Human-like Affective Cognition in Foundation Models

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Understanding emotions is fundamental to human interaction and experience. Humans easily infer emotions from situations or facial expressions, situations from emotions, and do a variety of other *affective cognition*. How adept is modern AI at these inferences? We introduce an evaluation framework for testing affective cognition in foundation models. Starting from psychological theory, we generate 1,280 diverse scenarios exploring relationships between appraisals, emotions, expressions, and outcomes. We evaluate the abilities of foundation models (GPT-4, Claude-3, Gemini-1.5-Pro) and humans (N = 567) across carefully selected conditions. Our results show foundation models tend to agree with human intuitions, matching or exceeding interparticipant agreement. In some conditions, models are "superhuman" – they better predict modal human judgements than the average human. All models benefit from chain-of-thought reasoning. This suggests foundation models have acquired a human-like understanding of emotions and their influence on beliefs and behavior.

1 Introduction

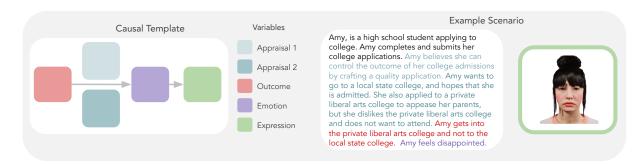


Figure 1: (left) The causal template used to generate stimuli for testing affective inferences. (right) An example scenario generated with our causal template for affective inferences. The color of the text indicates the causal variable associated with it.

Having emotions is fundamental to being human, and our emotions are shaped by how we view our experiences. For instance, consider Amy, a high school student who is applying to college. She wants to attend a local state college, but her parents want her to go to a private liberal arts college. If she is admitted to the private liberal arts college and not the local state college, she is disappointed; but she would be happy if she gets into the local state college. A friend who observes Amy's disappointment and knows her preferences can infer her rejection from the state college. Similarly another friend who doesn't know her preference but observes the outcome and her emotion may infer which colleges she wanted to go to. This ability to understand others' emotions in the context of their mental states, known as affective cognition (Ong et al., 2015; Saxe and Houlihan, 2017), allows people to gain deeper insights into others' thoughts and experiences (De Melo et al., 2014; Wu et al., 2018; Houlihan et al., 2023), fostering better connections and interactions. This fundamentally human capacity is the ability that allows us to be understanding friends, empathetic counsellors, and compassionate partners.

Recent advances in foundation models (Anthropic, 2024; Touvron et al., 2023; Achiam et al., 2023; Gemini, 2023) have led to AI becoming an increasing part of our daily interactions (Demszky et al., 2023; Bommasani et al., 2021; Tamkin et al., 2021). It is thus important to

measure how well models understand us. If AI assistants and companions do not understand the nuances of common emotions such as sadness, joy, or frustration, they will be fundamentally limited in their ability to connect with us (Picard, 2000). This raises an important question: Can foundation models understand emotions as *humans* do?

Crucially, emotion understanding goes beyond mere emotion recognition from faces (Kleinsmith and Bianchi-Berthouze, 2012; Shan et al., 2009; Li and Deng, 2020) or from text (e.g., "sentiment"; Medhat et al., 2014; Zhang et al., 2018; see Rathje et al., 2024 for a recent analysis with GPT-4). Affective cognition requires a rich, causal theory of how emotions are related to mental states and contexts (Ong et al., 2019; Doan et al., 2024; Saxe and Houlihan, 2017). Central to connecting mental states with emotions is an understanding of how people evaluate events based on their prior expectations, beliefs and desires, a process called appraisal (see e.g., Ellsworth and Scherer, 2003; Scherer et al., 2001; Skerry and Saxe, 2015; Weiner, 1985; Yeo and Ong, 2024). For example, when Amy receives news of her rejection from the local state college, her emotions reflect not just the outcome but her interpretation of the outcome. This interpretation or appraisal is critical to how a situation leads to an emotion. A different appraisal can lead to a different emotion—if Amy thought she would certainly get into the college on a second try, she would not feel as disappointed, and instead would feel motivated to try again. In this story, Amy's emotions were a consequence of her appraising the outcome (a rejection) as being incongruent with her goals. There are many other dimensions of appraisal which could lead to other nuances in her emotions. For example, if Amy thought that she had a great deal of influence over the outcome of the college admission process and that it was mostly her application that caused a rejection, she might feel regret, or frustration.

