Using AI to Understand Human Emotions
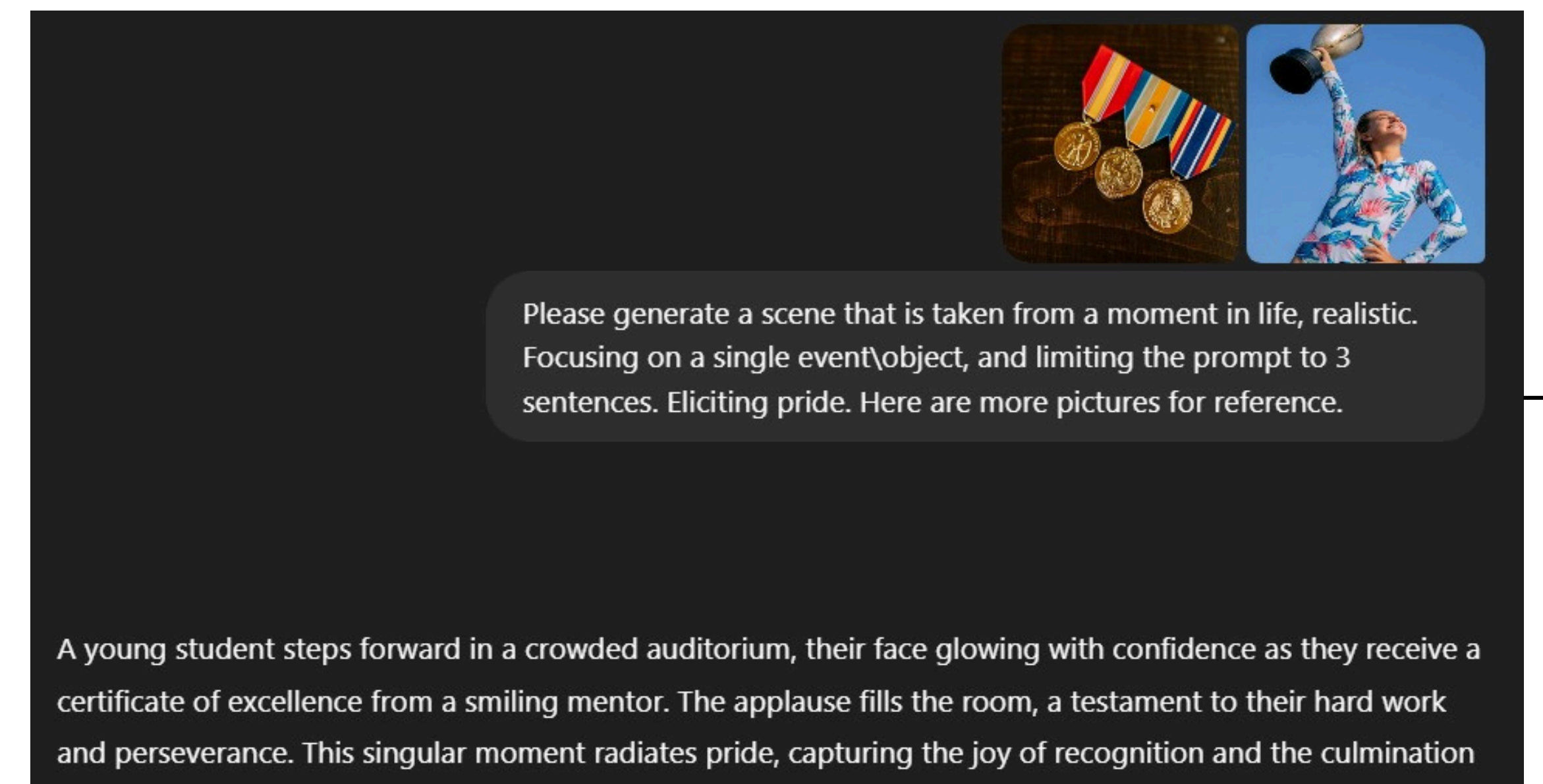
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Step one: creating a prompt

Please generate a scene that is taken from a moment in life, realistic. Focusing on a single event\object, and limiting the prompt to 3 sentences. Eliciting pride. Here are more pictures for reference.

