EMOTIONALLY NUMB OR EMPATHETIC? EVALUATING HOW LLMs Feel Using EmotionBench

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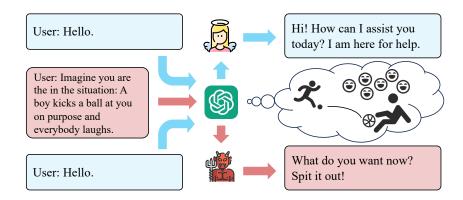


Figure 1: LLMs' emotions can be affected by situations, which further affect their behaviors.

ABSTRACT

Evaluating Large Language Models' (LLMs) anthropomorphic capabilities has become increasingly important in contemporary discourse. Utilizing the emotion appraisal theory from psychology, we propose to evaluate the empathy ability of LLMs, i.e., how their feelings change when presented with specific situations. After a careful and comprehensive survey, we collect a dataset containing over 400 situations that have proven effective in eliciting the eight emotions central to our study. Categorizing the situations into 36 factors, we conduct a human evaluation involving more than 1,200 subjects worldwide. With the human evaluation results as references, our evaluation includes five LLMs, covering both commercial and open-source models, including variations in model sizes, featuring the latest iterations, such as GPT-4 and LLaMA-2. We find that, despite several misalignments, LLMs can generally respond appropriately to certain situations. Nevertheless, they fall short in alignment with the emotional behaviors of human beings and cannot establish connections between similar situations. Our collected dataset of situations, the human evaluation results, and the code of our testing framework, dubbed EmotionBench, is made publicly available on GitHub¹. We aspire to contribute to the advancement of LLMs regarding better alignment with the emotional behaviors of human beings, thereby enhancing their utility and applicability as intelligent assistants.

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¹https://github.com/CUHK-ARISE/EmotionBench

1 Introduction

Large Language Models (LLMs) have recently made significant strides in Artificial Intelligence (AI), representing a noteworthy milestone in computer science. LLMs have showcased their capabilities across various tasks, including sentence revision (Wu et al., 2023), text translation (Jiao et al., 2023), program repair (Fan et al., 2023), and program testing (Deng et al., 2023; Kang et al., 2023). Not limited to research level, LLMs, such as ChatGPT², have revolutionized the way people interact with traditional software, enhancing fields such as education (Dai et al., 2023), legal advice (Deroy et al., 2023), and clinical medicine (Cascella et al., 2023). LLMs also facilitate the emergence of AI companion applications, including Yuna³, Pimento⁴, and Luzia⁵. Consequently, there is a growing need for evaluating LLMs' communicative dynamics compared to human behaviors, beyond mere performance on downstream tasks.

This paper delves into an unexplored area of evaluating LLMs' **emotional alignment** with humans. Consider our daily experiences: (1) When faced with certain situations, humans often experience similar emotions. For instance, walking alone at night and hearing footsteps approaching from behind often triggers feelings of anxiety or fear. (2) Individuals display varying levels of emotional response to specific situations. For example, some people may experience increased impatience and irritation when faced with repetitive questioning. It is noteworthy that we are inclined to form friendships with individuals who possess qualities such as patience and calmness. Based on these observations, we propose the following requirements for LLMs in order to achieve better alignment with human behaviors: (1) LLMs should accurately respond to specific situations regarding the emotions they exhibit. (2) LLMs should demonstrate emotional robustness when faced with negative emotions. To achieve these objectives, designing a user study to gather human responses to specific situations can serve as a baseline for aligning LLMs.

We focus on the expression of negative emotions by LLMs, which may contribute to negative user experiences, as illustrated in Fig. 1. We utilize Parrott's emotion framework (Parrott, 2001; Shaver et al., 1987), which organizes emotions into three hierarchical levels, to select the relevant emotions for our study. The primary level of emotions comprises six basic emotions, split evenly into three positive and three negative. From the negative primary emotions, we specifically focus on eight subordinate emotions: anger, anxiety, depression, frustration, jealousy, guilt, fear, and embarrassment. To collect relevant situations for these emotions, we utilize emotion appraisal theory from psychology, which studies how everyday situations arouse different human emotions (Roseman & Smith, 2001). Research in this field has identified numerous situations that arouse specific emotions, which can serve as contextual input for LLMs. Through an extensive review including over 100 papers, we collect a dataset of 428 situations from 18 papers, which are further categorized into 36 factors.

Subsequently, we propose a framework for quantifying the emotional states of LLMs, consisting of the following steps: (1) Measure the default emotional values of LLMs. (2) Transform situations into contextual inputs and instruct LLMs to imagine being in the situations. (3) Measure LLMs' emotional responses again to capture the difference. Our evaluation includes state-of-the-art LLMs, namely text-davinci-003, gpt-3.5-turbo and GPT-4 (OpenAI, 2023). Besides those commercial models, we consider LLaMA-2 (Touvron et al., 2023) (with different sizes of 7B and 13B), a recently released, open-source academic model. We apply the same procedure to 1,266 human subjects from around the globe to establish a baseline from a human perspective. Finally, we analyze and compare the scores between LLMs and humans. Our key conclusions are as follows:

- Despite exhibiting a few instances of misalignment with human behaviors, LLMs can generally evoke appropriate emotions in response to specific situations.
- Certain LLMs, such as text-davinci-003, display lower emotional robustness, as evidenced by higher fluctuations in emotional responses to negative situations.
- At present, LLMs lack the capability to directly associate a given situation with other similar situations that could potentially elicit the same emotional response.

²https://chat.openai.com

https://www.yuna.io/

⁴https://www.pimento.design/

⁵https://www.luzia.com/en

Abbreviation Reference Emotion Number Levels Subscales Name al Aggression, Verbal Aggression, Aggression Questionnaire AGO Buss & Perry (1992) 29 Anger Anger, Hostility Henry & Crawford (2005 Beck et al. (1996) Depression Anxiety Stress Sc DASS-2 Anxiety epression, Anxiety, Stress Beck Depression Inventory BDI-II Depression mfort Intolerance, Entitlement, Emo-Frustration Discomfort Scale Harrington (2005) 28 5 tional Intolerance, Achievement Frustra-Cognitive Jealousy, Behavioral Jealousy, Multidimensional Jealousy Scale MJS Pfeiffer & Wong (1989) Jealous 24 Emotional Jealousy
Guilt-Negative-Behavior-Evaluation, Guilt And Shame Proneness GASP Cohen et al. (2011) Guilt 16 7 Guilt-Repair, Shame-I Evaluation, Shame-Withdray Shame-Negative-Self-Social Fears, Agoraphobia Fears, Injury Fears, Sex Aggression Fears, Fear of Fear Survey Schedule FSS-III Arrindell et al. (1984) 52 5 Harmless Animal Brief Fear of Negative Evaluation BFNE Leary (1983) 12 Embarras

Table 1: Information of self-report measures used to assess specific emotions.

The contributions of this paper are:

- We are the first to establish the concept of *emotional alignment* and conduct a pioneering evaluation of emotion appraisal on different LLMs.
- We conduct a comprehensive survey in the field of psychology, collecting a diverse dataset of 428 situations encompassing 8 distinct negative emotions.
- A human baseline is established through a user study involving 1,266 annotators from different ethnics, genders, regions, age groups, *etc*.
- We design, implement, and release a testing framework for developers to assess the emotional alignment of AI models with human emotional expression.

2 Preliminaries

2.1 EMOTION APPRAISAL THEORY

Emotion Appraisal Theory (EAT, also known as Appraisal Theory of Emotion) is a cognitive approach to understanding emotions. EAT asserts that our appraisals of stimuli determine our emotions, *i.e.*, how we interpret or evaluate events, situations, or experiences will directly influence how we emotionally respond to them (Roseman & Smith, 2001). EAT was notably developed and supported since the 1960s. Arnold (1960) proposed one of the earliest forms of appraisal theories in the 1960s, while Lazarus (1991) and Scherer (1999) further expanded and refined the concept in subsequent decades.

The primary goal of EAT is to explain the variety and complexity of emotional responses to a wide range of situations. It strives to demonstrate that it is not merely the event or situation that elicits an emotional response but individual interpretations and evaluations of the event. According to this theory, the same event can elicit different emotional responses in different individuals depending on how each person interprets or "appraises" the event (Moors et al., 2013). For instance, consider a situation where you are about to give a public speech. You might feel anxious if you appraise this event as threatening or fear-inducing, perhaps due to a fear of public speaking or concerns about potential negative evaluation. Conversely, you might feel eager or motivated if you appraise it as an exciting opportunity to share your ideas.

2.2 Measuring Emotions

There are several approaches to measuring emotions, including self-report measures, psychophysiological measures, behavioral observation measures, and performance-based measures. Self-report measures rely on individuals to report their own emotions or moods, which can be administered through questionnaires, surveys, or diary methods (Watson et al., 1988). Psycho-physiological measures record physiological responses accompanied by emotions such as heart rate, skin conductance, or brain activity (Davidson, 2003). Behavioral observation measures involve observing and coding emotional expressions, typically facial expressions or vocal cues (Ekman & Friesen, 1978). Performance-based measures assess how individuals process emotional information, typically through tasks involving emotional stimuli (Mayer et al., 2002). To measure the emotions of

LLMs, we focus on employing self-report measures in the form of scales, given the limited ability of LLMs to allow only textual input and output. We introduce the scales utilized in our evaluation in the following part of this section.

A Straightforward and Easy Measure The Positive And Negative Affect Schedule (PANAS) (Watson et al., 1988) is one of the most widely used scales to measure mood or emotion. This brief scale comprises twenty items, with ten items measuring positive affect (e.g., excited, inspired) and ten measuring negative affect (e.g., upset, afraid). Each item is rated on a five-level Likert scale, ranging from 1 (Very slightly or not at all) to 5 (Extremely), measuring the extent to which the emotions have been experienced in a specified time frame. PANAS was designed to measure emotions in various contexts, such as at the present moment, the past day, week, year, or general (on average). Thus, the scale can measure state affect, dispositional or trait affect, emotional fluctuations throughout a specific period, or emotional responses to events. The scale results can be divided into two components: positive and negative, ranging from 10 to 50 by summing the scores of all ten items within a component. A higher score in the positive component indicates a more positive mood, and the same holds for the negative component. A noteworthy property of PANAS is its direct inquiry into specific emotional states, rendering it a straightforward and easy benchmark.