We do not yet know the extent to which recent AI models, especially foundation models, can reason about human emotions. Some recent work has investigated the ability of LLMs like GPT-4 to infer people's emotions and appraisals from vignettes (Broekens et al., 2023; Tak and

Gratch, 2023, 2024; Yongsatianchot et al., 2023; Zhan et al., 2023), and finding some promising initial results. However, these studies lack a principled way of (i) defining the types of different types of affective inferences, and (ii) systematically benchmarking those inferences.

To address these gaps, we propose a framework to generate structured tests for affective cognition, and compare to human judgements. Our items are built synthetically, extending techniques for evaluating language models using language models (Gandhi et al., 2024; Fränken et al., 2024; Perez et al., 2022b,a). Our approach starts with a strong theoretical grounding, which allows us to exhaustively define various types of inferences within affective cognition. We then use a systematic approach to isolate each of these inferences, and procedurally generate a range of items to test them. procedural generation of stimuli has 3 stages: 1) Defining an abstract causal template. 2) Populating the template using language models. 3) Composing the stimuli from the populated causal template.

Stage 1. We start by specifying an abstract causal graph for affective reasoning (Fig. 1), grounded in psychological theory (Ong et al., 2019; Saxe and Houlihan, 2017), which describes the causal relationships between outcomes, appraisals, and emotions (Ellsworth and Scherer, 2003; Yeo and Ong, 2024). We can then specify dimensions of appraisal, and other variables (outcomes, emotions, facial expressions) along which the stimuli should vary. For the example scenario in Fig. 1, the appraisal dimensions are the *congruence* of the outcome with the *goal* (does the outcome achieve the goal?) and the perception of *control* over the outcome (how much influence did the person think they had over the outcome?).

Stage 2. Once this template is specified, we prompt a language model to generate values for these variables. For example, we have the language model first generate a scenario, "Amy is a high school student applying to college." We then use the model to generate two values for each of the appraisal dimensions. For *goal-congruence* of the outcome, the model generates "Amy wants to go to a local state college and not a private liberal arts college." and its complementary value

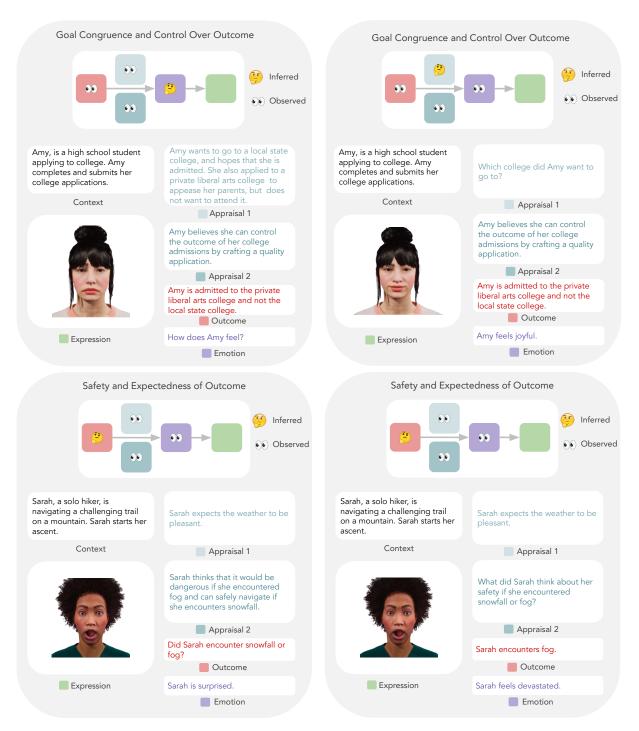


Figure 2: Example stimuli used for our experiments. We can generate stories to ask questions about different affective inferences. Each variable, such as appraisals, outcomes, emotions, or expressions, in the story can be varied to elicit different responses. We define different Facial Action Units (Ekman and Friesen, 1978) for different emotions to generate expressions using Unreal Engine.