A young student steps forward in a crowded auditorium, their face glowing with confidence as they receive a certificate of excellence from a smiling mentor. The applause fills the room, a testament to their hard work and perseverance. This singular moment radiates pride, capturing the joy of recognition and the culmination

Step two: creating an image

Step three: reviewing and choosing the best result

A young student steps forward in a crowded auditorium, their face glowing with confidence as they receive a certificate of excellence from a smiling mentor. The applause fills the room, a testament to their hard work and perseverance. This singular moment radiates pride, capturing the joy of recognition and the culmination of countless hours of dedication.
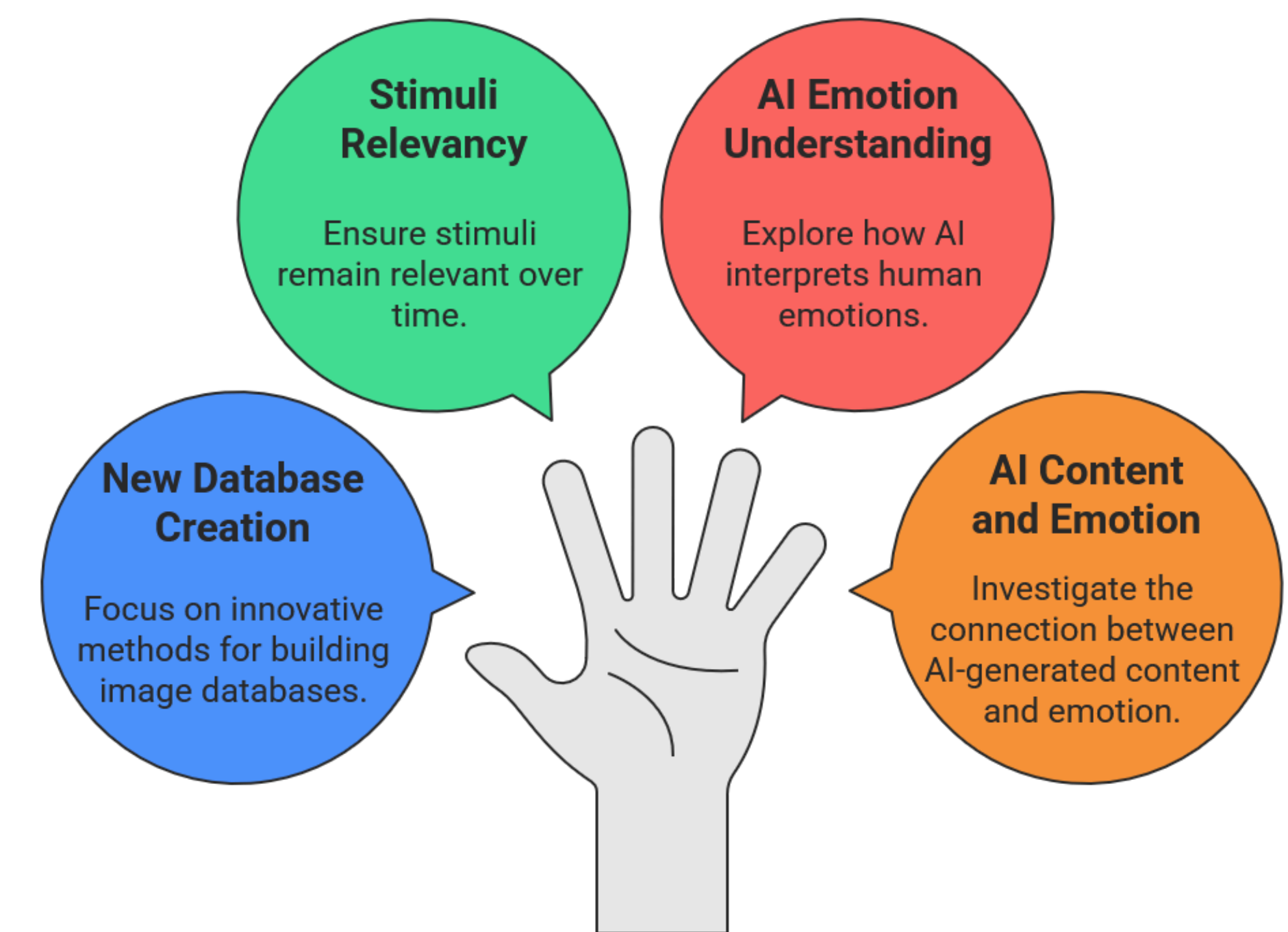