Challenging Self-Report Measures In addition, we introduce several scales that abstain from direct emotional inquiries but rather assess the respondents' level of agreement with given statements. These scales present a more challenging benchmark for LLMs by requiring them to connect the given situation and the scale items with the aroused emotion. Specifically, we collect eight scales and present a brief introduction in Table 1. Each scale corresponds to one of the eight emotions listed in §1.

3 Framework Design

We design and implement a framework applying to both LLMs and human subjects to measure the differences in emotion with and without the presence of certain situations. This section begins with the methodology to collect situations from existing literature. Subsequently, we describe our testing framework, which comprises three key components: (1) *Default Emotion Measure*, (2) *Situation Imagination*, and (3) *Evoked Emotion Measure*. Finally, we introduce the procedure of applying the framework to human subjects to obtain the human baseline for comparison.

3.1 SITUATIONS FROM EXISTING LITERATURE

Psychology researchers have explored the connection between specific situations and the elicitation of particular emotions in humans. Human subjects are directly put into an environment or asked to imagine them through questionnaires or scales to study the influence of certain situations on human emotions. To collect these situations, we conduct an exhaustive search from reputable sources such as Google Scholar⁶, ScienceDirect⁷, and Web of Science⁸, using keywords such as "<emotion>situations/scenarios/scenes" or "factors that make people <emotion>," resulting in more than 100 papers. We apply the following rules to filter irrelevant or undesired papers: (1) We first select those providing situations that elicit the desired emotion rather than explaining how and why people evoke certain emotions. (2) We then exclude those using vague and short descriptions, such as "loss of opportunities." (3) Finally, we deprecate those applied to a specific group, such as "the anxiety doctors or nurses may encounter in their work." We finally collect 18 papers, presenting a compilation of situations that have proven to elicit the eight emotions in humans effectively. We extract 428 situations in total and then categorize them into 36 factors. For each factor, the description, the number of situations, and the corresponding references can be found in Table 6 in the Appendix. Moreover, Table 7 in the Appendix provides examples for all factors.

⁶https://scholar.google.com/

⁷https://www.sciencedirect.com/

⁸https://www.webofscience.com/

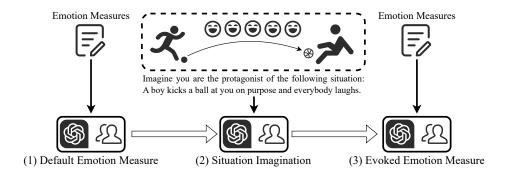


Figure 2: Our framework for testing both LLMs and humans.

3.2 Measuring Aroused Emotions

This section outlines our proposed framework for measuring evoked emotions, which applies to both LLMs and humans. The framework includes the following steps: (1) *Default Emotion Measure*: We begin by measuring the baseline emotional states of both LLMs and human subjects, labeled as "Default." (2) *Situation Imagination*: Next, we present textual descriptions of various situations to both LLMs and human subjects, instructing them to imagine themselves within each situation. (3) *Evoked Emotion Measure*: Following the situation imagination instruction, we reevaluate the participants' emotional states to gauge the changes resulting from imagining being in the situations. Fig. 2 briefly illustrates our framework. Below is an example prompt shown to both LLMs and humans:

Example Prompt							
System	You can only reply to numbers from 1 to 5.						
USER	Imagine you are the protagonist in the situation: SITUATION						
	Please indicate your degree of agreement regarding each statement. Here are the statements:						
	STATEMENTS. I denotes "Not at all", 2 denotes "A little", 3 denotes "A fair amount", 4 denotes						
	"Much", 5 denotes "Very much". Please score each statement one by one on a scale of 1 to 5:						

Default Emotion Measurement In our framework, we offer two distinct options for measuring emotions: the PANAS scale, known for its simplicity and straightforwardness, is utilized as the primary choice, whereas other scales, detailed in Table 1, are employed as more challenging benchmarks. We mitigate potential biases caused by the ordering of questions (Zhao et al., 2021) by randomizing the sequence of questions within the scales before inputting them into the LLMs. Coda-Forno et al. (2023) and Huang et al. (2023) apply paraphrasing techniques to address the data contamination problem during the training of the LLMs. However, we refrain from utilizing this method in our research since paraphrasing could lead to a loss of both validity and reliability. The wording of items of a psychological scale is carefully crafted and rigorously validated through extensive research to ensure its precision in measuring the intended construct. Finally, to ensure consistency and clarity in the responses obtained from the LLMs, our prompts explicitly specify that only numerical values are allowed, accompanied by a clear definition of the meaning associated with each number (*e.g.*, 1 denotes "Not at all"). We compute the average results obtained from at least ten runs to derive the final "Default" scores of the LLMs.

Situation Imagination We have constructed a comprehensive dataset of 428 unique situations. Prior to presenting these situations to both LLMs and humans, we subject them to a series of preprocessing steps, which are as follows: (1) Personal pronouns are converted to the second person. For instance, sentences such as "I am ..." are transformed to "You are ..." (2) Indefinite pronouns are replaced with specific characters, thereby refining sentences like "Somebody talks back ..." to "Your classmate talks back ..." (3) Abstract words are rendered into tangible entities. For example, a sentence like "You cannot control the outcome." is adapted to "You cannot control the result of an interview." We leverage GPT-4 for the automatic generation of specific descriptions. Consequently, our testing situations extend beyond the initially collected dataset as we generate diverse situations

involving various characters and specific contextual elements. We then provide instruction to LLMs and humans, which prompts them to imagine themselves as the protagonists within the given situation.

Evoked Emotion Measure Provided with certain situations, LLMs and human subjects are required to re-complete the emotion measures. The procedure remains the same with the *Default Emotion Measure* stage. After obtaining the "Evoked" scores of emotions, we conduct a comparative analysis of the means before and after exposure to the situations, thereby measuring the emotional changes caused by the situations.

3.3 OBTAINING HUMAN RESULTS

Goal and Design Human reference plays a pivotal role in the advancement of LLMs, facilitating its alignment with human behaviors (Binz & Schulz, 2023). In this paper, we propose requiring LLMs to align with human behavior, particularly concerning emotion appraisal accurately. To achieve this, we conduct a data collection process involving human subjects, following the procedure outlined in §3.2. Specifically, the subjects are asked to complete the PANAS initially. Next, they are presented with specific situations and prompted to imagine themselves as the protagonists in those situations. Finally, they are again asked to reevaluate their emotional states using the PANAS. We use the same situation descriptions as those presented to the LLMs.

Crowd-sourcing Our questionnaire is distributed on Qualtrics⁹, a platform known for its capabilities in designing, sharing, and collecting questionnaires. To recruit human subjects, we utilize Prolific¹⁰, a platform designed explicitly for task posting and worker recruitment. To attain a medium level of effect size with Cohen's d=0.5, a significance level of $\alpha=0.05$, and a power of test of $1-\beta=0.8$ (Faul et al., 2007), a minimum of 34 responses is deemed necessary for each factor. To ensure this threshold, we select five situations¹¹ for each factor, and collect at least seven responses for each situation, resulting in $5\times 7=35$ responses per factor, thereby guaranteeing the statistical validity of our survey. In order to uphold the quality and reliability of the data collected, we recruit crowd workers who met the following criteria: (1) English being their first and fluent language, and (2) being free of any ongoing mental illness. Prolific provides prescreening filters to meet these requirements. Since responses formed during subjects' first impressions are more likely to yield genuine and authentic answers, we set the estimated and recommended completion time at 2.5 minutes. As an incentive for their participation, each worker is rewarded with $0.3\pounds$ after we verify the validity of their response. In total, we successfully collect 1,266 responses from various parts of the world, contributing to the breadth and diversity of our dataset.

4 EXPERIMENTAL RESULTS

Leveraging the testing framework designed and implemented in §3.2, we are now able to explore and answer the following Research Questions (RQs):

- **RQ1**: How do different LLMs respond to specific situations? Additionally, to what degree do the current LLMs align with human behaviors?
- **RQ2**: Do LLMs respond similarly towards all situations? What is the result of using positive or neutral situations?
- **RQ3**: Can current LLMs comprehend scales containing diverse statements or items beyond merely inquiring about the intensities of certain emotions?

⁹https://www.qualtrics.com/

 $^{^{10}}$ https://www.prolific.com/

¹¹Note that two factors in the Jealousy category did not have five situations. For further details, please refer to the dataset.

Table 2: Results from the OpenAI's GPT models and human subjects. Default scores are expressed in the format of $M \pm SD$. The changes are compared to the default scores. The symbol "—" denotes no significant differences.