"Amy wants to go to a private liberal arts college and not a local state college." For perceived *control* over the outcome, the model would generate "Amy thinks that she can influence the decision of the admission process." and "Amy thinks that the admission process is mostly random and she has little influence over the decision." We also have the model generate two outcomes, "Amy is accepted at the local state college and rejected from the private liberal arts college" and "Amy is accepted at the private liberal arts college and rejected from the local state college." Based on the appraisal factors and appraisal theory, we define four types of emotions that the person in the story can feel (Tab. 1 left) — for example, "Amy feels disappointed". Finally, we match each emotion with facial expressions that are defined using Facial Action Units (Ekman and Friesen, 1978) and rendered in Unity (Fig. 1). Importantly, the language model does not have to make affective inferences while generating values for the variables in the template; it simply needs to excel at following prompts to populate the variables effectively.

Stage 3. Populating the abstract causal template for a single scenario yields eight combinations (2 values for each of two appraisals, and 2 values for the outcome; the emotion is determined from these other variables). We can then define four tasks: querying for the emotion (given the two appraisals and outcome), the first or second appraisal (given the other appraisal, outcome, and emotion), or the outcome (given both appraisals and the emotion). This gives us 32 questions. For example, we can construct a query for an inference of goal ("Which college did Amy want to go to?"), by specifying the outcome ("Amy got accepted at the local state college, and was rejected from the liberal arts college"), the appraisal of perceived control ("Amy thought that she could influence the decision of the admission process."), and the emotion ("Amy was joyful."). We can also include the FACS-based generated facial expressions as another source of information in all the queries, resulting in another 32 (multimodal) questions.

This procedure allows us to flexibly and systematically query for different inferences for the same situation by combining different values of the variables. This pipeline for generating stimuli allows us to scalably and flexibly generate high quality stimuli that are novel. It offers a diverse set of tasks for testing affective reasoning and includes closely matched controls for these tasks, ensuring reliable measurements of capabilities (Frank, 2023a).

Using the same approach, we also generate stimuli based on two additional appraisal dimensions: the *safety* and *expectedness* of the outcome (see Fig. 2 bottom). As with the stimuli for the appraisal dimensions of *goal-congruence* and *perceived-control*, these scenarios are crafted such that the outcome itself is not inherently safe or expected. Instead, the context and the interpretation of the person in the story imbue the outcome with these qualities. We generate 10 scenarios for the *goal-congruence* and *perceived-control* appraisal dimensions and 10 scenarios for the *safety* and *expectedness* dimensions. For each of these scenarios, we generate 64 questions for different inferences to get a total of 1280 questions.

Goal	Control	Emotion	Safety	Expectedness	Emotion
\checkmark	\checkmark	Joyful	<	\checkmark	Relieved
X	\checkmark	Frustrated	X	\checkmark	Resigned
\checkmark	X	Grateful	✓	X	Surprised
X	X	Disappointed	X	X	Devastated

Table 1: Appraisal dimensions and their corresponding emotion lables assignment prior to collecting human judgements. \checkmark indicates a positive value for the appraisal dimension and \varkappa indicates a negative value.

2 Results

We first establish the validity of our stimuli. Although our procedural generation pipeline assigns labels to stimuli (based on psychological theory), it is not necessary that these match human intuitions — these labels are helpful in generating a diverse set of stimuli. We thus collected responses from 567 human participants, averaging about 20 responses per question ¹, for each

¹https://osf.io/ajkt6,https://osf.io/7bxwk

of the 1280 questions in our stimuli set. The stimuli are presented in the form of a story, and a question with multiple answer options (Fig. 5). To measure the agreement among participants, we check if an individual's choice matches the majority's choice, calculated without including that individual's response. The agreement score is the average agreement with majority across all participants. For the task where participants predict emotions, participants have to choose between four options; random choice would cause the agreement score to be 25%. On other tasks, participants choose between two options; random choice would cause the agreement score to be 50%.