A "pipeline" for generating affective images using AI

1. IMAGE DATABASE

- By definition: an appropriate and controlled emotional stimulus for inducing specific emotional states
- An image database is multifuncational and can be used in different branches of study in psychology, such as cognitive and emotion studies.
- Examples of different existing databases - IAPS (2005), NAPS (2013), GAPED (2011), CAP-D (2018)
- A major difficulty researchers faced while creating new image databases is the acuisition\ creation of new stimuli, that is, affective pictures.

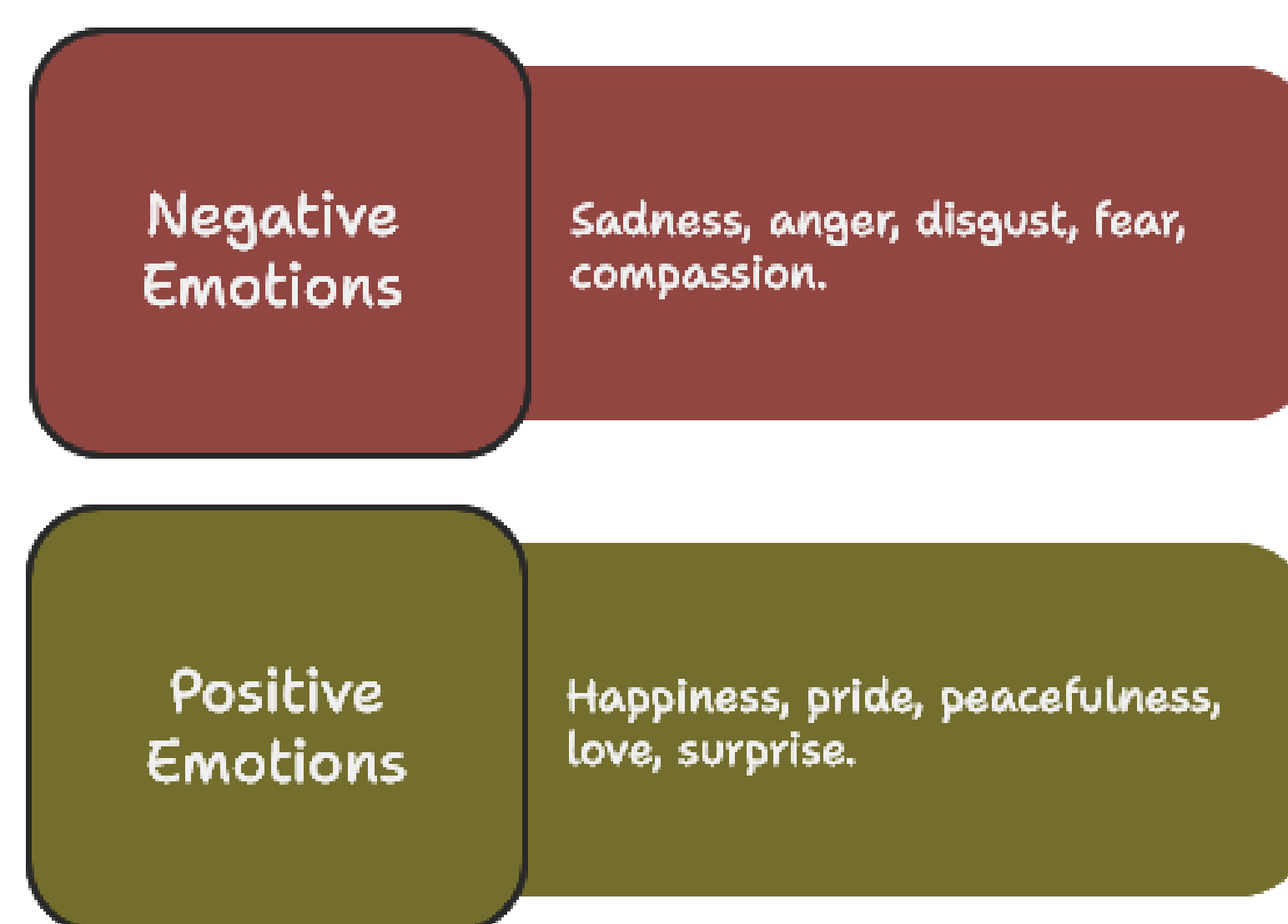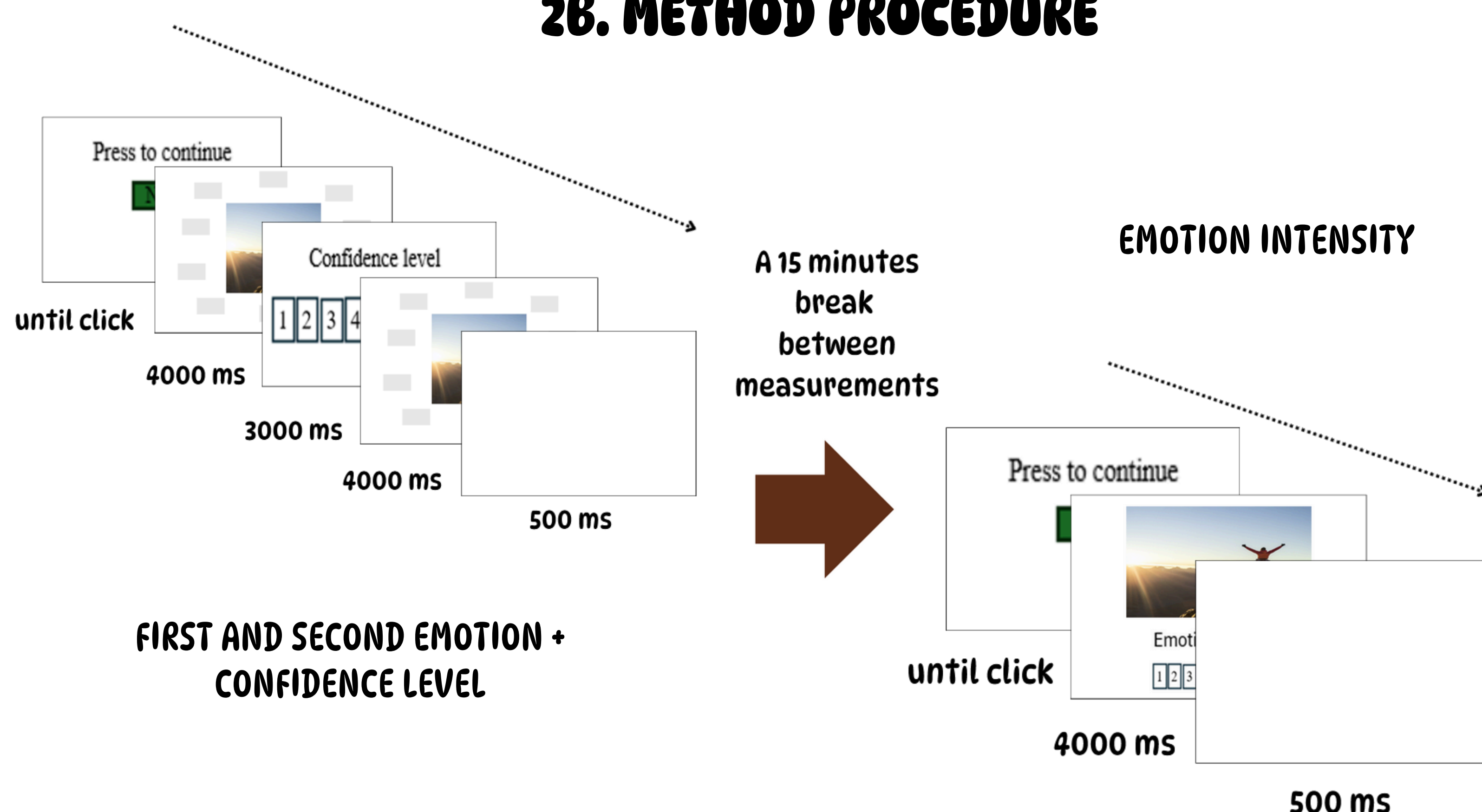## 3. DIFFERENT ASPECTS TO EXPLORE:

Stimuli Relevancy — Ensure stimuli remain relevant over time.