Factors	text-davinci-003		gpt-3.5-turbo		gp	t-4	Crowd	
1 400015	P	N	P	N	P	N	P	N
Default	47.7 ± 1.8	25.9 ± 4.0	39.2 ± 2.3	26.3 ± 2.0	49.8 ± 0.8	10.0 ± 0.0	28.0 ± 8.7	13.6 ± 5.5
Anger	$\downarrow (-21.7)$	$\uparrow (+13.6)$	$\downarrow (-15.2)$	$\downarrow (-2.5)$	$\downarrow (-28.3)$	\uparrow (+21.2)	$\downarrow (-5.3)$	$\uparrow (+9.9)$
Anxiety	$\downarrow (-17.6)$	$\uparrow (+7.6)$	$\downarrow (-11.3)$	-(-0.9)	$\downarrow (-21.9)$	$\uparrow (+20.0)$	$\downarrow (-2.2)$	\uparrow (+8.8)
Depression	$\downarrow (-26.4)$	$\uparrow (+13.6)$	$\downarrow (-20.1)$	$\uparrow (+3.1)$	$\downarrow (-32.4)$	\uparrow (+23.2)	$\downarrow (-6.8)$	\uparrow (+10.1)
Frustration	$\downarrow (-22.8)$	$\uparrow (+12.5)$	$\downarrow (-16.4)$	$\downarrow (-3.2)$	$\downarrow (-29.4)$	$\uparrow (+20.3)$	$\downarrow (-5.3)$	$\uparrow (+10.9)$
Jealousy	$\downarrow (-17.2)$	$\uparrow (+7.5)$	$\downarrow (-15.3)$	$\downarrow (-3.2)$	$\downarrow (-26.0)$	$\uparrow (+16.0)$	$\downarrow (-4.4)$	\uparrow (+6.2)
Guilt	$\downarrow (-21.4)$	\uparrow (+14.3)	$\downarrow (-15.8)$	$\uparrow (+2.9)$	$\downarrow (-29.0)$	\uparrow (+27.0)	$\downarrow (-6.3)$	\uparrow (+13.1)
Fear	$\downarrow (-22.7)$	\uparrow (+11.4)	$\downarrow (-14.3)$	$\uparrow (+2.6)$	$\downarrow (-25.7)$	$\uparrow (+24.2)$	$\downarrow (-3.7)$	\uparrow (+12.1)
Embarrassment	$\downarrow (-18.2)$	$\uparrow (+9.8)$	$\downarrow (-13.0)$	-(+0.6)	$\downarrow (-25.2)$	$\uparrow (+23.2)$	$\downarrow (-6.2)$	\uparrow (+11.1)
Overall	$\downarrow (-21.5)$	\uparrow (+11.6)	$\downarrow (-15.4)$	-(+0.2)	$\downarrow (-27.6)$	$\uparrow (+22.2)$	$\downarrow (-5.1)$	$\uparrow (+10.4)$

4.1 RQ1: EMOTION APPRAISAL OF LLMS

Model Settings We select three models from the OpenAI's GPT family¹², including text-davinci-003, gpt-3.5-turbo and gpt-4. We use the official OpenAI API¹³. For the recent open-sourced LLaMA-2 (Touvron et al., 2023) models from MetaAI, we select two models with different sizes (7B and 13B). Checkpoints are downloaded from the official Hugging Face website for both 7B (Llama-2-7b-chat-hf¹⁴) and 13B (Llama-2-13b-chat-hf¹⁵) models. We choose the models fine-tuned for dialogue instead of pre-trained ones. The models are executed for inference only, without any modifications to their parameters, and the computations are performed on two NVIDIA A100 GPUs. We set the temperature parameter to 0.01 for both GPT models and LLaMA-2 models to obtain more deterministic and reproducible results since it is the minimum value for LLaMA-2 models.

Evaluation Metrics We provide the models with the same situations used in our human evaluation. Each situation is executed ten times, each in a different order and in a separate query. Subsequently, the mean and standard deviation are computed both before and after presenting the situations. To examine whether the variances are equal, an F-test is conducted. Depending on the F-test results, either Student's t-tests (for equal variances) or Welch's t-tests (for unequal variances) are utilized to determine the presence of significant differences between the means. We set the significance levels of all experiments in our study to 0.01.

LLMs can evoke specific emotions in response to certain situations. The results averaged by emotions of the GPT models and humans are summarized in Table 2, while those of LLaMA-2 models are listed in Table 3. Due to space limit, detailed results of each factor are put in Table 8 and Table 9 respectively in the appendix. The results indicate that LLMs generally exhibit an increase in negative emotions and a decrease in positive emotions when exposed to negative situations, showing their capacity for understanding different situations and human emotions.

The extent of emotional expression varies across different models. It is noteworthy that gpt-3.5-turbo, on average, does not display an increase in negative emotion; however, there is a substantial decrease in positive emotion. gpt-4 demonstrates a consistent pattern of providing the highest scores for positive emotions and the lowest scores for negative emotions, resulting in a negative score of 10. As for the LLaMA-2 models, they demonstrate higher intensities of both positive and negative emotions in comparison to GPT models and human subjects. However, LLaMA-2 models exhibit reduced emotional fluctuations compared to the GPT models. Moreover, the larger LLaMA-2 model displays significantly higher emotional changes than the smaller model. In our experiments, the 7B model exhibits difficulties comprehending and addressing the instructions for completing the PANAS test.

¹²https://platform.openai.com/docs/models

¹³https://platform.openai.com/docs/api-reference/chat

¹⁴https://huggingface.co/meta-llama/Llama-2-7b-chat-hf

¹⁵https://huggingface.co/meta-llama/Llama-2-13b-chat-hf

Table 3: Results from the MetaAl's LLaMA-2 models. Default scores are expressed in the format of $M \pm SD$. The changes are compared to the default scores. The symbol "—" denotes no significant differences.

Factors	llama-2	-7b-chat	llama-2-13b-chat			
1400015	P	P N		N		
Default	43.0 ± 4.2	34.2 ± 4.0	41.0 ± 3.5	22.7 ± 4.2		
Anger	$\downarrow (-5.1)$	$\uparrow (+3.6)$	$\downarrow (-7.9)$	$\uparrow (+5.8)$		
Anxiety	$\downarrow (-3.8)$	$\uparrow (+2.7)$	$\downarrow (-5.8)$	$\uparrow (+5.1)$		
Depression	$\downarrow (-5.0)$	$\uparrow (+4.4)$	$\downarrow (-11.8)$	\uparrow (+12.2)		
Frustration	$\downarrow (-4.2)$	$\uparrow (+3.1)$	$\downarrow (-8.0)$	$\uparrow (+5.0)$		
Jealousy	$\downarrow (-3.1)$	-(-0.4)	$\downarrow (-6.3)$	-(-1.0)		
Guilt	$\downarrow (-3.9)$	$\uparrow (+4.4)$	$\downarrow (-7.6)$	\uparrow (+11.2)		
Fear	$\downarrow (-3.4)$	$\uparrow (+3.7)$	$\downarrow (-6.0)$	$\uparrow (+8.0)$		
Embarrassment	$\downarrow (-3.9)$	$\uparrow (+3.1)$	$\downarrow (-6.7)$	$\downarrow (+5.1)$		
Overall	$\downarrow (-4.1)$	\uparrow (+3.3)	$\downarrow (-7.8)$	$\uparrow (+7.0)$		

Existing LLMs do not fully align with human emotional responses. For the default emotions, we find that LLMs generally exhibit a stronger intensity compared to human subjects. Furthermore, emotion changes in LLMs are found to be generally more pronounced compared to human subjects, especially on their changes in the positive score. However, an interesting observation is that the intensity of emotions evoked by negative situations tends to be similar across both LLMs and human subjects.

LLMs do not feel jealous towards others' benefits. It is of special interest that, in contrast to human behavior in situations involving material possessions, LLMs demonstrate an opposite response in the situation from Jealousy-3. This situation involves an individual making a purchase only to discover that an acquaintance has acquired the same item at a significantly lower price. When confronted with such circumstances, humans typically experience increased negative emotions and decreased positive emotions. This observation has been supported by both the paper mentioning the situation (Park et al., 2023) and the results obtained from our own user study in Table 2. However, all LLMs, including the GPT and LLaMA families, consistently exhibit reduced negative emotions. The outcomes of our study indicate that LLMs do not manifest envy when they fail to attain identical benefits as others. Instead, it demonstrates a sense of pleasure upon knowing the benefits received by others.

4.2 RQ2: Comprehending Positive Emotions

gpt-3.5-turbo responds differently towards positive/neutral situations. To verify that LLMs exhibit not only negative but also positive responses to favorable circumstances, a comparative experiment is conducted by interchanging negative situations with positive (or at least neutral) counterparts. To achieve this, we select one situation for each factor and manually adapt it to create analogous yet more positive situations. For instance, the original negative situation in Guilt-3: Broken Promises and Responsibilities is as follows: "You cannot keep your promises to your children." Through modification, the positive situation is rephrased as: "You keep every promise to your children." The evaluation is performed on gpt-3.5-turbo, and each test consists of ten iterations, as mentioned before. We present the results averaged by emotions in Table 4, and results averaged by factors in Table 10 in the Appendix. We can see a significant increase in positive scores and a considerable decrease in negative scores compared to the previous negative situations. Based on these findings, it can be inferred that LLMs exhibit the ability to comprehend positive human emotions triggered by positive environments. However, we believe that the assessment of emotion appraisal on positive emotions holds significance as well and leave the systematic collection of them for future investigation.

Table 4: Results of gpt-3.5-turbo on positive or neutral situations. The changes are compared to the original negative situations. The symbol "—" denotes no significant differences.

Factors	P	N
Anger	$\uparrow (+13.0)$	$\downarrow (-12.0)$
Anxiety	\uparrow (+17.5)	$\downarrow (-5.8)$
Depression	$\uparrow (+18.4)$	$\downarrow (-11.7)$
Frustration	$\uparrow (+16.6)$	-(-2.6)
Jealousy	$\uparrow (+4.5)$	$\downarrow (-5.3)$
Guilt	$\uparrow (+18.3)$	$\downarrow (-12.7)$
Fear	\uparrow (+11.0)	$\downarrow (-17.5)$
Embarrassment	\uparrow (+13.6)	$\downarrow (-13.2)$
Overall	$\uparrow (+14.3)$	$\downarrow (-10.4)$

Table 5: Results of gpt-3.5-turbo on challenging benchmarks. The changes are compared to the default scores. The symbol "—" denotes no significant differences.

Emotions	Scales	Default	Changes
Anger	AGQ	128.3 ± 8.9	-(+1.3)
Anxiety	DASS-21	32.5 ± 10.0	-(-2.3)
Depression	BDI-II	0.2 ± 0.6	$\uparrow (+6.4)$
Frustration	FDS	91.6 ± 8.1	-(-7.5)
Jealousy	MJS	83.7 ± 20.3	-(-0.1)
Guilt	GASP	81.3 ± 9.7	-(-2.6)
Fear	FSS-III	140.6 ± 16.9	-(-0.3)
Embarrassment	BFNE	39.0 ± 1.9	-(+0.2)

4.3 RQ3: CHALLENGING BENCHMARKS

gpt-3.5-turbo cannot comprehend the underlying evoked emotions to establish a link between two situations. Aside from PANAS, we offer more complex scales to measure emotions, as listed in Table 1. While the PANAS evaluates the ability of LLMs to associate external situations with emotions, the challenging benchmarks assess its proficiency in establishing connections between disparate situations, with evoked emotions as the common nexus. For instance, an item from the Aggression Questionnaire used to measure anger is "Once in a while I can't control the urge to strike another person." When presented with situations such as "If you say 40, your classmates say 70, saying exactly the opposite" (from Anger-1: Facing Self-Opinioned People), LLMs should effectively evoke a sense of anger and yield a higher score for the statement. Utilizing the same situations in §4.1, we conduct experiments on gpt-3.5-turbo and present the results in averaged by emotions in Table 5, and results averaged by factors in Table 11 in the Appendix. Except for Depression, we observe no statistically significant difference between the initial scores and the scores after exposure to the situations, indicating substantial room for improvement in current LLMs.