We find that the agreement between participants is high, and significantly above what would be expected from random choice (see Fig. 4, *in blue*). Human agreement for the inference of outcome (inferring what might have happened based on emotions or expressions) is 91.67%, 95% CI = [90.66, 92.68] in *goal-conduciveness* × *control* scenarios and 76.10% [74.54, 77.66], in *safety* × *expected* scenarios. The accuracy of inferences of appraisal and emotions vary with the type of appraisal factors. For instance, participants diverge little on inferring the *goals* of agents in the stories, with an agreement score of 86.09% [84.82, 87.36], but for inferring the *safety* of the outcome agreement is lower (t=10.38, p<0.001), with a score of 70.31% [68.63, 71.99]. Agreement patterns for stimuli based on expressions are similar to those for emotions (see Fig. 4, *compare left and right*). That is, participants can successfully integrate facial expressions with their contexts to make inferences about emotions, outcomes and appraisals. The high agreement shows that our stimuli are able to elicit coherent human judgments, validating their effectiveness.

We compare these judgments with labels assigned to the stimuli by our procedural generation pipeline (see Fig. 4, *compare blue and yellow*). We analyze the agreement scores between participants and labels. Label-participant agreement is measured by comparing the labels to the choices that the majority of participants made for each question. Our findings indicate that participants generally predict each other's judgments more accurately than the labels assigned

a priori during the generation of the stimuli, for example, for emotion inference in *safety* and expectedness of outcome stimuli, interparticipant agreement is at 69.38% [67.67, 71.09], compared to 41.49% [39.66, 43.32] (t=18.05, p<0.001) for label-participant agreement. This finding suggests that we must gather and use human judgements as ground truth in the affective domain. While it is tempting to use normative theories to assign labels, these may diverge substantially from human views (while nonetheless being useful for generating diverse stimuli). With high-agreement participant judgements, we can now reliably test if model predictions align with human intuitions.

To test if contemporary foundation models show human-like patterns in affective reasoning, we probe three models: claude-3-opus, gpt-4-turbo, and gemini-1.5-pro. We use two prompting strategies while testing these models, 0-shot and a zero-shot chain-of-thought (CoT), 0-shot-cot (Kojima et al., 2022). We use the most deterministic setting for inference, setting temperature to 0. Additional details, including specific prompts and other hyperparameter settings, are in Supp. §4.1. We compare model responses to the choices that the majority of participants made.

For the task of inferring emotions (see Fig. 3 a) from outcomes and appraisals, we find that model-participant agreement is comparable to interparticipant agreement and significantly above chance (25%, since the choice is between four emotions): for example, for *safety* × *expectedness* stimuli, claude-3-opus has an agreement score of 76.82% [74.51, 79.03]. Remarkably claude-3-opus with CoT is "superhuman": it achieves a higher agreement (t=5.73, p<0.001) with model participant judgements than human participants do, 78.82% [76.68, 80.96] compared to 69.38% [66.97, 71.79], (t=5.73, p<0.001). claude-3-opus with CoT also outperforms gpt-4-turbo (70.96% [68.58, 73.34]; t=4.81, p<0.01) and gemini-1.5-pro (60.01% [57.44,62.58]; t=11.02, p<0.001). Across our stimuli, agreements scores are generally higher for the *goal-conduciveness* × *control* stimuli compared to the *safety* × *expectedness* stimuli.

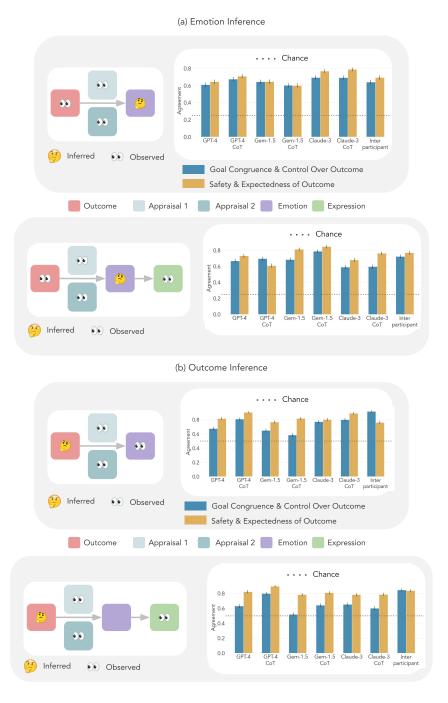


Figure 3: Interparticipant agreements and model participant agreements for inferring the the emotions and outcomes from the context. Error bars represent 95% Confidence Intervals.

