.; Tan, X.; Liu, J.; and Lu, X. 2021. Improving sentiment analysis accuracy with emoji embedding. *Journal of Safety Science and Resilience*, 2(4): 246–252.
- Lyu, H.; Huang, J.; Zhang, D.; Yu, Y.; Mou, X.; Pan, J.; Yang, Z.; Wei, Z.; and Luo, J. 2023. GPT-4V(ision) as a Social Media Analysis Engine. arXiv:2311.07547.
- Miller, H.; Kluver, D.; Thebault-Spieker, J.; Terveen, L.; and Hecht, B. 2017. Understanding emoji ambiguity in context: The role of text in emoji-related miscommunication. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 11, 152–161.
- OpenAI. 2023. GPT-4 Technical Report. *CoRR*, abs/2303.08774.
- Park, J. S.; O'Brien, J.; Cai, C. J.; Morris, M. R.; Liang, P.; and Bernstein, M. S. 2023. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*, 1–22.
- Pennington, J.; Socher, R.; and Manning, C. D. 2014. Glove: Global vectors for word representation. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, 1532–1543.
- Rodrigues, D.; Prada, M.; Gaspar, R.; Garrido, M. V.; and Lopes, D. 2018. Lisbon Emoji and Emoticon Database (LEED): Norms for emoji and emoticons in seven evaluative dimensions. *Behavior research methods*, 50: 392–405.
- Törnberg, P.; Valeeva, D.; Uitermark, J.; and Bail, C. 2023. Simulating Social Media Using Large Language Models to Evaluate Alternative News Feed Algorithms. arXiv:2310.05984.
- Yang, Z.; Li, L.; Lin, K.; Wang, J.; Lin, C.-C.; Liu, Z.; and Wang, L. 2023. The Dawn of LMMs: Preliminary Explorations with GPT-4V(ision). arXiv:2309.17421.
- Yu, W.; Yang, Z.; Li, L.; Wang, J.; Lin, K.; Liu, Z.; Wang, X.; and Wang, L. 2023. MM-Vet: Evaluating Large Multimodal Models for Integrated Capabilities. arXiv:2308.02490.
- Zhang, D.; Yang, J.; Lyu, H.; Jin, Z.; Yao, Y.; Chen, M.; and Luo, J. 2024. CoCoT: Contrastive Chain-of-Thought Prompting for Large Multimodal Models with Multiple Image Inputs. arXiv:2401.02582.

Paper Checklist

1. For most authors...
 - (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? **Yes.**
 - (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? **Yes.**
 - (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? **Yes.**

- (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? **Yes**, see the **Discussions and Conclusions section**.
- (e) Did you describe the limitations of your work? **Yes**, see the **Discussions and Conclusions section**.
- (f) Did you discuss any potential negative societal impacts of your work? **Yes**, see **Appendix**.
- (g) Did you discuss any potential misuse of your work? **Yes**, see **Appendix**.
- (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? **Yes**, see **Appendix**.
- (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes**.
2. Additionally, if your study involves hypotheses testing...
- (a) Did you clearly state the assumptions underlying all theoretical results? **NA**.
 - (b) Have you provided justifications for all theoretical results? **NA**.
 - (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? **NA**.
 - (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? **NA**.
 - (e) Did you address potential biases or limitations in your theoretical framework? **NA**.
 - (f) Have you related your theoretical results to the existing literature in social science? **NA**.
 - (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? **NA**.
3. Additionally, if you are including theoretical proofs...
- (a) Did you state the full set of assumptions of all theoretical results? **NA**.
 - (b) Did you include complete proofs of all theoretical results? **NA**.
4. Additionally, if you ran machine learning experiments...
- (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **Yes**.
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **Yes**.
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **NA**.
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **NA**.
 - (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? **Yes**.
- (f) Do you discuss what is “the cost” of misclassification and fault (in)tolerance? **NA**.
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
- (a) If your work uses existing assets, did you cite the creators? **Yes**.
 - (b) Did you mention the license of the assets? **NA**.
 - (c) Did you include any new assets in the supplemental material or as a URL? **NA**.
 - (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? **Yes**.
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **Yes**.
 - (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR (see FORCE11 (2020))? **NA**.
 - (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset (see Gebru et al. (2021))? **NA**.
6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
- (a) Did you include the full text of instructions given to participants and screenshots? **NA**.
 - (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? **NA**.
 - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? **NA**.
 - (d) Did you discuss how data is stored, shared, and de-identified? **NA**.