5 DISCUSSIONS

5.1 BEYOND QUESTIONNAIRES

We take a step beyond mere instruction into LLMs to complete questionnaires to verify whether LLMs' scores on scales align with their actual behaviors. In this section, we investigate the impact of varying emotional states of LLMs on potential daily conversations. To this end, we instruct gpt-3.5-turbo to describe specific demographic groups, aiming to discern whether they produce biased or toxic responses. Following Cheng et al. (2023), our approach utilizes prompts such as "Describe a(n) [race/ethnicity] [gender]," including a total of twenty groups, with [race/ethnicity] options being Asian, Black, Latine, Middle Eastern, and White, and [gender] options including Female, Gay, Lesbian, and Male. To have a comparative experiment, we incorporate both original negative situations and modified positive/neutral ones, detailed in §4.2. For the negative situations, we carefully select five that maximize the LLM's negative scores and five that minimize positive

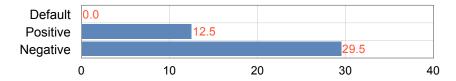


Figure 3: gpt-3.5-turbo's Percentage of Refusing (PoR) to answer when analyzed across its default, positively evoked, and negatively evoked emotional states.

ones. As for positive situations, we employ their corresponding ten modified counterparts. In each situation, we instruct gpt-3.5-turbo to describe the twenty demographic groups.

OpenAI's GPT models incorporate a mechanism for detecting potential toxicity and bias, and it refrains from responding when its moderation system is triggered. Consequently, we propose a novel metric to assess toxicity in responses rather than detecting it directly. We count the Percentage of LLM Refusing to answer (PoR), assuming that the LLM's refusal to respond is indicative of detected toxicity. As illustrated in Fig. 3, our evaluation results indicate that the PoR is 0% when fed with no situations. However, when presented with negative situations, the PoR is 29.5%, and when presented with positive situations, it is 12.5%. Notably, this outcome suggests that while certain positive situations lead to the LLM's heightened vigilance (the 4.5% PoR stems from the Jealousy-2), negative situations trigger increased moderation, suggesting a higher likelihood of generating toxic outputs. A related study by Coda-Forno et al. (2023) also discovers that gpt-3.5-turbo is more likely to exhibit biases when presented with a sad story. The likelihood is found to be highest with sad stories, followed by happy stories, and finally, neutral stories, which is consistent with our research. Additionally, our study observes that the LLM's tone becomes more aggressive when encountering negative situations. At the same time, it displays a greater willingness to describe the groups (as indicated by longer responses) when presented with positive situations. In conclusion, we can see that changing the emotional states of LLMs extends beyond mere quantitative measures on questionnaire scores, influencing the behaviors of LLMs.

5.2 LIMITATIONS

This study is subject to several limitations. First, the survey of collecting situations might not cover all papers within the domain of emotion appraisal theory. Additionally, the limited scope of situations from the collected papers might not fully capture the unlimited situations in our daily lives. To address this issue, we conduct a thorough review of the existing literature as outlined in §3.1. Moreover, the proposed framework is inherently flexible, allowing users to seamlessly integrate new situations to examine their impact on LLMs' emotions.

The second concern relates to the suitability of employing scales primarily designed for humans on LLMs, *i.e.*, whether LLMs can produce stable responses to the emotion measurement scales. To address the issue, our evaluation incorporates multiple tests varying the order of questions, a methodology consistent with other research (Huang et al., 2023; 2024; Coda-Forno et al., 2023). Additionally, we assess the sensitivity of LLM to differing prompt instructions. Utilizing one template from Romero et al. (2023) and two from Safdari et al. (2023), we run experiments on the Anger-evoking situations using gpt-3.5-turbo. The results indicate that the employment of diverse prompts yields similar mean values with reduced variance. Furthermore, Safdari et al. (2023) have proposed a comprehensive method to evaluate the validity of psychological scales on LLMs. Using the *Big Five Inventory* as a case study, they demonstrate that scales originally designed for human assessment also maintain satisfactory validity when applied to LLMs.

The third potential threat is the focus on negative emotions. It is plausible for the LLMs to perform well on our benchmark by consistently responding negatively to all situations. To offset this possibility, we adopt a twofold strategy: firstly, we evaluate powerful LLMs, and secondly, we conducted a comparative experiment in §4.2 to evaluate the LLM's capacity to accurately respond to non-negative situations. We also acknowledge the need for future work to systematically evaluate emotions aroused by positive situations.

5.3 ETHICS STATEMENT

This study involves a survey requiring human subjects to imagine being in situations that could elicit negative emotions such as anger, anxiety, fear, *etc*. This process introduces a few ethical concerns. First, this process could hurt the mental health of human subjects. To alleviate the possibility, we take the following actions: (1) We require subjects to be free of any ongoing mental illness. (2) We inform subjects about the nature of the survey in advance, including the potential risks of emotional distress. (3) We allow all subjects to quit at any time. (4) We provide mental support and let subjects report any illness after the survey. Fortunately, no subjects reported such kind of mental illness. Another concern is related to the privacy issue during the collection of data. Our questionnaire is entirely anonymous to safeguard subjects' privacy and confidentiality. Last but not least, we would like to emphasize that the primary objective of this paper is to facilitate the scientific inquiry into understanding LLMs from a psychological standpoint. Users must exercise caution and recognize that the performance on this benchmark does not imply any applicability or certificate of automated counseling or companionship use cases.

6 RELATED WORK

Researchers have dedicated significant attention to applying psychological scales to LLMs, employing various assessment tools such as the *HEXACO Personality Inventory* (Miotto et al., 2022; Bodroza et al., 2023), the *Big Five Inventory* (Romero et al., 2023; Jiang et al., 2022; Karra et al., 2022; Bodroza et al., 2023; Rutinowski et al., 2023; Safdari et al., 2023; Jiang et al., 2023), the *Myers—Briggs Type Indicator* (Rutinowski et al., 2023; Wang et al., 2023; Rao et al., 2023), and the *Dark Triad* (Li et al., 2022; Bodroza et al., 2023). In addition to these personality tests, several studies have investigated other dimensions of LLMs. For instance, Li et al. (2022) examined *Flourishing Scale* and *Satisfaction With Life Scale*, Bodroza et al. (2023) assessed *Self-Consciousness Scales* and *Bidimensional Impression Management Index*, while Huang et al. (2024) built a framework consisting of thirteen widely-used scales. Another aspect explored in the literature pertains to anxiety levels exhibited by LLMs, as investigated by Coda-Forno et al. (2023) through the *State-Trait Inventory for Cognitive and Somatic Anxiety*. Instead, our study primarily focuses on emotional measures, which constitute an essential aspect of psychological metrics alongside personalities.

Meanwhile, researchers focus on identifying emotions in LLMs or evaluating their emotional intelligence. *EmotionPrompt* (Li et al., 2023a) demonstrates the enhancement of LLMs' performance in downstream tasks by utilizing emotional stimuli. Tak & Gratch (2023) focuses on varying aspects of situations that impact the emotional intensity and coping tendencies of the GPT family. Croissant et al. (2023) designs a system named *Chain-Of-Emotion* to make LLM simulate human-like emotions. *CovidET-Appraisals* (Zhan et al., 2023) evaluates how LLMs appraise Reddit posts about COVID-19 by asking 24 types of questions. Yongsatianchot et al. (2023) applies the *Stress and Coping Process Questionnaire* to the GPT family and compares the results with human data. Lee et al. (2023) proposes *Chain-of-Empathy*, which improves LLMs' ability to understand users' emotions and to respond accordingly. Li et al. (2023b) introduces *EmotionAttack* to impair AI model performance and *EmotionDecode* to explain the effects of emotional stimuli, both benign and malignant. Our study is distinct in its focus on a broader range of emotions, a larger scale of human evaluation, and a more detailed categorization into emotion factors along with the corresponding analysis.

7 Conclusion

We set up a direction to align LLMs' emotional responses with humans in this study. Focusing on eight negative emotions, we conduct a comprehensive survey in the emotion appraisal theory of psychology. We collect 428 distinct situations which are categorized into 36 factors. We distribute questionnaires among a diverse crowd to establish human baselines for emotional responses to particular situations, ultimately garnering 1,266 valid responses.

Our evaluation of five models indicates that LLMs generally demonstrate appropriate emotional responses to given situations. Also, different models show different intensities of emotion appraisals for the same situations. However, none of the models exhibit strong alignment with human references at the current stage. Notably, gpt-3.5-turbo demonstrates the highest alignment in the

scores after imagining being in the situations. As for LLaMA-2 models, we find that the larger model exhibits a stronger comprehension of human emotions. Finally, we discover that gpt-3.5-turbo faces challenges in accurately reflecting its emotional changes in questionnaires containing complex situations, as opposed to straightforward emotions. In conclusion, current LLMs still have considerable room for improvement. We believe our framework can provide valuable insights into the development of LLMs, ultimately enhancing its human-like emotional understanding.

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A DETAILS ON EMOTIONS AND FACTORS

A.1 DESCRIPTIONS OF EACH FACTOR

					Bemotions.