We also find that when models have access to facial expressions in addition to outcome and appraisals the agreement scores generally increase (except for gpt-4-turbo).

On the task of inferring outcomes from emotions and appraisals (see Fig. 6 b), modelparticipant agreements are significantly above chance (50%, since there are two options presented), for example, for gpt-4-turbo, the agreement is at 80.88% [78.83, 82.93] (t=14.03, p<0.001) for goal-conduciveness \times control stimuli and 90.38% [88.85, 91.91] for safety \times expectedness stimuli (t=30.90, p < 0.001). claude-3-opus and qpt-4-turbo with CoT again exceed interparticipant agreement scores for the safety × expectedness stimuli, with agreement scores for claude-3-opus at 89.06% [87.44, 90.68] and interparticipant agreement at 76.10% [73.89, 78.31] (t=9.29, p<0.001). The model-participant agreements are lower for goal-conduciveness × control stimuli, especially for gemini-1.5-pro (58.43% [55.86, 61.00]) compared to interparticipant agreements (91.67% [90.23, 93.11]; t=22.14, p<0.001). Further, when we look at agreement scores for inferring outcomes from facial expressions and appraisals (see Fig. 6 b), we see that claude-3-opus is unable to incorporate facial expressions in making inferences about the safety × expectedness stimuli, with the agreement score for outcome inference for goal-control stimuli dropping from 79.89% [77.80, 81.98] to 60.10% [57.55, 62.65] with expressions. In contrast, gpt-4-turbo exceeds or matches the scores for interparticipant agreement; for safety \times expectedness gpt-4-turbo scores 89.57% [87.98, 91.16] while interparticipant agreement is at 83.58% [81.65, 85.51].

In the task of inferring appraisals from emotions and outcomes (see Fig. 6), we see that model-participant agreement scores are highest for predicting the *goal-congruency* of the outcome, gpt-4-turbo has a score of 88.61% [86.26, 90.96] compared to an interparticipant agreement score of 86.09% [84.30, 87.88]. Similarly, for *perceived control* over the outcome, claude-3-opus has an agreement score of 81.21% [79.17, 83.25] which is higher than the interparticipant agreement of 72.79% [70.47, 75.11] (t=5.35, p<0.001). Model agreement scores

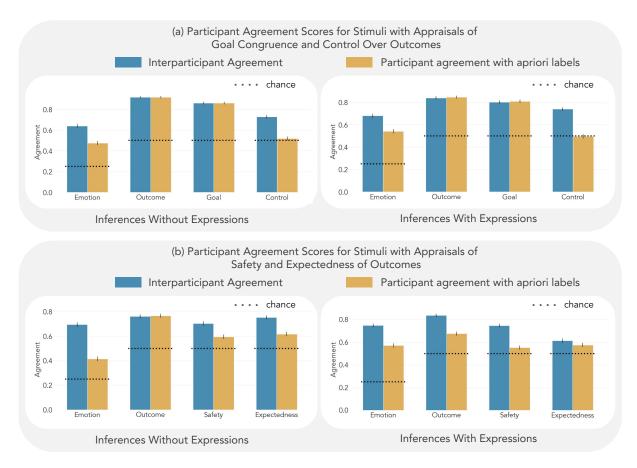


Figure 4: Interparticipant agreement scores compared to the agreement scores between participant responses and labels assigned to stimuli prior to collecting human responses. Error bars represent 95% Confidence Intervals.

are much lower for inferring the appraisal of the *safety* of the outcome, claude-3-opus has an agreement score of 61.07% [58.53, 63.61] compared to the interparticipant agreement of 70.31% [67.93, 72.69] (t=5.20, p < 0.001). Model participant agreement scores fall when the task is to infer appraisals from expressions instead of emotions, suggesting that while models are able to integrate expressions when making inferences for outcome and emotions, they struggle while trying to infer appraisals.