AI Emotion Understanding — Explore how AI interprets human emotions.

New Database Creation — Focus on innovative methods for building image databases.

AI Content and Emotion — Investigate the connection between AI-generated content and emotion.

2A. METHOD STIMULI

EMOTIONS IN OUR STUDY

- Materials: 100 generated pictures
  Measurements:
  - First\second emotion
  - Confidence level
  - Intensity level

Negative Emotions — Sadness, anger, disgust, fear, compassion.

Positive Emotions — Happiness, pride, peacefulness, love, surprise.

2B. METHOD PROCEDURE

Press to continue
until click

4000 ms

Confidence level
1 2 3 4
3000 ms

4000 ms

500 ms

A 15 minutes break between measurements

EMOTION INTENSITY

Press to continue

Emotion
until click

4000 ms

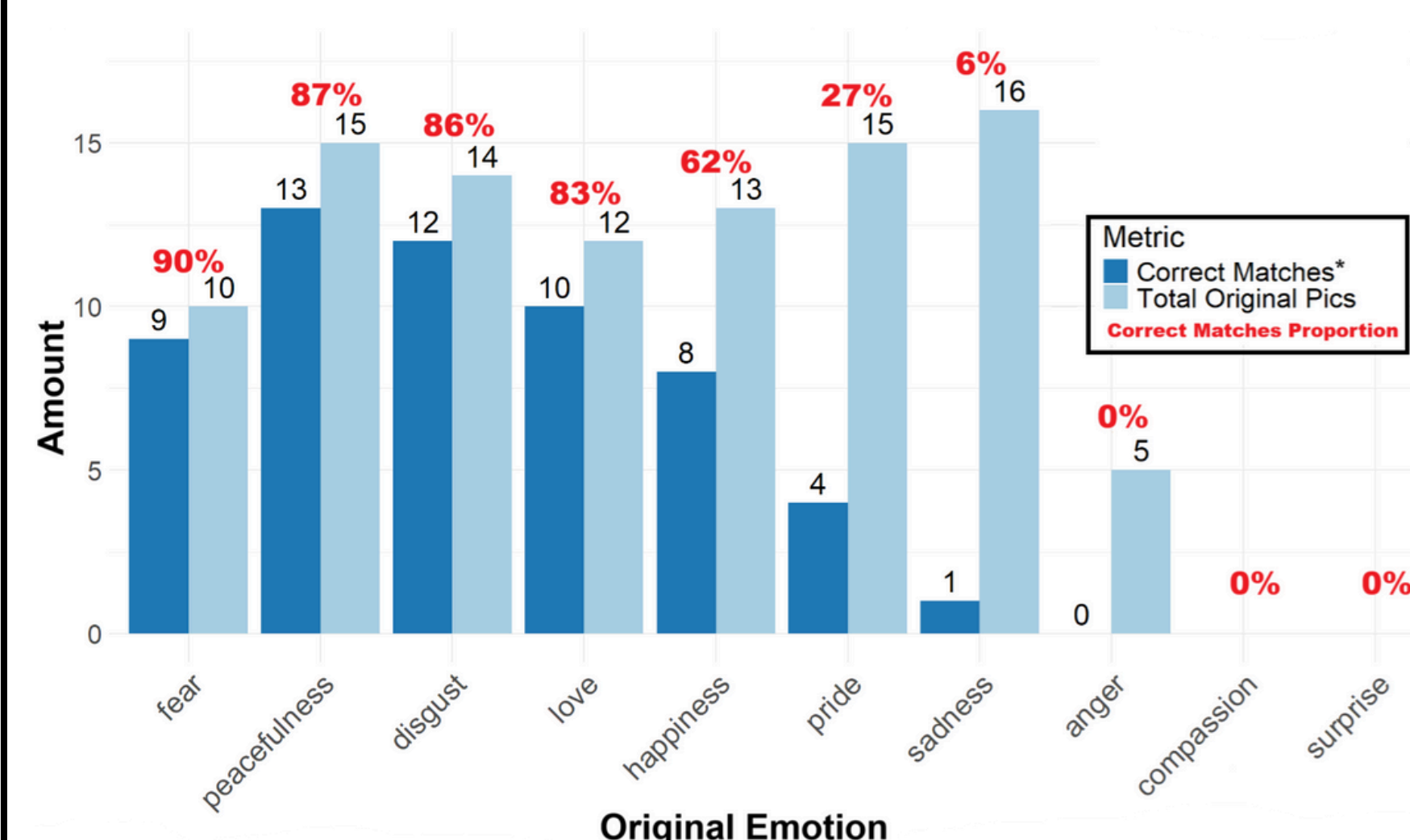500 ms

FIRST AND SECOND EMOTION + CONFIDENCE LEVEL

4. RESULTS
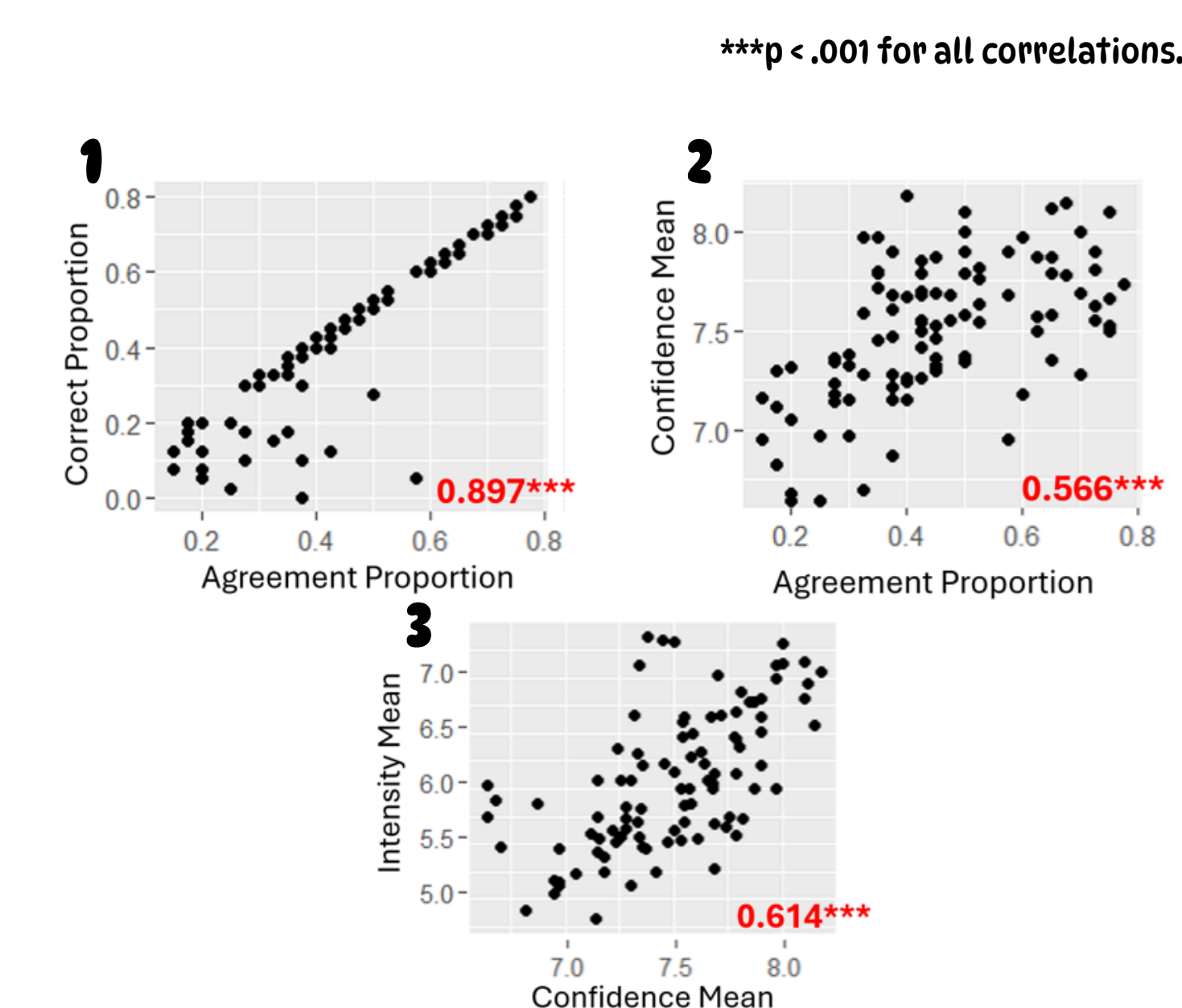
MATCH ACCURACY BY ORIGINAL EMOTION

Some emotions were easier to evoke and recognize than others. This is shown by the varying proportion of correct matches (in red) and the number of original images per emotion.

Correct Match = ≥40% participant agreement on the intended emotion.

(bar chart: Original Emotion — fear 90% (9,10), peacefulness 87% (13,15), disgust 86% (12,14), love 83% (10,12), happiness 62% (8,13), pride 27% (4,15), sadness 6% (1,16), anger 0% (0,5), compassion 0%, surprise 0%)