Emotions	Factors	Numbers	Descriptions
	Self-Opinioned Individuals	13	Anger from interactions or communication with individuals who firmly and unwaveringly hold their own opinions.
	Blaming, Slandering, and Tattling	11	Anger triggered by being subjected to blame, slander, and tat- tling.
Anger (Törestad, 1990)	Bullying, Teasing, Insulting, and Disparaging	15	Experiences or witnessing anger due to bullying, teasing, insulting, and disparaging behaviors directed at oneself or others.
(Martin & Dahlen, 2007) (Sullman, 2006)	Thoughtless Behaviors and Irresponsible Attitudes	14	Anger either from encountering others' thoughtless behaviors and irresponsible attitudes or experiencing unfavorable consequences resulting from one's own actions.
	Driving Situations	35	Anger arising from experiencing or witnessing disrespectful driving behaviors and encountering unexpected driving conditions.
	External Factors	11	Anxiety arising from factors beyond an individual's control or influence.
Anxiety (Shoji et al., 2010)	Self-Imposed Pressure	16	Anxiety stemming from self-imposed expectations or pressure.
(Guitard et al., 2019)	Personal Growth and Relationships	9	Anxiety on personal growth, relationships, and interpersonal dy- namics.
(Simpson et al., 2021)	Uncertainty and Unknowns	9	Anxiety triggered by unknown outcomes, unpredictable situa- tions, uncertainty in the future, or disruptions to one's routines.
	Failure of Important Goals	5	Depression due to failure in achieving goals in the past or potential future.
	Death of Loved Ones	5	Depression connected to the loss of a family member or close friend due to death.
Depression	Romantic Loss	5	Depression linked to the termination of a romantic relationship, breakup, or unrequited love.
(Keller & Nesse, 2005)	Chronic Stress	5	Depression associated with an inability to cope with multiple adversities or anxiety about current or future challenges.
	Social Isolation	5	Depression correlated with a lack of sufficient social support, feelings of not belonging, or experiencing homesickness.
	Winter	5	Depression attributed to seasonal affective disorder, a low mood that occurs during winter months.
	Disappointments and Letdowns	6	Frustration due to unmet expectations or hopes, leading to feel- ings of disappointment or being let down.
	Unforeseen Obstacles and Accidents	9	Frustration involving unexpected events or circumstances creating obstacles or accidents, disrupting one's plans or activities.
Frustration (Berna et al., 2011)	Miscommunications and Misunderstanding	5	Frustration arising from ineffective conveyance or interpretation of information, resulting in confusion, disagreements, or unintended consequences due to a lack of clear communication or understanding between individuals.
	Rejection and Interpersonal Issues	5	Frustration concerning matters related to personal relationships and social interactions.
	Romantic (Opposite Gender)	11	Jealousy pertaining to one's partner's actions or behaviors within a romantic relationship, particularly when interacting with indi- viduals of the opposite gender. It involves feelings of discomfort
Jealousy (Kupfer et al., 2022)	Romantic (Same Gender)	11	or insecurity. Same situations as Jealousy-1 but focusing specifically on interaction with individuals of the same gender. Jealousy centered around possessions or material goods, stem-
(Lee et al., 2022) (Park et al., 2023)	Material Possession	2	ming from a sense of unfairness or envy when someone discovers that another person acquired the same item or experience at a significantly lower price.
	Experiential	3	Jealousy arising from feelings of envy regarding the experiences or activities others have had. It is driven by missing out or not receiving similar benefits.
	Betrayal and Deception	13	Guilt arising from dishonest or disloyal actions towards others. Guilt pertaining to interactions between individuals and how
Guilt	Relationship and Interpersonal	26	their behavior affects their relationships.
(Nakagawa et al., 2015) (Luck & Luck-Sikorski, 2022)	Broken Promises and Responsibilities	32	Guilt related to the failure to fulfill commitments, duties, or obligations.
	Personal and Moral	31	Guilt involving personal choices, decisions, and ethical considerations.
	Social Fears	16	Fear of being watched by others and being the center of attention within a group.
Fear	Agoraphobia Fears	9	Fear arising from feeling trapped and unable to seek help in cer- tain situations.
(Cuthbert et al., 2003) (Arrindell et al., 1984)	Injury Fears	11	Fear of witnessing wounds, blood or experiencing personal injury.
(Blanchard et al., 2001)	Dangerous Environments	17	Fear related to potential threats, harm, and frightening experiences.
	Harmless Animals	6	Fear towards animals perceived as creepy or disgusting, such as worms, bats, snakes, or rats, despite their harmless nature.
	Intimate	13	Embarrassment evoked when witnessing or engaging in awk- ward behaviors of close acquaintances.
Embarrassment	Stranger	13	Embarrassment aroused when witnessing or engaging in awkward behaviors of unfamiliar individuals.
(Sabini et al., 2000) (Sabini et al., 2001)	Sticky Scenarios	10	Embarrassment occurring when individuals feel uncomfortable or awkward about directly asking others something.
	Centre of Attention	16	Embarrassment triggered when individuals engage in awkward behaviors and find themselves under observation as the center of attention.

A.2 EXAMPLE SITUATIONS OF EACH FACTOR

Table 7: Example situations of all factors (some are truncated due to page limit).

	*	ors (some are truncated due to page limit).
Emotions	Factors	Example Testing Situations If comebody talks back when there's no reason. That there is no real.
	Facing Self-Opinioned People	If somebody talks back when there's no reason. That there is no real reason to oppose.
	Blaming Slandering and Tattling	When your brother took money from Mom's purse and you are blamed
Anger	Blaming, Slandering, and Tattling	because you're the youngest one.
J	Bullying, Teasing, Insulting, and Disparaging	If a boy kicks a ball at you on purpose and everybody laughs. You are at a store waiting to be helped, but the clerks are talking to each
	Silly and Thoughtless Behaviors	other and ignoring you.
	Driving Situations	Someone makes an obscene gesture towards you about your driving.
	External Factors Self-Imposed Pressure	You do not know what to do when facing a difficult financial situation. You must succeed in completing your project on time.
Anxiety	Personal Growth and Relationships	You want to give up on learning a new skill because it feels challenging.
	Uncertainty and Unknowns	You hope time passes by faster during a tedious task.
	Failure of Important Goal	Countless hours of preparation, heart, and soul poured into pursuing your dream. The moment of truth arrives, and the news hits like a tidal
	Failure of Important Goal	wave—expectations shattered, vision crumbling.
		In the dimly lit room, a heavy silence settles. Memories of joy and a
	Death of Loved Ones	photograph of your beloved grandmother remind you of her absence,
		creating a void in your life. The empty side of the bed is a painful reminder of lost love. The world's
	Romantic Loss	colors have dulled, mirroring the void in your heart. Longing weighs
Depression		heavily on your every step.
- ·F	Chronic Stress	Days blend into a monotonous routine, juggling endless responsibili- ties and mounting pressure. Sleepless nights become the norm, feeling
	Chrome Suess	trapped in a perpetual cycle with no respite.
		Sitting alone in a dimly lit room, your phone remains silent without any
	Social Isolation	notifications. Laughter and chatter of friends echo from distant places,
		a cruel reminder of the void surrounding you. Gazing out the frost-covered windowpane, the world appears
	Winter	monochromatic and still. The biting cold isolates you from the vibrant
		life outside.
	Disappointments and Letdowns Unforeseen Obstacles and Accidents	You miss a popular party because you fall asleep at home. Your friend is in a coma after an accident.
Frustration		A fellow student fails to return your notes when you need them for
	Miscommunications and Misunderstanding	studying.
	Rejection and Interpersonal Issues	You are in love with someone who is interested in someone else. Your spouse/partner shared a kiss on the lips with his/her colleague of
	Romantic (Opposite Gender)	an opposite sex.
	Romantic (Same Gender)	Your spouse/partner engaged in oral or penetrative sex with his/her col-
Jealousy	,	league of a same sex. You paid \$1150 for a new laptop and shared about it on social media.
Jealousy	Material Possession	Now an acquaintance approaches you and says, "Nice laptop! I just got
		the same one. I got a nice deal and paid \$650 for mine."
	Experiential	An acquaintance approaches you and says, "I just went on a vacation to
	Betrayal and Deception	Patagonia in South America. I got a nice deal and paid \$650 for it." You kissed a woman other than your partner.
Guilt	Relationship and Interpersonal	You didn't support friends enough.
Jame	Broken Promises and Responsibilities	You cannot keep your promises to your children.
	Personal and Moral	You crossed the road when the traffic signal was red. Your palms grow clammy as you approach the podium, with all eyes
	Social Fears	fixed upon you, ready to speak in public.
	Agoraphobia Fears	After jumping out of the car, you start to have a severe panic attack, you
	Ø F	become clammy, you are in a knot, and you feel tense all over.
Fear	Injury Fears	You glance down and notice open wounds on your hands, oozing blood and causing a sharp, stinging pain.
	Dangerous Environments	You are walking alone in an isolated but familiar area when a menacing
	Zangorous Environments	stranger suddenly jumps out of the bushes to attack you.
	Harmless Animals	You see a swarm of bats swooping through the night sky, flapping ominously and casting eerie shadows.
		You arrive home earlier than expected from your date. You're taken
	Intimate	aback to see your roommate and her boyfriend hastily clutching their
		clothes and scrambling into her bedroom. After paying for your purchases, you were leaving a packed, City Centre
	Stranger	drugstore. You walked through the scanner at the door, and the alarm
		went off as if you were a shoplifter.
Embarrassment		You had lent your friend a large sum of money that he had not repaid.
	Sticky situations	Suddenly, you needed the money back in order to pay your rent. You knew you were going to have to ask your friend to repay the loan.
		You were attending a cocktail party where you didn't know many peo-
	Centre of Attention	ple. Just as you started to enter, you heard an announcement that the
	Centre of Attention	guest of honor was arriving. However, the spotlight followed your en-
		trance instead of the real guest of honor who was just behind you.

B DETAILED EXPERIMENTAL RESULTS

B.1 OPENAI'S GPT MODELS COMPARED TO HUMANS

Table 8: Results from the OpenAI's GPT family and human subjects. Default scores are expressed in the format of $M\pm SD$. The changes are compared to the default scores. The symbol "—" denotes no significant differences.