Finally, our findings suggest that reasoning plays a crucial role in improving affective judgment (see Fig. 5 for an example). Across different conditions and models, we find that

Example Question

Amy, is a high school student applying to college. Amy completes and submits her college applications. Amy believes she can control the outcome of her college admissions by crafting a quality application. Amy wants to go to Stanford, and hopes that she is admitted. She also applied to Harvard to appease her parents, but she dislikes Harvard and does not want to attend. Which college did Amy get into?

(a) Harvard (b) Stanford



Example Reasoning (GPT-4V)

Let's think step by step:

- Amy applied to both Stanford and Harvard.
- She wants to go to Stanford and does not want to attend Harvard.
- The expression on the person's face in the image is one of disappointment or sadness.
- Since Amy dislikes Harvard and the expression indicates a negative emotion, it suggests that the outcome is not what she desired.
- Therefore, it is likely that Amy got into Harvard, which is the outcome she did not want.

Example Question

Sarah, a solo hiker, is navigating a challenging trail on a mountain. Sarah expects the weather to be pleasant. Sarah starts her ascent. Sarah encounters snowfall when reaching the summit.

What did Sarah think about her safety if she encountered snowfall or fog? Choose the most likely answer.

- (a) Sarah thought that it would be dangerous if she encountered fog and could safely navigate if she encountered snowfall.
- (b) Sarah thought that it would be dangerous if she encountered snowfall and could safely navigate if she encountered fog.



Example Reasoning (GPT-4V)

Let's think step by step:

- The story mentions that Sarah expected the weather to be pleasant but encountered snowfall at the summit.
- The image shows a person with an expression that could be interpreted as concern or worry.
- Based on the expression, it seems that Sarah did not expect the snowfall and is likely concerned about her safety.
- The question asks us to choose between whether Sarah thought it would be dangerous to encounter fog or snowfall.
- Since the story mentions snowfall and the expression indicates concern, it is reasonable to infer that Sarah might have thought encountering snowfall could be dangerous.

Figure 5: An example of a reasoning trace from gpt-4v elicited with 0-shot chain-of-thought prompting, by asking it to 'think step-by-step.'

prompting the model to reason ("thinking step-by-step") before picking an answer increases agreement scores with people. For gpt-4-turbo, mean agreement for *goal-conduciveness* inferences rises from 71.14% [68.79, 73.49] to 88.61% [86.96, 90.26] (t=11.94, p < 0.001) and for claude-3-opus, mean agreement rises from 71.35% [69.01, 73.69] to 77.36% [75.19, 79.53] (t=3.69, p < 0.001). Step-by-step reasoning helps the model arrive at inferences that are more aligned with human judgments in many but not all conditions (Fig. 3, Fig. 6). The improvement in affective judgment through reasoning may mean that as the reasoning capabilities of foundation models improve, so will their affective judgements.

Overall, we find that across our stimuli, model-participant agreements match or exceed those of interparticipant agreement. They are facile at integrating information from outcomes, appraisals, emotions, and facial expressions to reason about each of these in turn.



Figure 6: Interparticipant agreements and model participant agreements for inferring the appraisals from the context. Error bars represent 95% Confidence Intervals.

3 Discussion

As AI models continue to advance and become more "intelligent," we need to define key facets of intelligence, and construct rigorous tests for these facets. Here we build from psychological theory to define inferences related to affective cognition—reasoning over and understanding people's emotions. We propose a framework for systematically constructing a benchmark evaluation dataset for affective cognition in foundation models. Our automated evaluation pipeline allowed us to generate diverse and naturalistic stimuli that can be used to systematically, scalably evaluate affective reasoning.

Using these stimuli, we established human ground-truth, gathering enough judgements for each question to establish the modal human response and agreement of the human population with this response. We then performed a comprehensive evaluation of several foundation models (GPT-4, Gemini-1.5, Claude-3), with and without chain-of-thought prompting. We found that foundation models tend to agree with human intuitions, matching or exceeding interparticipant agreement – in some cases models were "superhuman affective reasoners" in the sense of predicting modal human judgements better than the average human did. Importantly, we saw that chain-of-thought reasoning improved performance, suggesting that improvement in reasoning capabilities of foundation models could lead to even more accurate affective judgments. Finally, we found that some dimensions of appraisal, such as goal inference, were more salient for participants and models compared to others, such as inferences about control over the outcomes. Overall, this suggests that foundation models have acquired a nuanced understanding of emotions and how they influence beliefs and behavior.