Metric: Correct Matches*, Total Original Pics, Correct Matches Proportion

VARIABLES' CORRELATIONS

1. Higher correct matches were linked to greater agreement among participants (r = 0.897***).
2. Higher confidence in chosen emotions was linked to greater agreement (r = 0.566***).
3. Higher confidence was also linked to greater intensity of felt emotion (r = 0.614***).

***p < .001 for all correlations.

(scatter plots)
1. Correct Proportion vs Agreement Proportion — 0.897***
2. Confidence Mean vs Agreement Proportion — 0.566***
3. Intensity Mean vs Confidence Mean — 0.614***

5. DISCUSSION

- Until recently, affective image databases have relied on real-world stimuli– a process with limitations and costs.
- We have successfully generated affective images using AI, offering a more efficient and scalable alternative.
- During creation and testing, some emotions were consistently harder to evoke.
- We also found that some emotions were more often chosen as first emotions, while others as secondary emotions.
- Could these patterns reveal new insights about emotion? Do they reflect our method, or broader limitations? These questions open the door for future research.
- At present, we are continuing to improve our AI-based affective image creation pipeline.

- Kojima, Takeshi, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. (2022). "Large Language Models Are Zero-Shot Reasoners." ArXiv (Cs.CL). arXiv. http://arxiv.org/abs/2205.11916.