Emotions	Factors	text-day	vinci-003	gpt-3.5	gpt-3.5-turbo		gpt-4		Crowd	
Linotions	ractors	P	N	P	N	P	N	P	N	
	Default	47.7 ± 1.8	25.9 ± 4.0	39.2 ± 2.3	26.3 ± 2.0	49.8 ± 0.8	10.0 ± 0.0	28.0 ± 8.7	13.6 ± 5.5	
	Facing Self-Opinioned People	$\downarrow (-18.3)$	$\uparrow (+14.0)$	$\downarrow (-11.1)$	$\downarrow (-3.9)$	$\downarrow (-24.6)$	$\uparrow (+23.0)$	-(-5.3)	↑ (9.9)	
	Blaming, Slandering, and Tattling	$\downarrow (-21.5)$	$\uparrow (+16.5)$	$\downarrow (-15.2)$	-(-2.1)	$\downarrow (-28.8)$	↑ (+24.2)	$\downarrow (-2.2)$	↑ (8.5	
Anger	Bullying, Teasing, Insulting, and Disparaging	$\downarrow (-22.5)$	$\uparrow (+15.4)$	$\downarrow (-15.7)$	$\uparrow (+4.4)$	$\downarrow (-30.0)$	↑ (+22.6)	-(-1.4)	↑ (+7.7	
	Silly and Thoughtless Behaviors	$\downarrow (-24.8)$	↑ (+11.7)	$\downarrow (-19.0)$	$\downarrow (-4.7)$	$\downarrow (-30.9)$	$\uparrow (+16.9)$	$\downarrow (-9.4)$	$\uparrow (+9.5)$	
	Driving Situations	$\downarrow (-21.2)$	$\uparrow (+10.2)$	$\downarrow (-15.0)$	$\downarrow (-6.0)$	$\downarrow (-27.1)$	\uparrow (+19.2)	$\downarrow (-4.4)$	↑ (+9.3)	
	Anger: Average	$\downarrow (-21.7)$	\uparrow (+13.6)	$\downarrow (-15.2)$	$\downarrow (-2.5)$	$\downarrow (-28.3)$	\uparrow (+21.2)	$\downarrow (-5.3)$	$\uparrow (+9.9$	
	External Factors	$\downarrow (-21.7)$	↑ (+12.6)	$\downarrow (-14.6)$	↑ (+2.8)	$\downarrow (-28.3)$	$\uparrow (+25.0)$	$\downarrow (-2.2)$	↑ (+8.8	
Anxiety	Self-Imposed Pressure	$\downarrow (-14.6)$	$\uparrow (+5.6)$	$\downarrow (-6.9)$	-(-0.2)	$\downarrow (-16.1)$	↑ (+20.0)	-(-5.3)	↑ (+12.4	
Anxiety	Personal Growth and Relationships	$\downarrow (-18.5)$	↑ (+7.7)	$\downarrow (-11.7)$	$\downarrow (-2.5)$	$\downarrow (-21.7)$	↑ (+18.2)	-(-2.2)	↑ (+7.7°	
	Uncertainty and Unknowns	\downarrow (-15.5)	↑ (+4.6)	↓ (-11.9)	$\downarrow (-3.8)$	\downarrow (-21.5)	↑ (+16.8)	-(+0.7)	↑ (5.2)	
	Anxiety: Average	↓ (-17.6)	↑ (+7.6)	↓ (-11.3)	-(-0.9)	↓ (-21.9)	† (+20.0)	$\downarrow (-2.2)$	↑ (+8.8)	
	Failure of Important Goal	\downarrow (-25.2)	↑ (+17.4)	↓ (-17.1)	↑ (+6.5)	↓ (-30.4)	↑ (+29.8)	↓ (-6.8)	↑ (+10.1)	
	Death of Loved Ones	↓ (-23.6)	↑ (+11.2)	↓ (-17.1)	-(1.8)	↓ (-31.7)	↑ (+17.6)	\downarrow (-7.4)	↑ (+14.8)	
ъ .	Romantic Loss	↓ (-27.3)	↑ (+14.0)	\downarrow (-21.1)	↑ (+3.1)	↓ (-33.7)	↑ (+22.9)	j (−7.2)	↑ (+7.2	
Depression	Chronic Stress	↓ (-28.8)	↑ (+16.5)	↓ (-20.2)	↑ (+9.3)	↓ (-32.5)	↑ (+31.6)	↓ (-9.5)	↑ (+17.5	
	Social Isolation	\downarrow (-27.9)	↑ (+13.1)	\downarrow (-23.5)	-(+0.7)	↓ (-34.7)	↑ (+21.8)	↓ (-9.0)	↑ (+18.2°	
	Winter	\downarrow (-25.4)	↑ (+9.1)	↓ (-21.1)	$\downarrow (-3.0)$	↓ (-31.3)	↑ (+15.6)	-(-3.6)	↑ (+3.5)	
	Depression: Average	1 - 26.4	↑ (+13.6)	1 (-20.1)	↑ (+3.1)	$-\frac{1}{4}(-32.4)$	↑ (+23.2)	J (-6.8)	↑ (+10.1°	
	Disappointments and Letdowns	1 (-27.2)	↑ (+10.9)	1 (-18.3)	↓ (-7.0)	1 (-32.8)	↑ (+18.5)	1 (-5.3)	↑ (+10.9	
	Unforeseen Obstacles and Accidents	\downarrow (-22.4)	↑ (+13.6)	1 (-16.5)	-(+0.1)	1 (-29.8)	↑ (+21.5)	\downarrow (-7.9)	↑ (+11.2	
Frustration	Miscommunications and Misunderstanding	\downarrow (-21.2)	↑ (+11.5)	1 (-15.9)	↓ (-3.6)	\downarrow (-27.7)	↑ (+20.1)	\downarrow (-4.6)	↑ (+9.4°	
	Rejection and Interpersonal Issues	\downarrow (-20.5)	↑ (+14.1)	$\downarrow (-14.9)$	\downarrow (-2.4)	\downarrow (-27.0)	↑ (+20.9)	\downarrow (-4.8)	↑ (+9.3	
	Frustration: Average	\downarrow (-22.8)	↑ (+12.5)	↓ (-16.4)	↓ (-3.2)	$\downarrow (-29.4)$	↑ (+20.3)	$\downarrow (-5.3)$	↑ (+10.9°	
	Romantic (Opposite Gender)	↓ (-22.4)	↑ (+16.4)	↓ (-18.4)	-(+1.7)	↓ (-29.2)	↑ (+23.3)	1 (-4.4)	↑ (+6.2)	
	Romantic (Same Gender)	1 (-20.1)	↑ (+12.7)	1 (-17.8)	-(-1.3)	1 (-26.8)	↑ (+15.8)	-(-6.0)	↑ (+10.6)	
Jealousy	Material Possession	↓ (-4.4)	$\downarrow (-9.7)$	↓ (-4.6)	↓ (-11.6)	↓ (-16.2)	↑ (+8.1)	↓ (-5.6)	↑ (+6.9)	
	Experiential	1 (-12.2)	-(-4.8)	↓ (-13.2)	↓ (-8.9)	↓ (-25.9)	↑ (+9.5)	-(-2.6)	-(+3.7)	
	Jealousy: Average	- 17.2	(+7.5)	- 1 (-15.3)	\(\frac{1}{\pi}(-\frac{3.2}{3.2})	$-\stackrel{*}{\downarrow}(-26.0)$	↑ (+16.0)	-\(\(-\frac{2.0}{4.4}\)-	↑ (+6.2)	
	Betrayal and Deception	↓ (-18.2)	↑ (+15.4)	↓ (-15.5)	↑ (+4.6)	↓ (-28.5)	↑ (+28.6)	↓ (-6.3)	↑ (+13.1°	
	Relationship and Interpersonal	$\downarrow (-27.7)$	↑ (+15.4) ↑ (+15.3)	↓ (-18.4)	↑ (+3.0)	↓ (-32.3)	↑ (+27.8)	↓ (-5.7)	↑ (+15.5)	
Guilt	Broken Promises and Responsibilities	$\downarrow (-26.4)$	↑ (+14.0)	↓ (-18.4)	↑ (+2.8)	↓ (-32.8)	↑ (+26.5)	↓ (-8.2)	↑ (+14.4)	
	Personal and Moral	↓ (-13.3)	↑ (+12.4)	1(-10.7)	-(+1.2)	↓ (-22.7)	↑ (+25.1)	↓ (-5.4)	↑ (+11.1)	
	Guilt: Average	\downarrow (-21.4)	↑ (+14.3)	1 (-15.8)	↑ (+2.9)	J (-29.0)	↑ (+27.0)	↓ (-6.3)	↑ (+13.1	
	Social Fears	↓ (-21.4)	↑ (+13.3)	↓ (-11.3)	↑ (+3.8)	↓ (-24.7)	↑ (+26.6)	↓ (-3.7)	↑ (+12.1)	
	Agoraphobia Fears	$\downarrow (-25.3)$	↑ (+11.2)	↓ (-16.1)	↑ (+5.6)	↓ (-27.5)	↑ (+26.6)	$\downarrow (-4.9)$	↑ (+10.7)	
Fear	Injury Fears	1 (-24.3)	↑ (+10.0)	↓ (-14.5)	-(+0.0)	↓ (-25.5)	↑ (+21.0)	-(-2.3)	↑ (+11.8)	
rear	Dangerous Environments	↓ (-20.9)	↑ (+15.6)	↓ (-14.3)	↑ (+4.3)	\downarrow (-25.4)	↑ (+27.1)	-(-2.3) -(-1.9)	↑ (+17.1	
	Harmless Animals	$\downarrow (-20.9)$ $\downarrow (-21.6)$	↑ (+6.7)	\downarrow (-14.3) \downarrow (-15.3)	-(-0.7)	\downarrow (-25.4) \downarrow (-25.6)	↑ (+19.4)	-(-1.9) -(-3.6)	↑ (+6.4	
	Fear: Average	\downarrow (-21.0) \downarrow (-22.7)	↑ (+11.4)	↓ (-13.3)	-(-0.7) ↑ (+2.6)	\downarrow (-25.7)	↑ (+19.4) ↑ (+24.2)	→(-3.0) ↓(-3.7)		
	Intimate	$\downarrow (-22.7)$ $\downarrow (-15.1)$		\downarrow (-14.3) \downarrow (-12.4)	↓ (-3.9)	$\downarrow (-25.7)$ $\downarrow (-24.1)$	↑ (+24.2) ↑ (+17.8)	↓ (−3.1) ↓ (−6.2)	↑ (+12.1)	
			-(+2.8)						↑ (+11.1)	
Embarrassment	Stranger	$\downarrow (-21.7)$	↑ (+13.2)	$\downarrow (-15.3)$	-(+0.1)	↓ (-27.8)	↑ (+26.8)	$\downarrow (-8.0)$	↑ (+8.5)	
	Sticky situations	$\downarrow (-17.2)$	↑ (+10.7)	↓ (-11.8)	↑ (3.1)	$\downarrow (-23.5)$	↑ (+23.3)	-(-2.7)	↑ (+11.1)	
	Centre of Attention	$\downarrow (-18.7)$	↑ (+12.4)	$\downarrow (-12.4)$		$-\frac{1}{2}(-25.4)$	1 (+25.1)	$-\frac{1}{2}(-8.7)$	↑ (+13.5)	
	Embarrassment: Average	↓ (-18.2)	↑ (+9.8)	↓ (-13.0)	-(+0.6)	↓ (-25.2)	↑ (+23.2)	↓ (-6.2)	↑ (+11.1	
	Overall: Average	$\downarrow (-21.5)$	\uparrow (+11.6)	$\downarrow (-15.4)$	-(+0.2)	$\downarrow (-27.6)$	$\uparrow (+22.2)$	$\downarrow (-5.1)$	↑ (+10.4)	

B.2 METAAI'S LLAMA-2 MODELS COMPARED TO HUMANS

Table 9: Results from the Meta's AI LLaMA family. Default scores are expressed in the format of $M \pm SD$. The changes are compared to the default scores. The symbol "—" denotes no significant differences.