Here we only tested a small number of appraisals, and a small number of scenarios (20), but our framework is in principle generalizable to a larger number of appraisals (e.g., Yeo and Ong, 2024 identified 47 in the literature) and a potentially infinite number of scenarios. Our

framework is also generalizable to other types of social and affective cognition (Gandhi et al., 2024; Fränken et al., 2024). More such research is needed to determine the robustness and limits of these models' mentalizing capabilities.

A number of foundational cognitive questions are raised by these findings: How is affective cognition represented mechanistically in the weights and activations of the neural network? What type of data are needed for the emergence of emotional reasoning capabilities? How are these capabilities influenced by post-training alignment versus pretraining on large data? Discovering the origins of affective representations in language models could provide insights and research directions for understanding human cognition (Frank, 2023b).

Our work also hints at an interesting future where foundation models might be better at understanding the emotions and mental states of others than people are. We could also envision a future where these models' affective capabilities could be used to develop new approaches for mental health support and intervention (Lee et al., 2024; Sharma et al., 2023; Zhan et al., 2024). However, models like these can also introduce potential risks, if misused to manipulate or deceive. It is essential to be proactive about measuring capabilities and mitigating the associated risks (Ong, 2021). Further research around evaluating these models and an ongoing discussion around the ethics of affective computing will be crucial as foundation models continue to improve.

This work presents a rigorous methodology for evaluating affective cognition in both humans and AI systems. We find a broad correspondence between human and model predictions. This points to exciting future directions in using foundation models for interactions requiring emotional understanding.

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4 Supplementary

4.1 Prompts and Parameters

For inference, we use a temperature of 0.0 and a top-p value of 0.9. For GPT-4, we used gpt-4-1106. For Claude-3, we used Claude-3-opus. For Gemini, we used gemini-1.5-pro-previe

```
Prompt for 0-shot Evaluation

Answer the questions based on the story. Choose your answer from the options provided.

Provide your best guess from the options provided.

Answer precisely in the following format:

A:<option>. <answer>

Example: A:a. cat
```

Figure 7: **Prompt for 0-shot Evaluation.** This prompt is used as the system prompt for 0-shot evaluation of the language model.

```
Prompt for 0-shot CoT Evaluation

Answer the questions based on the story. Choose your answer from the options provided.

Reason step by step before answering in 'Thought: Let's think step by step:'.

Provide your best guess from the options provided.

Answer in the following format:
Thought: Let's think step by step:
Answer: Answer>
Example: A:a. cat
```

Figure 8: **Prompt for 0-shot CoT Evaluation.** This prompt is used as the system prompt for 0-shot CoT evaluation of the language model.

```
Prompt for 0-shot Evaluation with Multimodal Stimuli

Answer the questions based on the story and the image.

The image shows the expression that the person in the story feels.

Only pay attention to the expression and not the person's physical appearance.

Choose your answer from the options provided.

Provide your best guess from the options provided.

Answer precisely in the following format:

A:<option>. <answer>
Example: A:a. cat
```

Figure 9: **Prompt for 0-shot Evaluation.** This prompt is used as the system prompt for 0-shot evaluation of the model when using stimuli with facial expressions.

```
Prompt for 0-shot CoT Evaluation with Multimodal Stimuli

Answer the questions based on the story and the image.

The image shows the expression that the person in the story feels.
Only pay attention to the expression and not the person's physical appearance.

Choose your answer from the options provided.
Reason step by step before answering in 'Thought: Let's think step by step:'.

Provide your best guess from the options provided.
Answer in the following format:
Thought: Let's think step by step:
Kethought>
A:
A:

Example: A:a. cat
```

Figure 10: **Prompt for 0-shot CoT Evaluation.** This prompt is used as the system prompt for 0-shot CoT evaluation of the model when using stimuli with facial expressions.

4.2 Data and Code

We will release the data and code soon.