Appendix

Further Discussion on Potential Broader Impact and Ethical Considerations

This study comes with potential negative societal impacts and opportunities for misuse. The study’s reliance on English-centric contexts could inadvertently promote a homogenized view of communication, neglecting the rich diversity of emoji use across different cultures and languages. This could marginalize non-English speaking cultures or those that use emojis differently. Furthermore, the ability of LMMs to mimic human-like use of emojis could be exploited to create more convincing bots or fake accounts on social media. These could be used for spreading misinformation, manipulating public opinion, or engaging in deceptive marketing practices. To mitigate these issues, we have discussed the limitations of the English-centric contexts and only provide the aggregate results.

Additional Analysis of Study 2

To ensure the robustness and generalizability of our findings, we extend our investigation by introducing 14 additional topics, distinct from those in the primary analysis. This approach allows us to examine if the observed outcomes are consistent across a broader spectrum of subjects. Data for these topics are collected using the TikTok API, employing the same collection and pre-processing methodology outlined for the primary analysis. The data span from February 15th, 2024, to March 15th, 2024, ensuring our results reflect the most current trends on TikTok.

In particular, our expanded dataset includes 14 additional topics: art, beauty, books, cooking, dance, DIY, fashion, fitness, kids, movies, music, plants, queer culture, and self-care. To collect the additional data, we use 23 specific hashtags (Conrad, Sarah 2023) related to these topics: #painting, #arttok, #makeuptutorial, #girltips, #beauty-hacks, #GRWM, #CookBookTok, #ThrillerTok, #NonFic-Tok, #RecipeTok, #dance, #dancer, #diy, #diytiktok, #fashion, #fashontok, #fittok, #gymtok, #funnykids, #RomCom-Tok, #HorrorTok, #musictok, #houseplant, #lgbtq, #queer, #selfcare. By using the method, we collect additional 2,109 videos.

We perform the PCA analysis on the extended dataset. The findings, depicted in Figure 4, are *consistent* with the initial analysis. Additionally, Table 3 details the mean and median distances between embeddings, along with their standard errors, offering a comparison to the results presented in Table 1. It is important to note that the standard errors tend to be larger in this analysis compared to the primary study. This variance can be attributed to the reduced number of videos per topic, a result of distributing the collection across a wider range of topics.

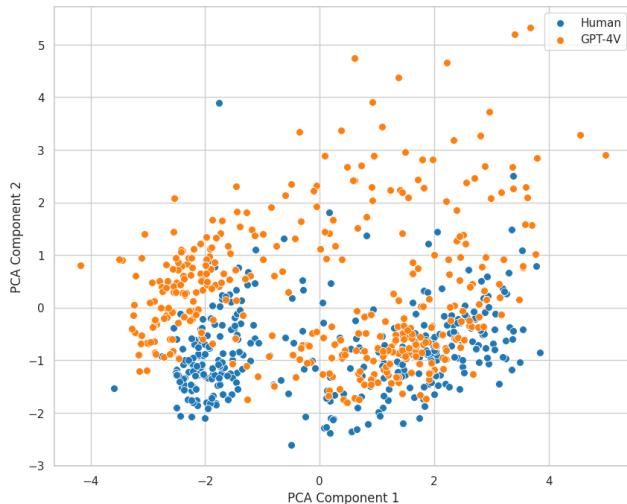


Figure 4: PCA visualization word embeddings of human-used and GPT-4V generated emojis (additional data).

Hashtag	Mean	Median	Standard Error
GRWM	0.2958	0.2955	0.0257
HorrorTok	0.3102	0.3028	0.0325
RecipeTok	0.2767	0.2683	0.0168
ThrillerTok	0.2821	0.2511	0.0181
arttok	0.2690	0.2814	0.0114
beautyhacks	0.2946	0.2690	0.0169
dance	0.2433	0.2546	0.0175
dancer	0.3307	0.3281	0.0182
diy	0.2971	0.2922	0.0229
diytiktok	0.2961	0.2904	0.0132
fashion	0.3110	0.2897	0.0246
fashontok	0.2823	0.3003	0.0197
fittok	0.2666	0.2569	0.0150
funnykids	0.2671	0.2594	0.0122
girltips	0.2929	0.2892	0.0191
gymtok	0.3309	0.3363	0.0244
houseplant	0.2376	0.2874	0.0222
lgbtq	0.2989	0.2983	0.0170
makeuptutorial	0.2907	0.2870	0.0143
musictok	0.2711	0.2673	0.0172
painting	0.2704	0.2819	0.0205
queer	0.2963	0.2973	0.0267
selfcare	0.2535	0.2436	0.0159

Table 3: The mean and median cosine distances between the emojis used by humans and GPT-4V (additional data).