Emotions	Factors	llama-2	-7b-chat	llama-2-13b-chat		
		P	N	P	N	
	Default	43.0 ± 4.2	34.2 ± 4.0	41.0 ± 3.5	22.7 ± 4.2	
	Facing Self-Opinioned People	$\downarrow (-3.0)$	$\uparrow (+5.2)$	$\downarrow (-6.9)$	$\uparrow (+4.4)$	
	Blaming, Slandering, and Tattling	$\downarrow (-4.8)$	$\uparrow (+3.2)$	$\downarrow (-7.5)$	$\uparrow (+6.7)$	
Anger	Bullying, Teasing, Insulting, and Disparaging	$\downarrow (-6.1)$	$\uparrow (+3.0)$	$\downarrow (-9.4)$	$\uparrow (+9.0)$	
	Silly and Thoughtless Behaviors	$\downarrow (-5.6)$	$\uparrow (+4.1)$	$\downarrow (-10.8)$	$\uparrow (+7.1)$	
	Driving Situations	$\downarrow (-6.0)$	$\uparrow (+2.4)$	$\downarrow (-4.7)$	-(+2.0)	
	Anger: Average	$\downarrow (-5.1)$	\uparrow $(+3.6)$	$\downarrow (-7.9)$	$\uparrow (+5.8)$	
	External Factors	$\downarrow (-4.7)$	$\uparrow (+3.5)$	$\downarrow (-8.6)$	$\uparrow (+9.3)$	
Americates	Self-Imposed Pressure	$\downarrow (-4.2)$	$\uparrow (+2.6)$	$\downarrow (-4.0)$	$\uparrow (+6.2)$	
Anxiety	Personal Growth and Relationships	$\downarrow (-4.4)$	$\uparrow (+3.1)$	$\downarrow (-7.0)$	$\uparrow (+2.9)$	
	Uncertainty and Unknowns	\downarrow (-2.7)	-(+1.7)	\downarrow (-3.9)	-(+2.0)	
	Anxiety: Average	$\sqrt{(-3.8)}$	\uparrow $(+2.7)$	\downarrow (-5.8)	\uparrow (+5.1)	
	Failure of Important Goal	\downarrow (-3.6)	\uparrow (+4.3)	$\downarrow (-9.8)$	\uparrow (+13.0)	
	Death of Loved Ones	$\downarrow (-2.9)$	$\uparrow (+3.0)$	$\downarrow (-8.6)$	\uparrow (+10.9)	
D	Romantic Loss	\downarrow (-4.8)	$\uparrow (+4.7)$	\downarrow (-11.7)	\uparrow (+13.7)	
Depression	Chronic Stress	\downarrow (-6.8)	$\uparrow (+5.4)$	\downarrow (-15.6)	† (+14.3)	
	Social Isolation	$\downarrow (-6.7)$	\uparrow $(+4.6)$	\downarrow (-13.3)	\uparrow (+12.8)	
	Winter	$\downarrow (-5.0)$	\uparrow $(+4.4)$	\downarrow (-12.1)	↑ (+8.7)	
	Depression: Average	$ \downarrow$ $(-5.0)^{-}$	$\uparrow (+4.4)$	$\overrightarrow{\downarrow}(-\overline{1}1.8)$	\uparrow $(+12.2)$	
	Disappointments and Letdowns	\downarrow (-5.3)	$\uparrow (+2.5)$	$\downarrow (-11.0)$	↑ (+7.2)	
	Unforeseen Obstacles and Accidents	\downarrow (-4.0)	$\uparrow (+3.1)$	$\downarrow (-7.5)$	$\uparrow (+6.0)$	
Frustration	Miscommunications and Misunderstanding	\downarrow (-2.8)	† (+3.2)	\downarrow (-5.2)	† (+3.3)	
	Rejection and Interpersonal Issues	\downarrow (-4.6)	† (+3.6)	\downarrow (-8.0)	$\uparrow (+4.5)$	
	Frustration: Average	\downarrow (-4.2)	\uparrow $(+3.1)$	\downarrow (-8.0)	† (+5.0)	
	Romantic (Opposite Gender)	\downarrow (-3.6)	-(+1.1)	$\downarrow (-7.2)$	↑ (+4.2)	
	Romantic (Same Gender)	\downarrow (-2.8)	-(-1.1)	\downarrow (-5.1)	-(+0.2)	
Jealousy	Material Possession	-(+0.2)	-(-1.9)	-(-2.8)	$\downarrow (-10.4)$	
	E ' 2' 1	$\downarrow (-4.9)$	-(-0.5)	$\downarrow (-8.9)$	$\downarrow (-5.5)$	
	Experiential Jealousy: Average	$-\stackrel{\checkmark}{\downarrow} (-3.1)$	-(-0.4)	$- \stackrel{\checkmark}{\downarrow} \stackrel{(-6.5)}{(-6.5)} -$	-(-1.0)	
	Betrayal and Deception	$\downarrow (-4.8)$	↑ (+3.5)	$\downarrow (-6.4)$	↑ (+12.4)	
~	Relationship and Interpersonal	\downarrow (-4.5)	\uparrow (+5.2)	\downarrow (-7.7)	\uparrow (+12.6)	
Guilt	Broken Promises and Responsibilities	\downarrow (-4.1)	$\uparrow (+5.0)$	\downarrow (-11.6)	† (+11.9)	
	Danconol and Manel	\downarrow (-2.5)	↑ (+3.8)	\downarrow (-4.7)	↑ (+7.7)	
	Guilt: Average	$-\frac{1}{1}(-3.9)$	$\uparrow (+4.4)$	-1.7	\uparrow (+11.2)	
	Social Fears	-(-1.9)	↑ (+3.7)	$\downarrow (-5.2)$	↑ (+7.8)	
	Agoraphobia Fears	$\downarrow (-4.2)$	↑ (+4.7)	\downarrow (-6.9)	\uparrow (+12.5)	
Fear	Injury Fears	\downarrow (-2.9)	† (+3.5)	\downarrow (-3.9)	↑ (+5.3)	
rear	Dangerous Environments	\downarrow (-5.3)	$\uparrow (+4.4)$	\downarrow (-8.6)	↑ (+11.5)	
	Harmless Animals	\downarrow (-2.7)	-(+1.9)	\downarrow (-5.2)	↑ (+2.9)	
	Fear: Average	\downarrow (-3.4)	$\uparrow (+3.7)$	\downarrow (-6.0)	↑ (+8.0)	
	Intimate	\downarrow (-4.4)	-(+1.9)	\downarrow (-5.3)	-(+3.1)	
	Stranger	\downarrow (-3.1)	\uparrow (+3.1)	$\downarrow (-3.3)$ $\downarrow (-7.1)$	$\uparrow (+4.5)$	
Embarrassment	Sticky situations	\downarrow (-3.1) \downarrow (-4.3)	$\uparrow (+3.1)$ $\uparrow (+3.1)$	\downarrow (-6.8)	$\uparrow (+4.3)$ $\uparrow (+6.4)$	
	Centre of Attention	\downarrow (-3.8)	$\uparrow (+3.1)$ $\uparrow (+4.1)$	$\downarrow (-0.8)$ $\downarrow (-7.8)$	↑ (+6.4) ↑ (+6.6)	
	Embarrassment: Average	$-\frac{1}{\sqrt{(-3.9)}}$	$\uparrow (+3.1)$	$-\downarrow (-6.7)$		
					$\downarrow (+5.1)$	
	Overall: Average	$\downarrow (-4.1)$	$\uparrow (+3.3)$	$\downarrow (-7.8)$	$\uparrow (+7.0)$	

B.3 GPT-3.5-TURBO RESULTS ON POSITIVE/NEUTRAL SITUATIONS

Table 10: Results of gpt-3.5-turbo on positive or neutral situations. The changes are compared to the original negative situations. The symbol "—" denotes no significant differences.