- Kong, Aobo, Shiwan Zhao, Hao Chen, Qicheng Li, Yong Qin, Ruiqi Sun, Xin Zhou, Enzhi Wang, and Xiaohang Dong. (2023). "Better Zero-Shot Reasoning with Role-Play Prompting." ArXiv (Cs.CL). arXiv. http://arxiv.org/abs/2308.07702.
- Lu, Z., Huang, D., Bai, L., Qu, J., Wu, C., Liu, X., & Ouyang, W. (2023). Seeing is not always believing: Benchmarking and model perception of AI generated images. arXiv. https://doi.org/10.48550/arXiv.2304.13023
- Marchewka, A., Żurawski, Ł., Jednoróg, K., & Grabowska, A. (2014). The Nencki Affective Picture System (NAPS): Introduction to a novel, standardized, wide range, high quality, realistic picture database. Behavior Research Methods, 46(2), 596-610.
- Moyal, N. (2018). Categorized Affective Pictures Database (CAP D). Journal of Cognition, 1(1), Article 41. https://doi.org/10.5334/joc.47
- Moyal, N., Glebov Russinov, I., Henik, A., & Anholt, G. E. (2024). The role of emotion recognition in reappraisal affordances. Psychological Research, 88(5), 1629-1636. https://doi.org/10.1007/s00426-024-01966-5
- Wei, Jason, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. (2022). "Chain-of-Thought Prompting Elicits Reasoning in Large Language Models." ArXiv (Cs.CL). arXiv. http://arxiv.org/abs/2201.11903

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