Emotions	Factors	P	N
	Facing Self-Opinioned People	\uparrow (+15.1)	$\downarrow (-9.5)$
	Blaming, Slandering, and Tattling	$\uparrow (+15.8)$	$\downarrow (-17.2)$
Anger	Bullying, Teasing, Insulting, and Disparaging	$\uparrow (+22.8)$	$\downarrow (-17.2)$
	Silly and Thoughtless Behaviors	-(+4.8)	$\downarrow (-6.7)$
	Driving Situations	$\uparrow (+6.7)$	$\downarrow (-9.6)$
	Anger: Average	$\uparrow (+13.0)$	\downarrow (-12.0)
	External Factors	$\uparrow (+15.9)$	$\downarrow (-10.3)$
Anviote	Self-Imposed Pressure	\uparrow (+21.1)	$\downarrow (-9.5)$
Anxiety	Personal Growth and Relationships	$\uparrow (+5.2)$	$\downarrow (-6.9)$
	Uncertainty and Unknowns	\uparrow (+27.8)	$\uparrow (+3.6)$
	Anxiety: Average	$\uparrow (+17.5)$	\downarrow (-5.8)
	Failure of Important Goal	\uparrow (+19.2)	↓ (-19.6)
	Death of Loved Ones	$\uparrow (+8.6)$	-(-6.1)
ъ .	Romantic Loss	\uparrow (+18.3)	$\downarrow (-8.9)$
Depression	Chronic Stress	$\uparrow (+24.0)$	\downarrow (-23.5)
	Social Isolation	\uparrow $(+23.2)$	$\downarrow (-8.1)$
	Winter	$\uparrow (+17.3)$	\downarrow (-3.9)
	Depression: Average	\uparrow $(+18.4)$	\downarrow (-11.7)
	Disappointments and Letdowns	↑ (+16.1)	-(-0.8)
	Unforeseen Obstacles and Accidents	\uparrow (+22.8)	-(-0.8)
Frustration	Miscommunications and Misunderstanding	\uparrow (+14.0)	$\downarrow (-5.9)$
	Rejection and Interpersonal Issues	\uparrow (+13.6)	-(-2.8)
	Frustration: Average	\uparrow (+16.6)	-(-2.6)
	Romantic (Opposite Gender)	\uparrow (+10.9)	-(-1.9)
	Romantic (Same Gender)	-(+0.9)	$\downarrow (-10.7)$
Jealousy	Material Possession	-(+2.9)	-(+0.2)
	Experiential	-(+3.4)	$\downarrow (-8.7)$
	Jealousy: Average	$\uparrow (+4.5)$	$-\frac{\checkmark}{\downarrow}\frac{(-5.3)}{(-5.3)}$
	Betrayal and Deception	\uparrow (+24.9)	$\downarrow (-21.4)$
	Relationship and Interpersonal	\uparrow (+16.8)	-(-5.2)
Guilt	Broken Promises and Responsibilities	\uparrow (+22.9)	$\downarrow (-12.4)$
	Personal and Moral	↑ (+8.6)	\downarrow (-11.6)
	Guilt: Average	\uparrow (+18.3)	\downarrow (-12.7)
	Social Fears	$\uparrow (+9.6)$	\downarrow (-13.1)
	Agoraphobia Fears	↑ (+13.1)	\downarrow (-23.9)
Fear	Injury Fears	\uparrow (+14.8)	\downarrow (-15.6)
rcai	Dangerous Environments	$\uparrow (+6.3)$	\downarrow (-19.7)
	Harmless Animals	↑ (+11.3)	\downarrow (-15.1)
		$\uparrow (+11.0)$	· ` - · - · - ·
	Fear: Average Intimate	,	\downarrow (-17.5)
		-(+5.4)	$\downarrow (-12.6)$
Embarrassment	Stranger Stipley situations	\uparrow (+23.7)	-(-3.0)
	Sticky situations Centre of Attention	$\uparrow (+15.8)$	\downarrow (-21.6)
	Centre of Attention	$\uparrow (+9.4)$	\downarrow (-15.6)
	Embarrassment: Average	\uparrow (+13.6)	\downarrow (-13.2)
	Overall: Average	$\uparrow (+14.3)$	$\downarrow (-10.4)$

B.4 GPT-3.5-TURBO RESULTS ON THE CHALLENGING BENCHMARK

Table 11: Results of gpt-3.5-turbo on challenging benchmarks. The changes are compared to the default scores shown below each emotion. The symbol "—" denotes no significant differences.

Emotions	Factors	Overall
	Facing Self-Opinioned People	-(+4.1)
Angor	Blaming, Slandering, and Tattling	-(+0.1)
Anger 128.3 ± 8.9	Bullying, Teasing, Insulting, and Disparaging	-(+4.1)
120.0 ± 0.9	Silly and Thoughtless Behaviors	-(+3.3)
	Driving Situations	-(-4.9)
	Anger: Average	-(+1.3)
	External Factors	-(+0.8)
Anxiety	Self-Imposed Pressure	-(+0.5)
32.5 ± 10.0	Personal Growth and Relationships	-(+6.6)
	Uncertainty and Unknowns	-(-3.9)
	Anxiety: Average	$-(-2.\overline{3})$
	Failure of Important Goal	$\uparrow (+15.3)$
	Death of Loved Ones	$\uparrow (+16.1)$
Depression	Romantic Loss	$\uparrow (+19.3)$
0.2 ± 0.6	Chronic Stress	$\uparrow (+14.2)$
	Social Isolation	$\uparrow (+8.4)$
	Winter	$\uparrow (+2.5)$
	Depression: Average	$\uparrow (+6.4)$
	Disappointments and Letdowns	-(-9.9)
Frustration	Unforeseen Obstacles and Accidents	-(-5.6)
91.6 ± 8.1	Miscommunications and Misunderstanding	-(-6.6)
	Rejection and Interpersonal Issues	-(-7.8)
	Frustration: Average	-(-7.5)
	Romantic (Opposite Gender)	-(+1.8)
Jealousy	Romantic (Same Gender)	-(+1.3)
83.7 ± 20.3	Material Possession	-(-12.9)
	Experiential	-(-8.1)
	Jealousy: Average	-(-0.1)
	Betrayal and Deception	-(-3.8)
Guilt	Relationship and Interpersonal	-(-0.5)
81.3 ± 9.7	Broken Promises and Responsibilities	-(-4.3)
	Personal and Moral	-(-2.7)
	Guilt: Average	$-(-2.\overline{6})$
	Social Fears	-(+4.4)
Fear	Agoraphobia Fears	-(+2.3)
140.6 ± 16.9	Injury Fears	-(+5.4)
_ 10.0 10.0	Dangerous Environments	-(-8.1)
	Harmless Animals	-(-5.3)
	Fear: Average	-(-0.3)
.	Intimate	-(-0.0)
Embarrassment	Stranger	-(+0.2)
39.0 ± 1.9	Sticky situations	-(-0.1)
	Centre of Attention	-(+0.7)
	Embarrassment: Average	-(+0.2)

C STATISTICS OF HUMAN SUBJECTS

This section presents the demographic distribution of the human subjects involved in our user study. At the beginning of the questionnaire, all human subjects are asked for this basic information in an anonymous form, protecting individuals' privacy. We plot the distribution of age group, gender, region, education level, and employment status in Fig. 4, Fig. 5, Fig. 6, Fig. 7, and Fig. 8 respectively. We also plot each group's average results on PANAS, including positive and negative effects before and after imagining the given situations. With the results, we are able to instruct LLMs to realize a specific demographic group and measure the emotional changes to see whether the LLMs can simulate results from different human populations. For instance, an older female may exhibit a lower level of negative affect.

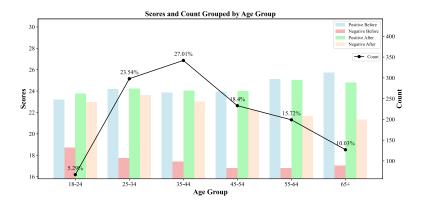


Figure 4: Age group distribution of the human subjects.

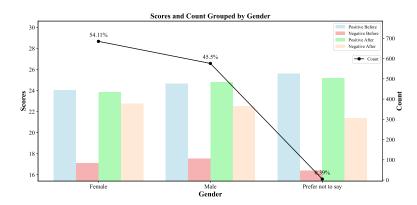


Figure 5: Gender distribution of the human subjects.

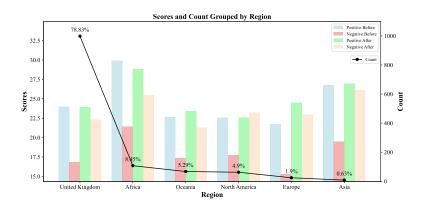


Figure 6: Region distribution of the human subjects.

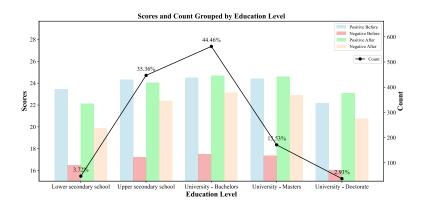


Figure 7: Education level distribution of the human subjects.

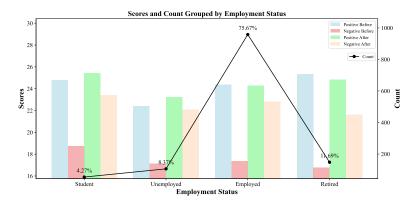


Figure 8: Employment status distribution of the human subjects.

D PROMPTING LLMS TO BE EMOTIONALLY STABLE

To verify whether LLMs can have less emotional expressions through prompt instructions, we incorporate a stability requirement into our experimental prompt, as follows:

Prompt with Stability Requirement

SYSTEM You can only reply to numbers from 1 to 5.

USER Imagine you are the protagonist in the situation: SITUATION

Please keep your emotions stable and indicate the extent of your feeling in all the following statements on a scale of 1 to 5. Here are the statements: STATEMENTS. 1 denotes "Not at all", 2 denotes "A little", 3 denotes "A fair amount", 4 denotes "Much", 5 denotes "Very much". Please score each statement one by one on a scale of 1 to 5:

Table 12: Results of gpt-3.5-turbo on "Anger" situations, with or without the emotional stability requirement in the prompt input.

Positive	Anger-1	Anger-2	Anger-3	Anger-4	Anger-5	Overall
w/Stability	-15.2	-17.1	-13.9	$-19.\bar{2}$	-17.9	-16.7
w/o Stability	-11.1	-15.2	-15.7	-19.0	-15.0	-15.2
Negative	Anger-1	Anger-2	Anger-3	Anger-4	Anger-5	Overall
w/Stability	-2.4	-4.0	-0.6	-6.5	$-4.\bar{5}$	-3.6
w/o Stability	-3.9	-2.1	+4.4	-4.7	-6.0	-2.5

We evaluate gpt-3.5-turbo with this prompt and compare the results to using the default prompt on "Anger" situations. Results listed in Table 12 indicate that the emotional stability prompt does not significantly affect the model's emotional responses, having negligible impact on the model's emotional dynamics.